REPORT S2-L03-RR-1

Analytical Procedures for Determining the Impacts of Reliability Mitigation Strategies

SHRP2 RELIABILITY RESEARCH

SHRP 2
STRATEGIC HIGHWAY RESEARCH PROGRAM
Accelerating solutions for highway safety, renewal, reliability, and capacity

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The Second

STRATEGIC HIGHWAY RESEARCH PROGRAM

SHRP 2 REPORT S2-L03-RR-1

Analytical Procedures for Determining the Impacts of Reliability Mitigation Strategies

CAMBRIDGE SYSTEMATICS, INC.

with

TEXAS A&M TRANSPORTATION INSTITUTE
UNIVERSITY OF WASHINGTON
DOWLING ASSOCIATES
STREET SMARTS
HERB LEVINSON
HESHAM RAKHA

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The need for SHRP 2 was identified in *TRB Special Report 260: Strategic Highway Research: Saving Lives, Reducing Congestion, Improving Quality of Life,* published in 2001 and based on a study sponsored by Congress through the Transportation Equity Act for the 21st Century (TEA-21). SHRP 2, modeled after the first Strategic Highway Research Program, is a focused, time-constrained, management-driven program designed to complement existing highway research programs. SHRP 2 focuses on applied research in four areas: Safety, to prevent or reduce the severity of highway crashes by understanding driver behavior; Renewal, to address the aging infrastructure through rapid design and construction methods that cause minimal disruptions and produce lasting facilities; Reliability, to reduce congestion through incident reduction, management, response, and mitigation; and Capacity, to integrate mobility, economic, environmental, and community needs in the planning and designing of new transportation capacity.

SHRP 2 was authorized in August 2005 as part of the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU). The program is managed by the Transportation Research Board (TRB) on behalf of the National Research Council (NRC). SHRP 2 is conducted under a memorandum of understanding among the American Association of State Highway and Transportation Officials (AASHTO), the Federal Highway Administration (FHWA), and the National Academy of Sciences, parent organization of TRB and NRC. The program provides for competitive, merit-based selection of research contractors; independent research project oversight; and dissemination of research results.

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SHRP 2 STAFF

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The research described in this report was performed by Cambridge Systematics, Inc., supported by the Texas Transportation Institute, Dowling Associates, the University of Washington, Street Smarts, Herb Levinson, and Hesham Rakha. Richard Margiotta, Cambridge Systematics, Inc., was the principal investigator, and Tim Lomax, Texas Transportation Institute, was the co-principal investigator. The other authors of this report are Mark Hallenbeck, Rick Dowling, Alex Skabardonis, and Shawn Turner. The authors acknowledge the contributions to this research from Weimin Huang, Kenny Voorhies, and Shawn Pope of Cambridge Systematics; Teresa Qu of the Texas Transportation Institute; David Reinke and Senanu Ashiabor of Dowling Associates; Herb Levinson; and Hesham Rakha.

FOREWORD

William Hyman, *SHRP 2 Senior Program Officer, Reliability*

Reliability of transport, especially the ability to reach a destination within a certain amount of time, is a regular concern of travelers and shippers. The definition of reliability used in this research is how travel time varies over time. The variability can apply to the travel times observed over a road segment during a specific time slice (e.g., 3 to 6 p.m.) over a fairly long period of time, say a year. The variability can also pertain to the travel times of repeated trips made by a person or a truck between a given origin and destination. Agencies are increasingly aware of the issue of reliability, although the transportation industry as a whole as yet lacks a firm understanding of the causes and solutions to failures of reliability. As the agenda for the SHRP 2 research on travel time reliability took shape, it became clear a fundamental study was required to be able to talk about travel time reliability in a meaningful way.

Basic reliability issues are addressed in this study, which is not concerned with average travel times, but rather ways of describing travel times that reflect the uncertainty in the amount of time required to travel between two points. Some of the uncertainty is systematic, such as the normal ebb and flow of traffic within the course of a work day or season of the year. Congestion associated with this systematic uncertainty is called recurrent. Congestion due to unpredictable or unexpected events is called nonrecurrent. Sources of nonrecurrent congestion include incidents (e.g., accidents), work zones, weather, special events, problems with traffic control devices, and unexpected fluctuations in demand.

If every travel time observed over a highway section for a year is plotted, a distribution of travel time is obtained. This plotted distribution is the picture of travel time variability. Such distributions are the focus of this research, especially the degree to which recurring and nonrecurring congestion influence the nature of the distribution. This research shows how to derive performance measures from such distributions and recommends a set for use by managers, planners, and systems operators. The research reexamines the composition of the congestion puzzle in terms of the fractions attributable to recurrent and various sources of nonrecurrent congestion. The project team used before-and-after studies to determine the effectiveness of different types of actions, both operational and capacity improvements, in improving reliability. This study also examined the effect of the downturn of the economy on travel time reliability. Finally, this research resulted in two types of models that can be used to estimate or predict travel time reliability. These models have broad applicability to planning, programming, and systems management and operations.

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Executive Summary

Project Background

The fundamental objective of SHRP 2 Project L03 was to develop predictive relationships between highway improvements and travel time reliability. In other words, how can the effect of an improvement on reliability be predicted? Alternatively, how can reliability be characterized as a function of highway, traffic, and operating conditions? A variety of challenging issues have been confronted in addressing this objective.

Significance of Travel Time Reliability in Transportation System Performance

Reliability is important to travelers and transportation practitioners for a variety of reasons:

- From an economic perspective, reliability is highly important because travelers must either budget extra time for their trips to avoid arriving late or suffer the consequences of being late. This extra time has value beyond the average travel time used in traditional economic analyses. Recent work has documented that reliability has value to travelers and influences their behavior (*1*, *2*).
- Because of the extra time required in planning trips and uncertainty about the amount of time actually needed for a trip, reliability influences decisions about where, when, and how travel is made.
- Transportation planners and operators need to include the extra economic cost of unreliable travel on users in project planning, programming, and selection processes. This is particularly true of strategies that deal directly with roadway events (e.g., incidents). In the past, most assessments of these types of strategies have missed this important aspect of travel.

New Concept of Travel Time Reliability

Although use of travel time–based performance measures in planning and operations applications has taken on greater significance in the past few years, *travel time reliability*—how consistent (or variable) travel conditions are from day to day—is a relatively new concept to which much of the transportation profession has had only limited exposure. Congestion has been growing nationwide, and planners increasingly have become involved in short-term activities such as performance monitoring, as well as operations and management strategies. These activities have been elevated in importance by transportation agencies in order to be responsive to the demands of the public and state legislatures. Anecdotal reports and technical studies indicate that average congestion levels have grown, and continue to grow, in our cities.

However, talking about typical or average conditions in a transportation system that experiences wide performance fluctuations tells only part of the story. The notion of travel time reliability has taken on increasing importance as variation in travel times is now understood as a separate component of the public's and business sector's frustration with congestion problems. Reliability is a major part of system performance and of travelers' perceptions of performance. It has not been widely used to describe performance, but increasingly agencies are recognizing its value in assessing their own performance and in communicating performance to the public.

Defining Travel Time Reliability

The Future Strategic Highway Research Program (F-SHRP) defined highway travel time variability as synonymous with reliability:

> . . . from a practical standpoint, *travel-time reliability can be defined in terms of how travel times vary over time* (e.g., hour-to-hour, day-to-day). This concept of variability can be extended to any other travel-time-based metrics such as average speeds and delay. For the purpose of this study, travel time variability and reliability are used interchangeably. (*3*)

A slightly different view of reliability is based on the notion of the probability of *failure*, which is often used to characterize industrial processes. With this view, failure is defined in terms of travel times, and the number of times a given threshold is not achieved or exceeded can be counted.

In recent years, some non-U.S. reliability research has defined the probability of failure in terms of traffic flow breakdown. A corollary concept, *vulnerability*, is a measure of how vulnerable the network is to breakdown conditions. This concept can be applied at the link or network level.

Understanding Travel Time Reliability

To understand travel time reliability, it is essential to understand the factors that cause travel times to be unreliable. L03 research built on what the original F-SHRP Reliability Research Plan identified as seven sources of congestion that cause travel times to be unreliable and contribute to total congestion: incidents, inclement weather, work zones, special events, traffic control device timing, demand fluctuations, and inadequate base capacity. These categories were developed to move away from the more general recurring–nonrecurring nomenclature.

Operational Strategies and Capacity Expansion

This project studied operational strategies and capacity expansion projects, both of which were expected to affect reliability. Many operational strategies are aimed specifically at the factors that cause unreliable travel (e.g., incident management, work zone management). It is generally expected that adding capacity will affect reliability.

Travel Time Measurements

Travel time is the starting point for sound congestion measurement because it reflects the actual experience of system users. When measured directly, it is independent of theoretical capacity concerns, such as what happens in oversaturated conditions. Further, once travel time is obtained, a whole family of additional measures can be created using basic information (e.g., volume, free-flow speed) about the system. Delay is one example of the metrics that naturally derives from travel time measurements.

Project Approach

Data Collection

The research team undertook an empirical approach based on their familiarity with the data used to characterize congestion and reliability and the sufficient quality and amount of data available. Reliability can only be characterized by a long history of travel times, and the use of

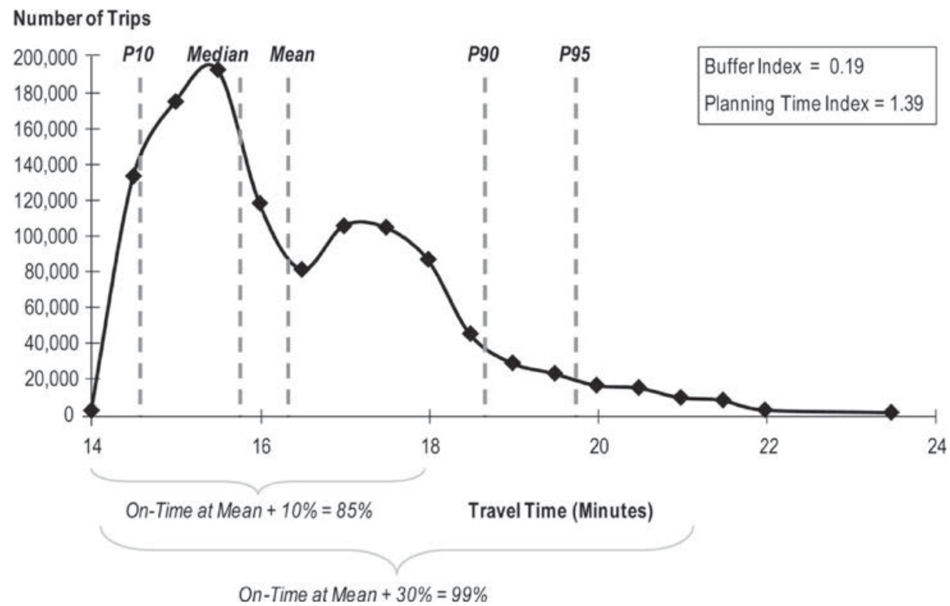

Figure ES.1. Reliability is defined by how travel times vary.

automated equipment is the only feasible method of data collection. Because of the cost of collecting new data, the team relied on data already being collected by transportation agencies, primarily in support of operations programs.

Figure ES.1 shows the distribution of travel times along a section of highway. This distribution, and the statistics that describe it, are the basis for research. The statistics superimposed on the distribution in the figure represent the reliability metrics used in the research. P10, P90, and P95 are the 10th, 90th, and 95th percentiles, respectively, of the distribution. The remaining metrics are defined elsewhere in this report.

A very large data set (Figure ES.2), most of which covered urban freeways, was assembled from various traffic management centers (Tables ES.1 through ES.3). A separate data set for urban freeways was compiled for the Seattle area for the congestion by source analysis.

Data on the basic characteristics of incidents were available from three sources and were used to varying degrees, depending on the team's assessment of the data sources for each city's situation. Incident data were available from a private vendor, Traffic.com. Incident and event data were provided to the project team by Traffic.com at no cost from their traveler information management system. This system provided a standardized source of information for traffic incidents,

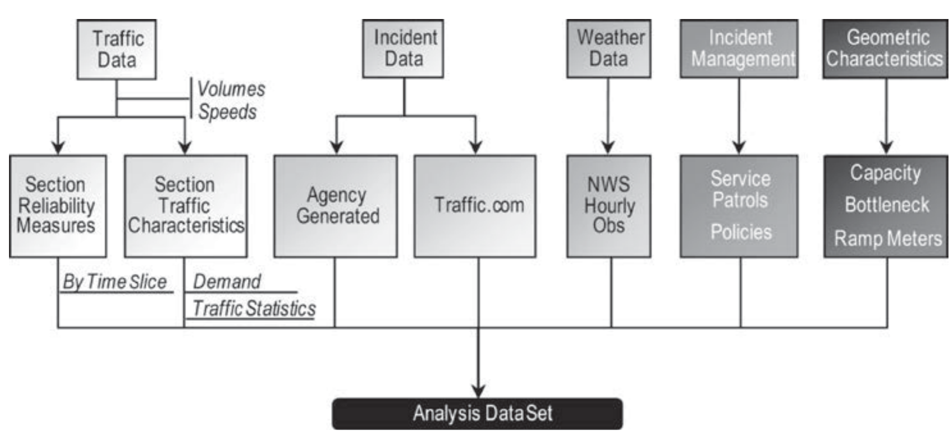

Figure ES.2. The analysis data set fused data from a variety of sources.

Table ES.1. Urban Freeway Study Section Summary

City	Number of Directional Study Sections	Total Directional Mileage
Houston, Texas	13	58.80
Minneapolis, Minnesota	16	62.63
Los Angeles, California	3	50.27
San Francisco Bay Area, California	4	19.98
San Diego, California	6	28.04
Atlanta, Georgia	10	54.66
Jacksonville, Florida	8	17.71
Total	**60**	**292.09**

events, scheduled and unscheduled construction, and other events that could affect traffic conditions (e.g., severe weather or transit delays). Weather data consisting of hourly weather observations (e.g., precipitation, temperature, wind, fog) at multiple points within the urban areas were obtained from the National Climatic Data Center of the National Oceanic and Atmospheric Administration. Geometric data were obtained from satellite imagery (lane configurations) and the 2007 Highway Performance Monitoring data. Operating and improvement data were obtained directly from state departments of transportation. The most important data in this category were those elements related to calculating capacity for each individual link.

Table ES.2. Signalized Arterial Study Sections

City	Arterial	From	To	Length (mi)	Travel Time Data	
					Data Technology	Period
Orlando, Florida	Section 1: SR 50 eastbound	Florida Turnpike	SR 408 West	6.85	Tag-based probe	March 2008+
	Section 2: SR 50 westbound	SR 408 West	Florida Turnpike	6.85	Tag-based probe	March 2008+
	Section 3: U.S. 441 northbound	SR 417	SR 408	10.67	Tag-based probe	March 2008+
	Section 4: U.S. 441 southbound	SR 408	SR 417	10.67	Tag-based probe	March 2008+
	Section 5: U.S. 441 northbound	SR 408	N. John Young Parkway	4.35	Tag-based probe	March 2008+
	Section 6: U.S. 441 southbound	N. John Young Parkway	SR 408	4.35	Tag-based probe	March 2008+
Los Angeles, California	Santa Monica Boulevard	I-405	N. Gardner Street	6.9	GPS probe (Inrix)	2006–2007
Phoenix, Arizona	E. Camelback Road	44th Street	Highway 51	4.2	GPS probe (Inrix)	2006–2007
Minneapolis, Minnesota	Washington Avenue	County Highway 153	U.S. 65	3.4	GPS probe (Inrix)	2006–2007
Miami, Florida	U.S. 1	17th Avenue	Le Jeune Road	3.8	GPS probe (Inrix)	2006–2007
Houston, Texas	Westheimer Road	W. Sam Houston	I-610	6.9	GPS probe (Inrix)	2006–2007

Note: GPS = global positioning system. Probe tag technology provides direct estimates of travel time over the segment.
Inrix-provided data are supplied as speed estimates by link (approximately 0.5- to 1-mile long). Only the Orlando sections were used in the analysis because of sample size limitations on the other sections.

Table ES.3. Rural Freeway Study Sections

State	Route	From	To	Length (mi)	Travel Time Data	
					Data Technology	Period
Texas	I-45	Exit 213, Navarro County	Exit 267, Ellis County	54.1	GPS probe (Inrix)	2006–2007
South Carolina	I-95	South Carolina–Georgia border	SR 68, Hampton County	38.2	GPS probe (Inrix)	2006–2007

Analysis Approach

The analysis was based on a conceptual model previously developed by members of the research team (Figure ES.3). As the model indicates, the sources of congestion interact to produce total congestion. Reliability, an aspect of total congestion, is greatly influenced by the complex interactions of traffic demand, physical capacity, and roadway events.

The analysis proceeded with four tracks:

1. Exploratory analysis, which was used to improve the understanding of reliability and establish many of the research parameters;
2. Before-and-after studies on selected study sections that resulted in empirical measurements of the change in reliability;
3. Cross-sectional statistical modeling, which was used to develop statistically based predictive models of reliability as a function of traffic, operating, and geometric conditions. The cross-sectional modeling was extremely important because it allowed a study of all of the possible improvement types in the field using a before-and-after approach; and
4. Congestion by source analysis, which was a microlevel approach to separating daily congestion into its component sources.

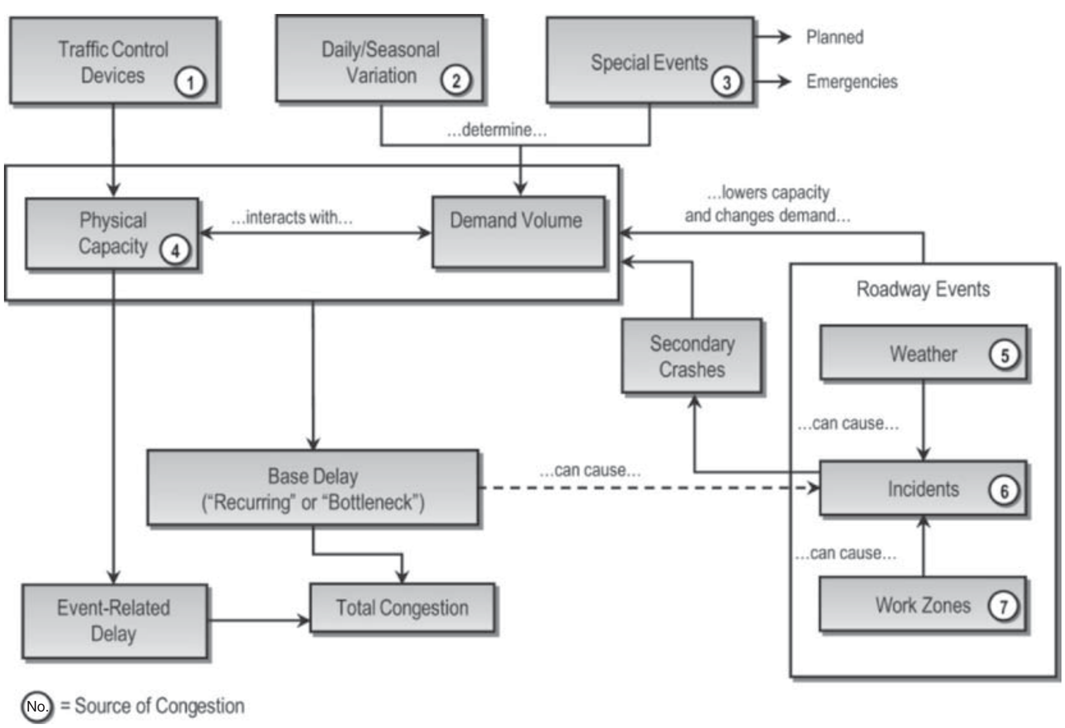

Figure ES.3. A model of congestion and its sources.

Findings

Data Set Compilation and Usage

The large and comprehensive data set included many levels of aggregation and summarization. Traffic data from urban freeways comprised the largest portion of the data set and included the original measurements from roadway detectors (5-minute intervals by lane), numbering in the hundreds of millions of records. The traffic data were also summarized at several spatial and temporal aggregation levels. The most-summarized portion of the data set was the one used for the cross-sectional statistical analysis: every record is an annual summary of traffic and reliability characteristics, with annual event characteristics and roadway features merged into it. The data processing included new procedures specifically created by the research team for the project.

Exploratory Analyses

A large variety of exploratory analyses were undertaken before the main analyses to test assumptions, develop data processing methods, and more thoroughly understand the manifestation and ramifications of reliability.

Recommended Reliability Metrics

The Travel Time Index (TTI) is the ratio of the actual travel time to the ideal or free-flow travel time. Based on empirical tests, it was found that the performance metrics defined in the early stages of the research were sensitive to the effects of improvements. The 95th percentile TTI may be too extreme a value to be influenced significantly by operations strategies, but the 80th percentile was more sensitive to these improvements. As a result, the 80th percentile TTI was added to the list of reliability performance metrics for the remainder of the research. The final set of reliability metrics, which also are appropriate for general practice, appears in Table ES.4.

Travel Time Distributions

Developing travel time distributions is the starting point for defining reliability metrics. Travel time distributions also allow for visualization of general congestion and reliability patterns for a

Table ES.4. Recommended Reliability Metrics

Reliability Performance Metric	Definition	Units
Buffer Index	Difference between 95th percentile TTI and average travel time, normalized by average travel time. Difference between 95th percentile TTI and median travel time (MTT), normalized by MTT.	%
Failure and on-time measures	Percentage of trips with travel times <1.1 MTT and <1.25 MTT. Percentage of trips with space mean speed less than 50, 45, and 30 mph.	%
Planning Time Index	95th percentile TTI.	None
80th Percentile TTI	Self-explanatory.	None
Skew statistic	(90th percentile TTI – median)/(median – 10th percentile TTI).	None
Misery Index (modified)	Average of highest 5% of travel times divided by free-flow travel time.	None

highway section or trip. An examination of the distributions from the research study section reveals several characteristics:

- The shape of the travel time distribution for congested peak times (nonholiday weekdays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad shoulder of travel times decreases as the congestion level decreases.
- Likewise, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, the highest travel times occur during the peaks.
- Despite the fact that peaks have been defined, a number of trips still occur at close to free flow; there are more of these trips in the peak period than in the peak hour (see discussion below of peak period and peak hour). This is probably because peak times actually shift slightly from day to day, as traffic demand can be shifted by events.

Data Requirements for Establishing Reliability

Because reliability is defined by the variability of travel conditions (travel time), it must be measured over a substantial portion of time to allow all of the influences of random events to be exerted. Tests showed that an absolute minimum of 6 months of data is required to establish reliability within a small error rate in areas where winter weather is not a major factor. A full year of data is preferred.

Supplemental Reliability Metric

The Atlanta study (detailed in Chapter 5) raised doubts about the use of the Buffer Index as the primary metric for tracking trends in reliability. The problem comes from how the Buffer Index is calculated: it is the buffer time (difference between the 95th percentile and the mean) normalized by the mean.

The Buffer Index is considered to be too erratic and unstable for use as the primary reliability metric for tracking performance trends or for studying the effects of improvements. However, as a secondary metric, it provides useful information; rather than being discarded, it should be included in a suite of reliability performance metrics.

Defining Peak Hour and Peak Period

Most studies of reliability and congestion have defined fixed time periods for the peak hour and peak period. However, the research team decided that the most appropriate method would be to define peak hour and peak period specifically for each study section. The team used a definition based on the most typical start and end times of continuous congestion. The resulting time slices were reviewed against local anecdotal knowledge and required very little adjustment.

Estimating Demand in Oversaturated Conditions on Freeways

Because the study took an empirical approach, the team had to deal with the thorny issue of how to measure demand given that measured volumes under congested flow are actually less than capacity on freeways. A method for assigning the demand stored in queues during periods of flow breakdown was developed and used, particularly in defining the demand-to-capacity ratio for the statistical modeling.

Reliability Breakpoints on Freeways

It was shown that travel time reliability on a freeway is not a function of counted traffic volumes until a breakpoint volume is reached. Once the breakpoint volume is exceeded, the decrease in travel time reliability (increase in the variance) is extreme and abrupt enough to suggest it is a vertical function, with a nonsingular relationship to further volume increases. The breakpoint volume varies significantly between facilities and even within the same freeway facility (by location and direction of travel on the same facility). The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed according to the method in the *Highway Capacity Manual* (HCM).

But this peaking effect does not entirely explain the difference. The breakpoint volume is significantly lower than the theoretical capacity partly because most freeway sections are upstream of a bottleneck and, thus, are affected by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, traffic-influencing events (especially incidents) effectively lower capacity when they occur, and over time they cause reliability to degrade. This effect manifests itself in lower breakpoint volumes than capacity related strictly to physical features. Finally, even for bottlenecks, the data suggest that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

Sustainable Service Rates on Freeways

Just as travel times vary over time, capacity is not a fixed value but also varies over time. The same factors that influence reliability affect capacity variability. The research did not specifically tease out all the factors, but they all are imbedded in the final capacity distributions. The team developed a large set of capacity distributions that look roughly like travel time distributions in reverse: the tail of the distribution is skewed to the left (lower capacity values) rather than to the right. Because these distributions were developed from year-long data measurements, they include the effect of the influencing factors, resulting in capacity values that could be used in a stochastic framework to model congestion and reliability.

Travel Time Distributions on Urban Freeways, Signalized Arterials, and Rural Freeways

An analysis of travel time distributions for different time slices and congested levels revealed the following characteristics:

- All distributions feature a tail that is skewed to the right (i.e., higher travel times). Most of these abnormally high travel times can be attributed to one or more of the sources of congestion; that is, they occur in the presence of an event(s) and/or high demand;
- Uncongested periods are characterized by a sharp peak of travel time frequencies near the free-flow speed;
- When congestion dominates the time slice (e.g., peak hour, peak period), the travel time distribution becomes more broad and less peaked;
- Travel time distributions on signalized arterials are uniformly broad in shape, even for relatively low levels of congestion; and
- As trips become longer, the travel time distributions assume the typical uncongested shape.

Vulnerability to Flow Breakdown

Examination of the 5-minute data at individual stations (groups of detectors in a direction on a highway segment) reveals that just 20 to 45 minutes before the start of what is considered the normal peak period, there is an upsurge in the 95th percentile TTIs. This upsurge begins before the uptick in average travel times and indicates that this window of time is vulnerable to flow breakdown. These windows are extremely important for operators to focus on, as breakdowns during this time will strongly influence the duration and severity of the peak.

Reliability of Urban Trips Based on the Reliability of Links

For extended travel on urban freeways (trips of 10 to 12 miles in length), the reliability of the entire trip can be predicted as a function of the reliability of the links that comprise the trip. Although not specifically tested, it should be possible to construct trip reliability for trips that include other types of highways in addition to freeways, subject to the issue of time dependency for long trips.

Before-and-After Studies on Selected Study Sections

The primary goal of the research was to develop relationships for predicting the change in reliability due to improvements. The best way to accomplish this goal was with controlled before-and-after studies. However, such analyses offer a substantial challenge because of their data requirements: to establish reliability empirically, at least 6 to 12 months of data are required. The preferred data collection period is 12 months, including a long period of continuously collected data before and after the improvement. Instead of designing traditional before-and-after experiments, the team concentrated on collecting continuous traffic data from areas with quality data, interesting congestion, and good records of event data. The team identified 17 cases of improvements that coincided with the identified data, although the types of improvements were somewhat limited:

- Ramp meters—four;
- Freeway service patrol implementation—two;
- Bottleneck improvement—three;
- General capacity increases—five;
- Aggressive incident clearance program—two; and
- High-occupancy toll (HOT) lane conversion—one.

The analysis produced reliability adjustment factors that can be applied to the various improvements (Table ES.5).

A global finding from the before-and-after analyses is that all forms of improvements, including capacity expansion, affect both average congestion and reliability in a positive way (i.e., average congestion is reduced and reliability is improved). Conceptually, this makes sense: one of the seven sources of congestion and reliability identified earlier was the amount of base capacity. All things being equal, more capacity (in relation to demand) means that the roadway is able to absorb the effects of some events that would otherwise cause disruption. The size of this effect was greater than originally anticipated; that is, a large part of the benefits of capacity expansion projects greatly contributes to the value of reliability.

Cross-Sectional Statistical Modeling

Because only a limited number of before-and-after studies were possible, much of the effort for the study went into the creation of a cross-sectional data set from which statistical models could be developed. The final analysis data set for the statistical modeling is highly aggregated: each record represents reliability, traffic, and event data summarized for a section for a year, and reliability is measured as the variability in travel times over the course of a year. As such, the cross-sectional model is a macroscale model; it does not seek to predict the travel time for a particular set of circumstances, and it is not appropriate for real-time travel time prediction. For example, it does not suggest an expected travel time if incident and demand characteristics for a given day are known. Rather, it seeks to predict the overall travel time characteristics of a highway section in terms of both mean and reliability performance. It is appropriate for adaptation to many existing models and applications that seek similar predictions, and it can serve as the basis for conducting a cost–benefit analysis.

Table ES.5. Summary of Urban Freeway Before-and-After Studies

Case No.	Urban Area	Highway Covered	Improvement	Reliability Impacts (Peak Period)
1	Los Angeles	I-210	Ramp metering: design, field implementation, and evaluation of new advanced on-ramp control algorithms on westbound I-210.	Slight increases in average travel time and Planning Time Index (PTI) were observed. However, subsequent to this evaluation, the algorithms have been adjusted.
2	San Francisco Bay Area	I-580	Ramp metering.	22% reduction in average travel time. 20% reduction in PTI.
3	Seattle	SR 520	Ramp metering.	11% reduction in average travel time. 12% reduction in PTI.
4	Atlanta	I-285, Northern Arc	Ramp metering.	9% reduction in average travel time. 7% reduction in PTI. 3% increase in sustainable service rate.
5	Atlanta	All freeways inside beltway perimeter	Incident management: incentive program for reducing large-truck crash incident duration (90 minutes).	13% reduction in large-truck crash incident duration. 9% reduction in lane hours lost per large-truck crash.
6	Los Angeles	I-710	Incident management: evaluation of pilot project to deploy towing service for big-rig tractor trailers.	10% reduction in average travel time. 20% reduction in PTI.
7	San Diego	I-8	Incident management: expansion of the existing Freeway Service Patrol Beat-7 on I-8.	3% reduction in average travel time. 4% reduction in PTI.
8	San Diego	SR 52	Incident management: expansion of the existing Freeway Service Patrol.	20% reduction in average travel time. 10% reduction in PTI.
9	Minneapolis–St. Paul	I-94	Capacity expansion: add third lane in each direction.	43% reduction in average travel time. 46% reduction in PTI.
10	Minneapolis–St. Paul	I-494	Capacity expansion: add third lane in each direction.	31% reduction in average travel time. 16% reduction in PTI.
11	Minneapolis–St. Paul	I-394	Capacity expansion: add auxiliary lanes westbound.	35% reduction in average travel time. 38% reduction in PTI.
12	Minneapolis–St. Paul	Highway 169	Capacity expansion: convert signalized intersections to diamond interchanges.	16% increase in average travel time. 11% reduction in PTI.
13	Minneapolis–St. Paul	Highway 100	Capacity expansion: add third lane northbound; add auxiliary lane southbound; convert Highway 7 interchange from a clover leaf to a folded diamond.	20% reduction in average travel time. 30% increase in PTI.
14	Seattle	I-405 southbound	Capacity expansion: addition of one general-purpose lane.	11% reduction in average travel time. 11% reduction in PTI.
15	Seattle	I-405 northbound	Capacity expansion: addition of one general-purpose lane.	42% reduction in average travel time. 35% reduction in PTI.
16	Seattle	I-405/SR 167 interchange	Capacity expansion: grade separation ramp connecting southbound I-405 off-ramp with southbound SR 167 on-ramp.	20% reduction in average travel time. 23% reduction in PTI.
17	Minneapolis–St. Paul	I-394	HOT lane conversion.	8% reduction in average travel time. 30% reduction in PTI.

Note: Long study segment = 16 miles; study section influenced by downstream bottleneck.

Two model forms were developed: simple and complex. The simple model form relates all the reliability metrics to the mean TTI for the three highway types studied (urban freeways, rural freeways, and signalized arterials). These relationships are convenient for many applications that produce mean travel time–based measures as output. Because the mean TTI developed from the research data included the effects of all the possible influences of congestion, which produced a mean value greater than model results that usually are for typical (nonextreme) conditions, an adjustment factor was developed to convert model output to the overall mean TTI so that the relationships could be applied. An example of the strong relationship between mean TTI and 95th percentile TTI is shown in Figure ES.4.

A more detailed model form was developed that related reliability measures to the factors that influence reliability. A series of statistical predictive models was developed that related the reliability metrics over highway sections (multiple links, usually 4 to 5 miles long) to

- The critical demand-to-capacity ratio (maximum from the individual links);
- Lane hours lost due to incidents and work zones combined (annual); and
- Number of hours during which rainfall was ≥0.05 inch (annual).

Models were developed for the peak hour, peak period, midday, and weekday time periods. Guidance was developed from readily available data on how to estimate demand, capacity, and lane hours lost. Guidance was also provided on how improvements affect changes in the models' independent variables. The model structure is flexible and can easily incorporate new research on the effects of transportation improvements on reliability.

Congestion by Source

An assignment of congestion causality was made for the measured delay in the Seattle data (detailed in Chapter 5). Taken at face value, these data support the common thinking that incidents and crashes cause between 40% and 60% of all delay. In reality, a considerable portion of the delay associated with incidents and crashes is caused by large traffic volumes. Therefore, the amount of delay caused by incidents is actually less than can be reasonably assigned by simply observing the occurrence of events. Numerous examples in the analysis data set of significant crashes and other incidents caused little or no congestion because of when they occurred. Without sufficient volume, an incident causes no measurable change in delay.

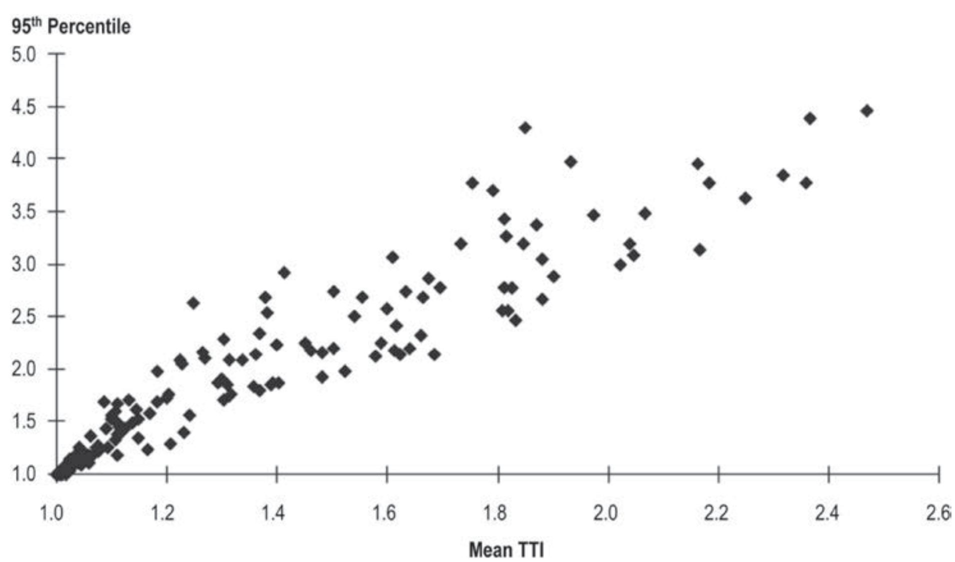

Figure ES.4. Section-level relationship for mean TTI and 95th percentile.

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse as a result of the interwoven effects of incidents, bad weather, and traffic volumes on travel times. In addition, all types of disruptions to normal roadway performance (rain, crashes, and noncrash incidents) cause congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times. Incidents and other disruptions also can cause congestion to form during times that are normally free from congestion. However, congestion only forms when the disruption lowers functional capacity below traffic demand. Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion. Disruptions significantly increase the delay that the basic volume condition creates.

The fact that traffic volume is the basis of congestion also affects how various traffic disruptions affect travel patterns. Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions have a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite is true.

Analysis of 42 roadway segments in the Seattle area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions plays a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption varies considerably from corridor to corridor.

In peak periods, incidents add only a marginal percentage increase to total delay, but they shift when and where those delays occur, as well as who suffers from those delays. That is, many incidents shift where a normally occurring bottleneck occurs, freeing up some roadway sections, while causing others to suffer major increases in congestion. But taken as a total, if a roadway section is normally congested, the added delay from incidents is modest (at least in Seattle) compared with the daily delay from simply too many vehicles for the available physical capacity.

In congested urban areas, traffic incidents more often cause unreliable traffic patterns than increases in total delay. While the total delay value does goes up, the big change is often the shift in *who* gets delayed. For an individual severe incident, many travelers may value the extra (unplanned) delay highly, and are more likely to remember these extreme cases. However, some of that (total) delay is offset by other travelers who reach their destination early because their trip is downstream of the incident-caused bottleneck, and consequently volume on their downstream trip segment has probably been metered by the upstream bottleneck.

Significance of Demand for Reliability Estimation

A major finding was that demand (volume) is an extremely important determinant of reliability, especially relative to capacity. Demand's interaction with physical capacity is the starting point for determining congestion. The research team initially postulated that the effect of most events would be determined by the level of demand under which they occurred. For example, if an incident or work zone blocked a traffic lane, the impact would only be felt if volumes were high enough to be affected by the lost capacity. Although demand was not expected to have a strong effect, it emerged as a significant factor throughout the various analyses.

The influence of demand is probably related not only to the sheer volume of traffic but also the volume's characteristics. As volumes approach theoretical capacity, traffic flow becomes unstable and increasingly susceptible to breakdown from even small changes. These small changes can occur at a point substantially less than theoretical capacity; when they occur near potential bottleneck areas such as on-ramps, weaving areas, and lane drops, the team postulates that their effect is enhanced.

In addition to variations in demand as a source of unreliable travel times, evidence exists that physical capacity also varies. The work of Brilon and preliminary research conducted by other

SHRP 2 contractors suggest that capacity varies even in the absence of disruptions (*4*). The team postulates that fluctuations in traffic conditions at a microscale are the most likely causal factors for variations in capacity.

There are several implications of the findings that demand and capacity strongly influence travel time reliability:

- Capacity additions and demand reductions will improve congestion on nearly all days. Strategies geared to disruptions (e.g., incident management) will only affect congestion when those disruptions appear;
- Demand management strategies (e.g., pricing) also will lead to improvements in reliability; and
- Accounting for volumes in relation to available capacity can provide a tool for efficiently allocating operations strategies, particularly incident management.

Reliability As a Feature of Congestion

The intertwined relationship between demand, capacity, and disruptions documented in the L03 research led to another major conclusion: reliability is a feature or attribute of congestion, not a distinct phenomenon. Any influence on congestion that leads to unreliable travel reliability cannot be considered in isolation. Reliability has generally been considered to be related primarily to disruptions and the operational treatments aimed at those disruptions. However, analysis showed that a substantial amount of variability in travel times exists for recurring (e.g., bottleneck-related) conditions. Therefore, the most inclusive view of travel time reliability sees it as part of overall congestion. Just as congestion can be defined by extent and severity, it can also be defined by how it varies over time. Operational treatments are effective in dealing with unreliable travel times, but so are other congestion-relief measures.

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CHAPTER 1

Introduction

The fundamental objective of this project was to develop predictive relationships between highway improvements and travel time reliability. In other words, how can the effect of an improvement on reliability be predicted? Alternatively, how can reliability be characterized as a function of highway, traffic, and operating conditions? A variety of challenging issues were confronted in addressing this objective.

Significance of Travel Time Reliability on Transportation System Performance

Reliability is important to travelers and transportation practitioners for a variety of reasons:

- From an economic perspective, reliability is highly important because travelers must either build in extra time to their trips to avoid arriving late or suffer the consequences of being late. This extra time has value beyond the average travel time used in traditional economic analyses. Recent work has documented that reliability has value to travelers and influences their behavior (*1, 2*);
- Because of the extra time required in planning trips and the uncertainty about how much time will be required for a trip, reliability influences decisions about where, when, and how travel is made; and
- Transportation planners and operators need to include the extra economic cost of unreliable travel to users in project planning, programming, and selection processes. This is particularly true of strategies that deal directly with roadway events (e.g., incidents). In the past, most assessments of these types of strategies have missed this important aspect of travel.

New Concept of Travel Time Reliability

Although use of travel time–based performance measures in planning and operations applications has taken on greater significance in the past few years, *travel time reliability*—how consistent (or variable) travel conditions are from day to day—is a relatively new concept to which much of the transportation profession has had only limited exposure. Congestion has been growing nationwide, and planners increasingly have become involved in short-term activities such as performance monitoring, as well as operations and management strategies. These activities have been elevated in importance by transportation agencies in order to be responsive to the demands of the public and state legislatures. Anecdotal reports and technical studies indicate that average congestion levels have grown, and continue to grow, in our cities. In a 2005 report, Travel Time Index (TTI) researchers found that congestion levels in 85 of the largest metropolitan areas have grown in almost every year from 1982 to 2003 for all population groups (*3*).

Recently, anecdotal reports and empirical information have suggested that congestion levels have eased; TTI researchers noted in the 2007 *Urban Mobility Report* that

> Congestion, by every measure, has increased substantially over the 25 years covered in this report. The most recent two years of the report, however, have seen slower growth or even a decline in congestion. Delay per traveler—the number of hours of extra travel time that commuters spend during rush hours—was 1.3 hours lower in 2007 than 2005. This change would be more hopeful if it was associated with something other than rising fuel prices (which occurred for a short time in 2005 and 2006 before the sustained increase in 2007 and 2008) and a slowing economy. This same kind of slow growth/decline over a few years occurred in the early 1990s when spending and growth in the high-tech and defense sectors of

> the economy declined dramatically. The decline means congestion is near the levels recorded in 2003, not exactly a year remembered for trouble-free commuting. (*4*)

However, talking about typical or average conditions in a transportation system that experiences wide fluctuations in performance tells only part of the story. Travel time reliability has taken on increasing importance. Variation in travel times now is understood as a separate component of the public's and business sector's frustration with congestion problems. Reliability is a major part of system performance and of travelers' perceptions of performance. Although reliability has not been widely used to describe performance, agencies are increasingly recognizing its value in assessing their own performance and in communicating performance to the public.

Defining Travel Time Reliability

In terms of highway travel, the Reliability Research Program of the Future Strategic Highway Research Program (F-SHRP) defined highway travel time variability as synonymous with reliability:

> . . . from a practical standpoint, *travel-time reliability can be defined in terms of how travel times vary over time* (e.g., hour-to-hour, day-to-day). This concept of variability can be extended to any other travel-time-based metrics such as average speeds and delay. For the purpose of this study, travel-time variability and reliability are used interchangeably. (*5*)

A slightly different view of reliability is based on the notion of a probability or the occurrence of failure often used to characterize industrial processes. With this view, it is necessary to define *failure* in terms of travel times; in other words, a threshold must be established, and the number of times the threshold is not achieved or exceeded can be counted. These types of measures are similar to *on-time performance,* since performance is measured relative to a preestablished threshold. The only difference is that failure is defined in terms of how many times the travel time threshold is exceeded, but on-time performance measures how many times the threshold is not exceeded.

The authors of NCHRP Project 3-68 note that the definitions for variability and failure have an underlying theme: they both imply that a history or distribution of travel times exists (*6*). The history over which travel times are measured must be sufficiently long to capture the variations that result from the random and planned events on the roadway system. Once this distribution is established, any number of measures can be constructed to describe its size and shape. The presence of a distribution of travel times leads to a more general definition of travel time reliability as the *level of consistency in travel conditions over time.* Travel time reliability is measured by describing the distribution of travel times that occur over a substantial period of time.

In recent years, some non-U.S. reliability research has focused on another aspect of reliability—the *probability of failure,* in which failure is defined in terms of traffic flow breakdown. A corollary concept, *vulnerability,* is a measure of how vulnerable a network is to breakdown conditions. This measure can be applied at the link or network level (*7*).

Understanding Travel Time Reliability

To understand travel time reliability, it is essential to understand the factors that cause travel times to be unreliable. Previous work indicates that reliability is determined by the variability in conditions that travelers encounter from day to day. Reliability metrics show that variability exists in the system, but they do not tell what causes it. The original F-SHRP Reliability Research Plan identified seven sources of congestion as the factors that cause travel times to be unreliable and contribute to total congestion: incidents, inclement weather, work zones, special events, traffic control device timing, demand fluctuations, and inadequate base capacity. These categories were developed to avoid the recurring–nonrecurring nomenclature that has been in wide use but is not detailed enough for the purpose of SHRP 2 research.

Operational Strategies and Capacity Expansion

Both operational strategies and capacity expansion projects were postulated to affect reliability, and both were studied in the research. Many operational strategies are aimed specifically at the factors that cause unreliable travel (e.g., incident management, work zone management). Note, however, that one of the seven sources of congestion affecting reliability is inadequate base capacity. The effect of physical capacity on congestion is well established and has been the focus of analytic procedures for the past several decades (e.g., the *Highway Capacity Manual*). Physical capacity also affects reliability because it interacts with all the other sources of congestion. For example, consider an incident that blocks one lane of traffic. Its effect is much greater if there are only two lanes available than if three or more were available. So, adding physical capacity definitely will have an effect on reliability.

Travel Time Measurements

Travel time measurements are critical to any definition of reliability and reliability metrics. Travel time is the starting point for sound congestion measurement because it reflects the actual experience of system users. When measured directly, it also is independent of theoretical capacity concerns, such as what happens in oversaturated conditions. Once travel time is obtained, a whole family of additional measures can be created using other basic information about the system (e.g., volume, free-flow speed). Delay is one example of a metric that naturally derives from travel time measurements.

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CHAPTER 2

Preparatory Analyses

Introduction

The project was organized in three phases: foundational research, data collection and preliminary analyses, and reliability prediction models.

Phase 1: Foundational Research

The foundational research effort included

- Conducing a literature review;
- Identifying the reliability metrics to be used in the research;
- Defining the improvement strategies that affect travel time reliability;
- Specifying an experimental design for the research;
- Identifying the types of data that were needed to conduct the research; and
- Defining an analysis plan for conducting the research, including the model forms to be investigated.

Phase 2: Data Collection and Preliminary Analyses

The data collection effort and preliminary analyses were documented and included

- A description of the data sets that were assembled; and
- Exploratory analyses of the data to establish fundamental concepts for the detailed analyses.

Phase 3: Reliability Prediction Models

The Phase 3 effort is documented for the first time here in the final report.

Literature Review

Reliability Performance Metrics

The recognition that travel time reliability is a problem is reflected in changes to traditional monitoring programs that examine average or typical congestion. Increasingly, traffic monitoring agencies understand that those traditional studies must be supplemented with tracking efforts that include day-to-day measures, as well (*1*). The National Transportation Operations Coalition Performance Measurement Initiative, for example, identified travel time reliability (buffer time) as one of the 14 key measures for operations programs (*2*). Data and analysis procedures, however, are not being developed as fast as the recognition of the problem.

Table 2.1 displays several transportation agencies that have included travel time reliability as a portion of mobility measurement in their performance evaluations. Some of the evaluations are performed on a corridor basis, and others are done on a systemwide or statewide basis. Table 2.1 includes only those cases in which reliability measures have been endorsed or adopted by a public entity responsible for operating and/or maintaining transportation systems, such as a state department of transportation (DOT). The table does not include recommendation or use of performance measures by academic or research groups.

NCHRP Project 3-68 identified several measures of travel time reliability that provide a basis for selecting measures for the research:

- Buffer Index—Difference between the 95th percentile travel time and the average travel time, divided by the average travel time;
- Planning Time Index—95th percentile Travel Time Index (TTI). A TTI of 1.2 indicates that a trip takes 20% longer than it would under ideal conditions;

Table 2.1. Reliability Measures in Selected Transportation Agencies

Agency	Reliability Metrics Used	Data Source	Coverage
Freeway			
Georgia Regional Transportation Authority (for annual mobility performance in Atlanta) and Georgia DOT (*3, 4*)	Buffer Index, Planning Time Index	Georgia DOT and local agencies	Facilities
Florida DOT (*5*)	Buffer Index, on-time arrival	Florida DOT and local agencies	Facility Statewide
Southern California Association of Governments (for goods movement study) (*6*)	Buffer Index	Caltrans and local agencies	Facility
Washington State DOT (WSDOT; for performance monitoring and traveler information) (*7*)	95th percentile travel time	WSDOT and local agencies	Facility (time is the sum of link times)
National Transportation Operations Coalition (for performance measure initiative); potential case study with I-95 Corridor Coalition (*2*)	Buffer Index	Various agencies	To be determined
Arterials			
NCHRP 3-68	Buffer Index	Various agencies	Facilities
PRUEVIIN (process for regional understanding and evaluation of integrated ITS networks)	Coefficient of trip time variation	WSDOT	Facilities
Private companies—Inrix and Traffic.com		Private	Facilities
Maryland State Highway Administration and Delcan-NET		Private	Facilities
Freight			
American Transportation Research Institute (ATRI) (FHWA freight performance measurement) (*8*)	Buffer Index	Private	State- and national-level Interstates
Missouri DOT		ATRI	I-70 across state

Note: ITS = intelligent transportation system.

- Percentage of trips with space mean speeds ≤50 mph; and
- Percentage of trips (section or origin–destination) with space mean speeds ≤30 mph (*4*).

Tu et al. classified travel time reliability measures into five types: (*a*) statistical range methods, (*b*) buffer time methods, (*c*) tardy-trip measures, (*d*) probabilistic measures, and (*e*) skew-width methods (*10*). The first three measures were first defined by Lomax et al. (*11*). Probabilistic measures, which are in the same category as failure-based or on-time measures, have been proposed for use in Florida, in combination with a buffer time measure (*12*). Skew-width methods are based on the observation that most travel time distributions are skewed to the right, as shown with example measures in Figure 2.1. It has been suggested that travel times follow either a lognormal distribution or gamma distribution with an adequately scaled shape parameter (*13*).

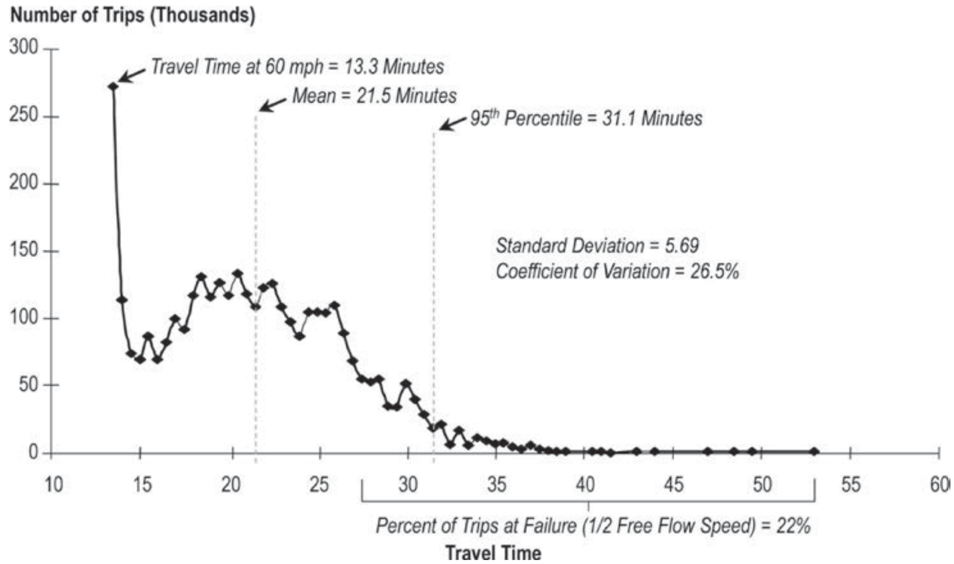
In traditional statistics, two standard measures are used to express the unevenness of distributions:

- *Skewness* is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point; and
- *Kurtosis* is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case (*14*).

Van Lint and van Zuylen noted that buffer time and Misery Index measures based on the mean may not be appropriate because of the underlying skewed distribution (*15*). They also defined two measures that describe the size and shape of the travel time distribution:

1. A skewness statistic, defined as (90th percentile – median)/(median – 10th percentile); and
2. A width statistic, defined as (90th percentile – 10th percentile)/median.

Total number of trips, shown in Figure 2.1, for the time period = 3,485 million (each point on the line represents the number of trips grouped by 30-second travel time intervals). Note that about 8% of trips (275,000 out of 3.485 million) occurred at free flow during this period.



Note: Analysis of NavGAtor data from I-75 northbound from I-285 to Wade Green Road (13.33 miles), Atlanta, Georgia, from 5:00 to 7:00 p.m. on weekdays, 2004.

Figure 2.1. Travel time reliability is determined by the distribution.

Freight Efforts

In terms of economic value, reliability is probably more important to freight carriers and shippers than to personal travelers. With the rise in just-in-time deliveries (largely as a replacement to extensive warehousing), providing dependable (reliable) service has become extremely valuable. Conversely, failure to provide dependable service can increase costs significantly.

The chemicals supply chain provides an example of how reliability affects truck freight operations. Increases in transportation reliability play an important role in reducing inventory in the chemicals supply chain. Because of the many nodes, up to one-third of chemical inventory is in transit at any point. Inventory managers keep safety or buffer stock to cushion against the variability of inbound arrivals, and the amount of safety stock increases with the degree of unreliability and the number of stocking locations. However, capacity to receive chemical stocks is limited by the size of the liquid storage silos. Balancing capacity with demand is a challenge. As one industry consultant explains: "If the tank is full, there's no place to put it [incoming chemicals] and you pay demurrage [storage charges] on the railcar. But if the vessel is early, you have wait time or dead freight." As transportation reliability decreases, wait time, dead freight, and cost increase (*16*).

Conceptually, reliability for trucks is no different than for personal travel; that is, it is measured the same way (the travel time distribution) with the same metrics (e.g., Buffer Index). Also, all roadway, demand management, and operations improvement types (except for those that specifically target trucks, such as lane and service restrictions) affect both truck and personal travel. A practical difference is the length of the trip. Much truck travel is intercity, and therefore occurs on long sections of rural highways that are not routinely congested. This means that only a small portion of the entire trip is within urban areas, where most of the delay and associated unreliability occur.

In 2002, the American Transportation Research Institute (ATRI) partnered with the Federal Highway Administration (FHWA) to develop methods for measuring freight performance on U.S. highways (*8*). With the freight performance measurement project, ATRI demonstrated that it is possible to collect roadway operational data for trucks using satellite technology and that individual truck data could be rendered unidentifiable through a cleansing process. The trucking companies wanted some assurance (primarily caused by safety and security concerns) that their trucks could not be tracked once the identity cleansing process had been performed. The freight performance measurement results were deemed successful in identifying freight-significant corridors and developing measures for evaluating the performance of full highway corridors, as well as providing information on individual segments within these corridors.

Missouri Department of Transportation

The Missouri Department of Transportation (Missouri DOT) has developed a set of performance measures to grade its activities and system performance. The measures are housed in Tracker, a report that includes average truck speed as one of its freight performance measures (*17*). The average truck speed is updated monthly for the entire length of I-70 across Missouri as well as I-70 nationwide. This speed estimate is supplied as a monthly average to the Missouri DOT by ATRI and the freight performance measurement database described above.

Washington State Department of Transportation

A research project by the Washington State Transportation Center analyzed options for collecting travel time data for trucks to determine the benefits provided by freight mobility projects in Washington State (*18*). The report identifies two types of travel time data that need to be collected for trucks: first, the average travel time experienced while making routine trips; and second, travel time data that demonstrate what happens when trucks experience severe, unexpected delay. The report states that collecting truck travel times using floating car techniques is not practical to gather enough data to show truck trip reliability. In addition, travel times must be collected for trip lengths longer than just the affected portion of a corridor where improvements have been made. Since some trucks would change their travel patterns to make use of the improved roadway, the travel time between truck origin–destination pairs should be used to determine the effect of the improvement on delay reduction for the area.

Texas Department of Transportation Work Zone Studies

The Texas Transportation Institute developed two case studies using archived speed data and more detailed work zone data from Houston and San Antonio in an ongoing TxDOT research project (*19*). This study related detailed information on work zone start–stop times, weather information, and crash information to determine the delay that is caused by the work zone.

PRUEVIIN

A research effort in the Seattle, Washington, area developed a technique to combine regional travel demand models and commercially available traffic simulation software into a scenario-based framework (*20*). The process for regional understanding and evaluation of integrated intelligent transportation systems (ITS) networks (PRUEVIIN) has two main features. First, it uses state-of-the-art traffic simulation models to identify the impacts of ITS on a transportation system under average conditions. Second, it provides a method to incorporate system variability, which links the simulation analysis to the travel demand modeling framework. This second feature allows the evaluations to include realistic conditions (e.g., inclement weather, collisions, vehicle breakdowns, work zones) rather than to model the expected or best-day conditions. In one analysis, the coefficient of trip time variation was calculated by examining the variation in travel times across each of the different modeled scenarios for a specific trip. Results showed that as the coefficient gets larger, the variability of trip times increases, and reliability for the trip decreases. PRUEVIIN demonstrates that reliability measures can be generated without enormous amounts of travel time data collection and may provide a means of obtaining travel time reliability measures on arterial streets, where data can be scarce.

Inrix and Traffic.com

Several private companies have been collecting travel time data on freeways and arterial streets in many U.S. cities for several years. Inrix (*21*) and Traffic.com (*22*) collect travel time data by tracking fleets of probe vehicles in each area using global positioning system (GPS) tracking. They also obtain data from state DOT web sites and other sources of speed data to supplement the probe vehicle data. They produce real-time travel speed estimates that are posted to web sites and provided to the media in the majority of these areas. These real-time data are generally archived and could be used to calculate travel time reliability on arterial streets. Few independent analyses have been performed on the GPS-tracked travel time data from these two sources, so there is a great deal of uncertainty as to the composition of the data. The Maricopa Association of Governments (the metropolitan planning organization for the Phoenix, Arizona, urban area) compared private vendor travel time data from two firms with their own sources (freeway detectors and floating car runs). The evaluation indicated that on freeways, both companies' historic average speeds compared favorably with data from eight accurate loop detector freeway locations maintained by Arizona. The evaluation also found that on arterial streets, both companies' historic average speeds compared favorably with the Maricopa Association's traffic speed data.

Beyond Reliability: The Seven Sources

Reliability metrics provide an understanding of how dependable or variable travel conditions are, but they do not identify the cause of the variability. In this sense, reliability measures are top-level outcome measures. A deeper understanding of what causes unreliable travel (and congestion, in general) is useful because it indicates which general areas or specific strategies should be emphasized. The original research plan for the SHRP 2 Reliability areas recognized the need for this deeper understanding and identified seven

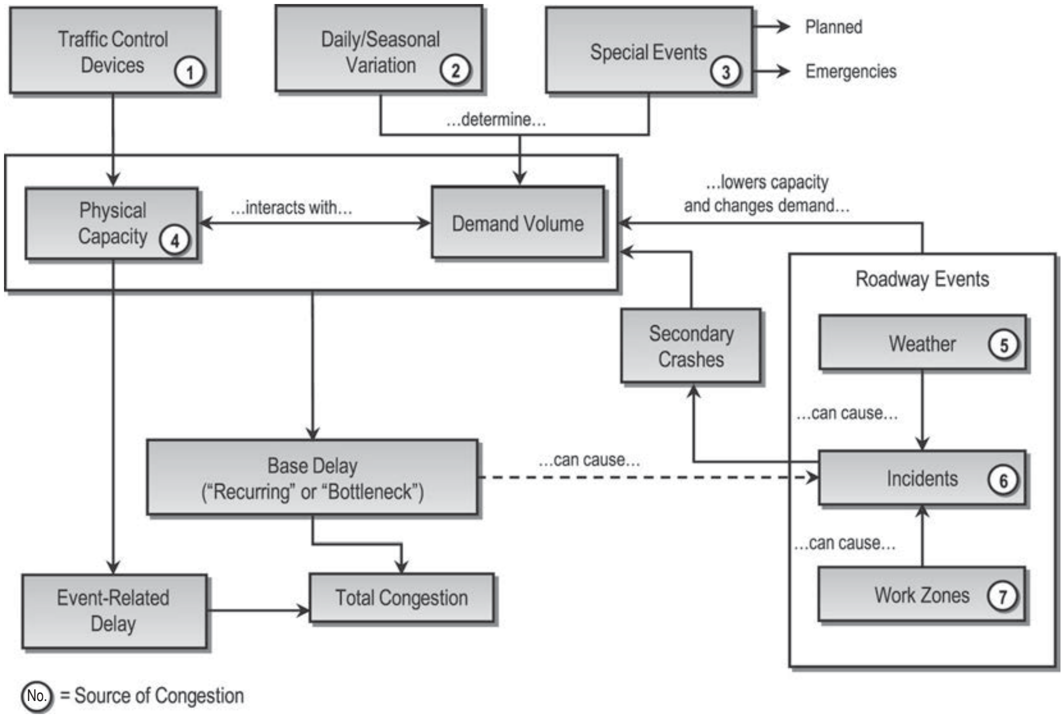


Figure 2.2. A model of congestion and its seven sources.

sources of congestion. Figure 2.2 shows how these seven sources interact to produce total congestion. Reliability is an aspect of total congestion that is greatly influenced by the complex interactions of traffic demand, physical capacity, and roadway events.

An understanding of how each source contributes to total congestion (as well as reliability) is limited, although the current research attempted to determine these contributions analytically. National estimates have been produced by FHWA (Figure 2.3), but these were determined by consensus

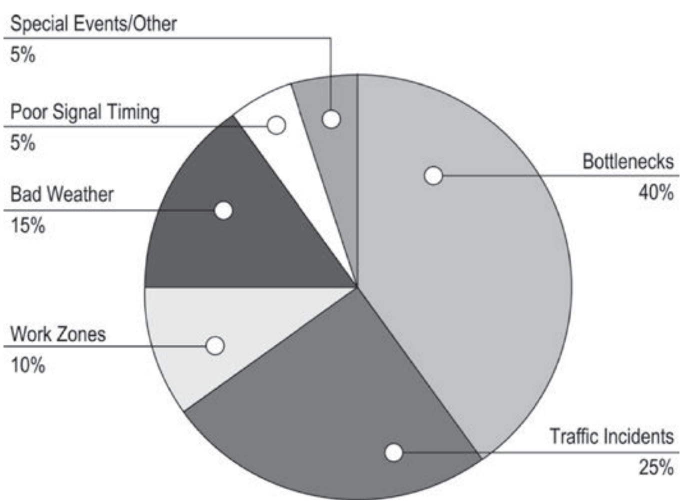


Figure 2.3. FHWA national estimates of delay by source (23).

rather than analysis. FHWA estimates also are meant to be a national snapshot, not indicative of individual corridors or highways. For example, in rural conditions, delays are nearly always a function of events rather than a bottleneck. In urban conditions, especially on a facility with a dominant bottleneck, most of the delay will be determined by the bottleneck.

Improvements That Affect Reliability

Tables 2.2, 2.3, and 2.4 show an effects matrix for the three major categories of improvement: capacity additions, operational improvements, and demand management, respectively. The list is illustrative rather than exhaustive. The assessment listed in the far-right column (Significance of Expected Effect on Reliability) of each of the three tables is based on the team's initial subjective judgment about the magnitude of the strategy's effect on reliability; it does not reflect the results of any of the research conducted for the project.

Experimental Design

Types of Analyses Conducted

Three main forms of analysis were undertaken, as described below. In addition, a large set of exploratory analyses were conducted before the primary analyses as part of Phase 2 (see

Table 2.2. Congestion Strategy Effects Matrix: Add Capacity

Strategy	Expected Effect on Reliability	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Add Capacity—Freeways			
New freeways	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Widen freeways	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
New toll roads	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
New toll lanes on existing roads	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium
Interchange improvements	Add capacity at bottleneck, reduce potential for secondary incidents	HCM, simulation	Medium
New HOV–managed lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium
Truck-only lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, reduce level of incident impacts, and reduce crash potential by eliminating auto–truck speed and braking differential	HCM, simulation	Medium
Add Capacity—Arterials			
New arterials	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Widen arterials	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, planning model	Medium
Street connectivity	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	Simulation	Medium
Grade separations	Reduce delay at intersections and reduce crash potential	HCM, simulation	Medium
HOV–managed lanes	Add new system capacity, reduce demand on adjacent freeways and arterials, and reduce level of incident impacts	HCM, simulation	Medium

Note: HCM = *Highway Capacity Manual;* HOV = high-occupancy vehicle.

Chapter 4) to identify the parameters necessary to conduct the primary analyses.

1. **Before-and-after analysis—**Since the major objective of the research was the development of models that could predict the change in reliability due to improvements, before-and-after analysis was the most appropriate experimental design. Here, *before* is a period of time prior to implementing the improvement, and *after* is a period of time after the improvement has been implemented. Ideally, before-and-after analysis is applied with a control group to help account for the influence of background factors. In this approach, the same highway section or network is studied with and without the improvement. However, it was recognized early in the research that it would be impossible to study all the possible improvement types in the field due to data limitations. Therefore, a second approach was developed that could handle reliability prediction.

Table 2.3. Congestion Strategy Effects Matrix: Operational Improvements

Strategy	Substrategies Included	Effect on Congestion Sources	Factors Affecting Reliability Strategy Implementation	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
		Operational Improvements—Freeways			
TMC Operations	Integrated real-time incident management, verification, detection, and traveler information	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Service patrols	Must include incident scene management methods	Reduces delay due to incidents	Geographic coverage, vehicle route density, congestion level, and program aggressiveness	IDAS	High
On-scene incident management improvements	Response agency coordination and training	Reduces delay due to incidents	Program aggressiveness	IDAS	Medium
Remote verification (CCTV)	Camera views available to multiple agencies and in TMC	Reduces delay due to incidents	Geographic coverage, equipment density, and program aggressiveness	IDAS	High
Event management	Incident management coordination among agencies and event ingress–egress planning and coordination	Reduces delay due to special events	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	Medium
Ramp metering	Ramp meter algorithms based on real-time traffic information	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, simulation	High
Lane controls	DMS over lanes to close lanes in advance of incidents	Reduces delay to incidents, special events, and work zones	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, simulation	High
Managed lanes	HOV lanes, HOT lanes, truck-only lanes, and TOT lanes	Reduces delay due to incidents and bottlenecks	Geographic coverage, equipment density, congestion level, and program aggressiveness	Simulation	High
Electronic toll collection	Toll payment by electronic toll tags	Reduces or eliminates delay at toll booths	Geographic coverage, equipment density, congestion level, and program aggressiveness	Simulation	High
Real-time traveler information	Pretrip information by 511, web sites, subscription alerts; en route information on DMS, 511, and real-time navigation systems	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Work zone management	Active management in TMC coverage areas, real-time information from portable equipment in non-ITS areas	Reduces delay in work zones	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS, simulation, QuickZone	High
Road weather information systems	Weather information supplied to TMCs from roadside weather stations	Reduces delay due to incidents and weather	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Road weather pretreatment	Application of anti-icing chemicals on defined road segments to prevent or retard icing	Reduces delay to incidents and weather	Geographic coverage, equipment density, and program aggressiveness	IDAS	Medium

(continued on next page)

Table 2.3. Congestion Strategy Effects Matrix: Operational Improvements (continued)

Strategy	Substrategies Included	Effect on Congestion Sources	Factors Affecting Reliability Strategy Implementation	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Variable speed limits	DMS to change speed limits based on current conditions	Reduces delay due to incidents, weather, special events, and work zones	Geographic coverage, equipment density, and program aggressiveness	Simulation	High
Ramp improvements	Construct additional ramp lanes and lengthen ramps to provide longer acceleration space	Reduces delay due to bottlenecks	Extent of improvement	Simulation	Medium
Ramp closures	Close entrance ramps in areas with closely spaced ramps	Reduces delay due to bottlenecks	Extent of closures and ramp spacing	Simulation	Medium
Bottleneck removal	Add auxiliary lanes and improve road geometrics	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Travel demand models, simulation	High
Integrated multi-modal corridors	Integrated control of freeways and arterials within a corridor	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Geographic coverage, equipment density, and program aggressiveness	Travel demand models, simulation	High
Advanced technol-ogy for freight management	Fleet management, advanced vehicle location, real-time truck traveler information, roadside permitting–inspection, and weigh-in-motion	Reduces truck delay	Geographic coverage, equipment density, and program aggressiveness	IDAS	Medium
Operational Improvements—Arterials					
Geometric improvements	Reduce grade and curvature	Reduces delay due to incidents and bottlenecks	Geographic coverage and congestion level	HCM, HERS	Low
Intersection improvements	Add turn lanes, improve intersection geometrics	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Simulation, HCM	Low
One-way streets	Convert two-way streets to one-way	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Travel demand models, simulation	Medium

(continued on next page)

Table 2.3. Congestion Strategy Effects Matrix: Operational Improvements (continued)

Strategy	Substrategies Included	Effect on Congestion Sources	Factors Affecting Reliability Strategy Implementation	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Access management	Reduce driveways on arterials, provide interparcel access	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Travel demand models	Medium
Advanced signal systems	Centrally controlled signals, advanced detection, and advanced signal control strategies	Reduces delay due to poor signal timing	Geographic coverage, equipment specifications, and program aggressiveness	Simulation	High
Signal retiming and optimization	Regularly scheduled signal optimization programs	Reduces delay due to poor signal timing	Geographic coverage, equipment specifications, and program aggressiveness	Simulation	High
Changeable lane assignments	Reversible lanes	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Simulation	Medium
HOV by-pass ramp	Provide by-pass lanes for HOVs and buses at entrance ramps	Reduces delay due to ramp bottlenecks	Congestion level	Simulation	Medium
Parking restrictions	Restrict parking on arterial streets during peak hours	Reduces delay due to bottlenecks	Geographic coverage and congestion level	Simulation	Medium
Incident management	Incident management coordination among agencies focused on arterials	Reduces delay due to incidents	Geographic coverage, vehicle route density, congestion level, and program aggressiveness	IDAS	Medium
Event management	Incident management coordination among agencies and event ingress–egress planning and coordination	Reduces delay due to special events	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	Medium
Road weather information systems	Weather information supplied to TMCs from roadside weather stations	Reduces delay due to incidents and weather	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High
Remote verification (CCTV)	Camera views available to multiple agencies and in TMC	Reduces delay due to incidents	Geographic coverage, equipment density, and program aggressiveness	IDAS	High
Real-time traveler information	Pretrip information by 511, web sites, subscription alerts; en route information on DMS, 511, and real-time navigation systems	Reduces delay due to incidents, weather, special events, work zones, and bottlenecks	Geographic coverage, equipment density, congestion level, and program aggressiveness	IDAS	High

Note: TMC = traffic management center; IDAS = ITS deployment analysis system; HOT = high-occupancy toll; TOT = truck-only toll; DMS = dynamic message sign; HERS = Highway Economic Requirements System.

Table 2.4. Congestion Strategy Effects Matrix: Demand Management

Category	Strategy	Substrategies Included	Expected Effect on Reliability	Existing Methodology to Calculate Effects	Significance of Expected Effect on Reliability
Travel alternatives	Public education on aggressive driving	Public service announcements, driver training, and brochures	Reduce crashes due to aggressive driving, fewer incidents	None	Low
Travel alternatives	Reduction in trips, diversion to other modes and/or times	Transit trip itinerary planning, real-time transit information, and commercial vehicle fleet scheduling	Reduce trips and reduced congestion	Travel demand modeling	Medium
Land use	Smart growth policies	Transit-oriented design, access management, street connectivity, bike–pedestrian facilities, and mixed use development	Reduce trips and reduced congestion	Travel demand modeling	Medium
Pricing	Reduction in trips or time shift due to pricing	Toll roads, HOT lanes, time-of-day pricing, cordon pricing, parking pricing, and HOV parking	Reduce trips and reduced congestion	Travel demand modeling	Medium
HOV	Rideshare programs	Vanpool and carpool programs, transportation management associations	Reduce trips and reduced congestion	Travel demand modeling	Medium
Freight	Truck-only toll lanes	Toll lanes exclusively for trucks and time-of-day pricing	Removes trucks from general purpose lanes, reduces truck–auto conflicts, reduces crashes, and reduces congestion in general-purpose lanes by removing slower trucks	Simulation	Low
Freight	Lane restrictions	Restrict left lanes from use by trucks	Reduces truck conflicts in restricted lanes, reduces crashes, reduces congestion in restricted lanes	Simulation	Low
Freight	Delivery restrictions	Restrictions on deliveries in peak hours	Reduces congestion in restricted areas during peak hours	Travel demand modeling	Low

2. **Cross-sectional analysis—**Patterned after classical experimental design, this approach establishes a matrix of factors and their levels. Ideally, observations are taken for each combination of factors. But as noted, strict control of all factors was not achievable; consequently, there were missing combinations, which precluded studying interactions directly from the field data. Statisticians refer to this situation as a *quasi-experimental design.* In this approach, experimental design is used to ensure that a range of conditions is represented in the data.
3. **Congestion by source analysis—**Identifying the contributing factors (the seven sources) to congestion and reliability is a major concern for the transportation profession. Table 2.5 shows how several previous studies identified congestion by source. The primary issue is how to split up delay so that each contributing source gets a share. The analyst must decide how much delay would have occurred in the absence of the event and how to reasonably split the delay when multiple sources are at work. These decisions are further complicated if a crash occurs when congestion sources such as inclement weather and work zones, which can increase the likelihood of a crash, are present. Should the resulting delay be charged completely to the weather or work zone category, or shared with the incident category?

Table 2.5. Results from Previous Studies Identifying Congestion by Source

Statistics	Study			
	Dowling Associates et al. (*24*)	Kopf et al. (*25*)	Kwon et al. (*26*)	CDTC (*27*)
Metro area	Los Angeles	Seattle	San Francisco	Albany
Route	I-10	I-405, I-90, SR 520	I-880	I-87, I-90
Freeway (mi)	10	42	45	15
Amount of data	7 days	4 months	6 months	1 year
Total Delay				
Recurrent delay	69%	71%	80%	72%
Nonrecurrent delay	31%	29%	20%	28%
Nonrecurrent Sources				
Incident	31%	16%	13%	28%
Work zone	Not studied	Not studied	Not studied	Not studied
Weather	Not studied	9%	2%	Not studied
Special events	Not studied	Not studied	5%	Not studied
High volume	Not studied	4%	Not studied	Not studied

Factors Considered

The experimental design is detailed in Table 2.6. The top-level design in Table 2.6 shows the overarching factors that were studied. The experimental design does not specify a classic factorial experiment because the number of locations needed to cover all possible factorial combinations was prohibitive. Rather, the experimental design was used to ensure that a range of conditions was covered by the data and to identify the important factors and levels of those factors that were desirable, but not necessarily achievable. The combinations of factors that resulted, therefore, were dependent on the data that could be assembled. However, it was useful to document what the experimental design matrix looked like after the data were assembled, as it provided a basis for seeing what interactions could be studied.

The approach outlined in Table 2.6 is obviously a compromise, but it was decided early in the study that if empirical data were used, then for cost control the team would have to access data already being collected by transportation agencies. A long history of travel time data is needed to establish reliability, and the cost of undertaking special instrumentation to collect these data would have been exorbitant. Instead, team members identified areas in which their past experience indicated that data were of sufficiently high quality to undertake the research. Originally, it was thought that rural two-lane highways could be studied, but data availability at the time of the study was nonexistent, and the team wanted to focus new data collection efforts on signalized highways, where reliability and congestion are greater issues.

One key factor common to all improvement types and any predictive relationship of reliability is traffic pressure or demand level. In Table 2.6, the AADT/C ratio is used as a general measure of congestion level to ensure that roadways at all levels are considered in the analysis. AADT/C also may be used directly as an independent (predictor) variable in reliability relationships, but doing so masks the peaking characteristics of the facility. Other indicators of traffic pressure may include single- or multiple-hour volume-to-capacity ratios. Variations in traffic demand variability also influence traffic pressure.

Accurately characterizing traffic demand was a critical part of the research. The data collection plan was clearly oriented to facility-level rather than corridor- or system-level analysis. Existing continuous data collection activities by public agencies, on which the research heavily relied, were concentrated on major facilities, usually freeways; data on parallel nonfreeways were scarce to nonexistent. During times of severe congestion, traffic demand can be suppressed by travelers switching to alternative routes or delaying their trips. Controlling for this diversion effect was handled by carefully measuring traffic demand on the test facilities; original data collection to capture diversion was cost prohibitive for this study, given the wide range of conditions that needed to be addressed.

The entry in Table 2.6 for proximity to a major bottleneck requires elaboration. If a major bottleneck (e.g., a freeway-to-freeway interchange) is immediately downstream of a study segment, then it will tend to dominate congestion on it (i.e., queues will routinely form on the study segment). It is, therefore, important to note both the presence and characteristics

Table 2.6. Experimental Design

Factors	Levels	Highway Type		
		Urban		Rural
		Freeways	Signalized Arterials	Freeways
Area size	Small, medium	●	●	
	Large, very large	●	●	
Base congestion	Low (AADT/C[a] <7)			●
	Moderate (AADT/C ~9)	●	●	
	Severe (AADT/C ~12)	●	●	
Number of lanes	4	●	●	●
	6	●	●	
	8+	●	●	
Base crash rate[b]	Low	●	●	●
	High	●	●	●
Trucks (%)	<10%	●	●	●
	>10%	●	●	●
Traffic variability[c]	Low	●	●	●
	High	●	●	●
Traffic signal density	<2/mile		●	
	2–5/mile		●	
	>5/mile		●	
Proximity to major bottleneck	<1 mile downstream from segment	●		
	>5 miles downstream from segment	●		
Improvement type	Incident management	●	●	●
	Work zone management	●	●	●
	Weather management[d]	●		●
	Traffic device control[e]	●	●	
	Demand management	●	●	
	Special event management	●	●	
	Traveler information	●	●	●
	Physical expansion and/or changes	●	●	●

[a] AADT/C is annual average daily traffic-to-capacity ratio (specifically, two-way hourly capacity).
[b] Categories were based on comparison to each state's average crash rate by type of highway.
[c] For urban highways, traffic variability was determined based on the coefficient of variation (CV) of weekday peak period travel. For rural highways, the CV of the 24-hour volume was used.
[d] Weather management depended on what was being covered in other research activities, such as FHWA's Road Weather Research and Development Program.
[e] Ramp meter control on freeways; signal control on signalized arterials.

(e.g., capacity) of a nearby downstream bottleneck. If the bottleneck is upstream of the study segment, then flow onto the study segment will be limited or metered as a result of the lower discharge rate from the oversaturated bottleneck. This is a potential problem because the study segment may not ever receive enough demand to cause recurring congestion.

Additional subfactors varied by type of improvement or type of source delay. The key was ensuring that a spread of conditions was represented:

- **Incidents—**Presence of a usable shoulder on each side of the highway; levels of incident management that lead to low, medium, or high average incident durations;
- **Work zones—**Nature of geometric change, translated into *Highway Capacity Manual*–based capacity loss to account for multiple combinations (such as lane narrowing with and without shoulder loss): <5%, 5% to 15%, 15% to 30%, 30% to 50%, and 50% to 75%; and
- **Traffic signals—**Type of progression: actuated, central control, or adaptive.

Facility-Based Spatial Measurement Scale

Because nearly all the data were based on measurements taken at the roadway (not the trip) level, the focus of the work was to define reliability at the facility level. This focus provided the most practical results for implementation, at least in the short run. Several spatial levels were investigated:

- Urban links (distance between signalized intersections and freeway interchanges);
- Urban facility segments (distance between multiple signalized intersections and multiple freeway interchanges):
  - 2 to 5 miles for freeways, and
  - 1 to 3 miles for arterials; and
- Rural extended sections (long stretches of rural highways, probably 30 to 200 miles in length).

Temporal Measurement Scale

Reliability measurements for the following time periods were captured and used in the analysis:

- Peak hour and peak direction (based on maximum volume);
- Peak period (to encompass typical commuting times that include most delay, broken down by a.m. and p.m. and directionality);
- Midday or overnight;
- Daily (to encompass all delay); and
- Weekday versus weekend.

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CHAPTER 3

Data Collection, Assembly, and Fusion

Introduction

The research team decided at the beginning of the project that an empirical approach would be used to develop predictive relationships for reliability. The alternative would have been to conduct a large number of simulation-based experiments. However, team members had conducted several previous projects using empirical data and were confident that these data could be used successfully. In addition, the large amount of empirical data that would be assembled could not only be used in this project but would have value for future research. Such an approach is not without risk. Real-world data can be subject to measurement error, and it was clear that the extremely large amount of data that would be needed could not be uniquely collected by the project; that is, the data collection itself was outside of the team's control. Nevertheless, continuous travel time data collected for a sufficiently long period of time is an absolute requirement for empirical studies of reliability, as reliability is defined by how travel times vary over a considerable time span. Given the myriad of factors that influence reliability, the team estimated that a complete year of data would be needed.

The majority of the project's effort was the creation of analysis data sets. Data set creation involved obtaining, cleaning, and integrating data collected primarily by public agencies, but also private vendors. The research team selected agencies that had a long history of data collection and (based on the team's experience) had data of the coverage and quality required to undertake the research. The challenges in this approach were twofold: (*a*) processing, reviewing, and reducing the raw data to summary measurements for the analysis; and (*b*) matching the different types of data geographically.

Assembling empirical data from locations around the country proved to be challenging, but manageable. Traffic data are relatively consistent from location to location, but incident and work zone data do not seem to follow any standard definitions. Fusion of the event data with the traffic data also posed problems; in some cases these had to be matched manually.

Traffic and Travel Time Data

Urban Freeways

The project team assembled urban freeway data from traffic management centers (TMCs) that were considered to be at the forefront of maintaining quality traffic data. Other considerations in selecting the cities were the availability of incident data from the TMCs, the presence of before-and-after improvement situations, and a fairly long history of archiving data. Table 3.1 summarizes the cities and Table 3.2 summarizes the study sections. The locations of the sections appear in Figures 3.1 through 3.7. All these sections were considered in the exploratory analyses (Chapter 4) and the statistical modeling (Chapter 7), and several sections were used in the before-and-after analysis (see boldface portion of Table 3.2). A separate data set of urban freeways was compiled for the Seattle area for the congestion by source analysis.

Seattle freeways are not included in Table 3.2. Seattle data were used in the congestion by source analysis and before-and-after studies (described further in Chapter 5).

The urban freeway data set was the most complete of all the data sets assembled for the project. In addition to traffic data, all the sections had incident and weather data available.

Signalized Arterials

Table 3.3 shows the data assembled for signalized arterials. Data were derived from both public and private sources and several technologies. The privately provided data were purchased from Inrix, which has nationwide agreements with private fleets to capture travel time information. Inrix sells these data primarily for real-time traveler information to both private and public entities (such as the I-95 Corridor

Table 3.1. Urban Freeway Study Section Summary

City	Number of Directional Study Sections	Total Directional Mileage
Houston, Texas	13	58.80
Minneapolis, Minnesota	16	62.63
Los Angeles, California	3	50.27
San Francisco Bay Area, California	4	19.98
San Diego, California	6	28.04
Atlanta, Georgia	10	54.66
Jacksonville, Florida	8	17.71
Total	**60**	**292.09**

Coalition), but it also archives the data for other uses. In late 2007, the research team asked Inrix to review their data quality and to provide suggestions for arterial sections they felt had the best quality of data and the highest sample sizes. However, upon review of the data, it was determined that the Inrix data for signalized arterials had an insufficient number of samples to define reliability for the research. Although the sources of the travel time measurements are proprietary, the small number of measurements during traditional peak periods, at least during the 2006 to 2007 period, led the team to surmise that most of the Inrix measurements were derived from fleet vehicles. The team was also cautious about the use of Inrix measurements for signalized highways, as they are not distance-based measurements like those taken from toll tags. They may have been adequate, but given the sample size problems, they were not tested. The net result was that only the two arterials in Orlando could be used for the analysis.

Table 3.2. Urban Freeway Study Sections

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (mi)	Time Period Covered
1	Houston	U.S. 290 Northwest	Eastbound	Barker Cypress	FM 1960	4.05	1/1/2006–12/31/2007
2	Houston	U.S. 290 Northwest	Eastbound	FM 1960	Sam Houston	5.10	1/1/2006–12/31/2007
3	Houston	U.S. 290 Northwest	Eastbound	Fairbanks–N Houston	W 34th	5.35	1/1/2006–12/31/2007
4	Houston	U.S. 290 Northwest	Westbound	Pinemont	Sam Houston	4.45	1/1/2006–12/31/2007
5	Houston	U.S. 290 Northwest	Westbound	Sam Houston	FM 1960	4.25	1/1/2006–12/31/2007
6	Houston	U.S. 290 Northwest	Westbound	FM 1960	Barker Cypress	4.90	1/1/2006–12/31/2007
7	Houston	I-45 Gulf	Northbound	Nasa Road 1	Dixie Farm Road	5.10	1/1/2006–12/31/2007
8	Houston	I-45 Gulf	Northbound	Dixie Farm Road	Fuqua	2.80	1/1/2006–12/31/2007
9	Houston	I-45 Gulf	Northbound	Edgebrook	Broadway	4.70	1/1/2006–12/31/2007
10	Houston	I-45 Gulf	Northbound	Woodridge	Scott Street	4.15	1/1/2006–12/31/2007
11	Houston	I-45 Gulf	Southbound	Scott Street	Woodridge	4.15	1/1/2006–12/31/2007
12	Houston	I-45 Gulf	Southbound	Broadway	Edgebrook	4.70	1/1/2006–12/31/2007
13	Houston	I-45 Gulf	Southbound	Dixie Farm Road	Nasa Road 1	5.10	1/1/2006–12/31/2007
14	Minneapolis–St. Paul	I-35 W	Northbound	W 106th Street	South of I-494	3.47	1/1/2006–12/31/2007
15	Minneapolis–St. Paul	I-35 W	Southbound	South of I-494	W 106th Street	3.64	1/1/2006–12/31/2007
16	Minneapolis–St. Paul	I-35 W	Northbound	T.H. 36	I-694	3.37	1/1/2006–12/31/2007
17	Minneapolis–St. Paul	I-35 W	Southbound	I-694	T.H. 36	3.29	1/1/2006–12/31/2007

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Table 3.2. Urban Freeway Study Sections (continued)

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (mi)	Time Period Covered
18	Minneapolis–St. Paul	T.H. 36	Eastbound	Fairview Avenue	I-35 E	4.41	1/1/2006–12/31/2007
19	Minneapolis–St. Paul	T.H. 36	Westbound	I-35 East	Fairview Avenue	4.35	1/1/2006–12/31/2007
20	Minneapolis–St. Paul	I-35 E	Northbound	W 7th Street	I-94	3.48	1/1/2006–12/31/2007
21	Minneapolis–St. Paul	I-35 E	Southbound	I-94	W 7th Street	3.59	1/1/2006–12/31/2007
22	Minneapolis–St. Paul	T.H. 77	Northbound	T.H. 13	I-494	3.43	1/1/2006–12/31/2007
23	Minneapolis–St. Paul	T.H. 77	Southbound	I-494	T.H. 13	3.43	1/1/2006–12/31/2007
24	**Minneapolis–St. Paul**	**I-94**	**Eastbound**	**Highway 100**	**I-494**	**7.00**	**09/2000–09/2001 and 11/2004–11/2005**
25	**Minneapolis–St. Paul**	**I-94**	**Westbound**	**I-494**	**Highway 100**	**7.00**	**09/2000–09/2001 and 11/2004–11/2005**
26	**Minneapolis–St. Paul**	**I-494**	**Eastbound**	**Highway 100**	**Highway 5/312**	**4.00**	**05/2002-05/2003 and 11/2005–11/2006**
27	**Minneapolis–St. Paul**	**I-394**	**Westbound**	**Highway 100**	**Highway 169**	**3.17**	**07/2004–07/2005 and 11/2005–11/2006**
28	**Minneapolis–St. Paul**	**Highway 169**	**Southbound**	**T.H. 62**	**I-494**	**2.00**	**06/2005–06/2006 and 11/2006–11/2007**
29	**Minneapolis–St. Paul**	**Highway 100**	**Northbound**	**36th Street**	**I-394**	**2.80**	**04/2005–04/2006 and 11/2006–11/2007**
30	**Los Angeles**	**I-210**	**Westbound**	**Foothill Highway and Ventura Freeway Interchange**	**S. Asuza Avenue and Foothill Freeway Interchange**	**13.63**	**10/2000–12/2002**
31	**Los Angeles**	**I-710**	**Northbound**	**Interchange: I-710 and I-5**	**I-710 and W. Ocean Boulevard**	**18.32**	**04/2004–06/2006**
32	**Los Angeles**	**I-710**	**Southbound**	**Interchange: I-710 and I-5**	**I-710 and W. Ocean Boulevard**	**18.32**	**04/2004–06/2006**
33	Bay Area	I-880	Northbound	Oak Street Ramps	I-980 Ramps	1.35	01/2008–12/2008
34	Bay Area	I-880	Southbound	Oak Street Ramps	I-980 Ramps	1.35	01/2008–12/2008
35	**Bay Area**	**I-580**	**Eastbound**	**Eden Canyon Ramps**	**1st Street and I-580 Interchange, Livermore**	**8.64**	**06/2002–07/2004**
36	**Bay Area**	**I-580**	**Westbound**	**Eden Canyon Ramps**	**1st Street and I-580 Interchange, Livermore**	**8.64**	**06/2002–07/2004**
37	**San Diego**	**SR 52**	**Eastbound**	**Santo Road Ramps**	**SR 52 and SR 125 Interchange**	**5.96**	**06/2004–12/2006**
38	**San Diego**	**SR 52**	**Westbound**	**Santo Road Ramps**	**SR 52 and SR 125 Interchange**	**5.96**	**06/2004–12/2006**
39	San Diego	I-5	Northbound	Del Mar Heights Road Ramps	Carmel Valley Road Interchange	3.38	06/2001–08/2006
40	San Diego	I-5	Southbound	Del Mar Heights Road Ramps	Carmel Valley Road Interchange	3.38	06/2001–08/2006

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Table 3.2. Urban Freeway Study Sections (continued)

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (mi)	Time Period Covered
41	**San Diego**	**I-8**	**Northbound**	**North 2nd Street Interchange**	**Lake Jennings Park Interchange**	**4.68**	**06/2004–08/2006**
42	**San Diego**	**I-8**	**Southbound**	**North 2nd Street Interchange**	**Lake Jennings Park Interchange**	**4.68**	**06/2004–08/2006**
43	Atlanta	I-75	Northbound	I-285	Roswell Road	5.19	01/2006–12/2008
44	Atlanta	I-75	Southbound	I-285	Roswell Road	5.19	01/2006–12/2008
45	Atlanta	I-75	Northbound	I-20	I-85	4.43	01/2006–12/2008
46	Atlanta	I-75	Southbound	I-20	I-85	4.43	01/2006–12/2008
47	**Atlanta**	**I-285**	**Eastbound**	**I-75**	**GA 400**	**6.50**	**01/2006–12/2008**
48	**Atlanta**	**I-285**	**Westbound**	**I-75**	**GA 400**	**6.50**	**01/2006–12/2008**
49	**Atlanta**	**I-285**	**Eastbound**	**GA 400**	**I-85**	**6.03**	**01/2006–12/2008**
50	**Atlanta**	**I-285**	**Westbound**	**GA 400**	**I-85**	**6.03**	**01/2006–12/2008**
51	Atlanta	I-75	Northbound	Roswell Road	Barrett Parkway	5.18	01/2006–12/2008
52	Atlanta	I-75	Southbound	Roswell Road	Barrett Parkway	5.18	01/2006–12/2008
53	Seattle	SR 520	Eastbound–westbound	I-5	I-405	7.00	01/2006–12/2008
54	Seattle	SR 520	Eastbound–westbound	I-405	SR 202	5.50	01/2006–12/2008
55	Seattle	I-90	Eastbound–westbound	I-5	West End Floating Bridge	1.24	01/2006–12/2008
56	Seattle	I-90	Eastbound–westbound	West End Floating Bridge	I-405	4.76	01/2006–12/2008
57	Seattle	I-90	Eastbound–westbound	I-405	West Lake Sammamish	4.00	01/2006–12/2008
58	Seattle	I-90	Eastbound–westbound	West Lake Sammamish	West of High Point Road	6.37	01/2006–12/2008
59	Seattle	SR 167	Northbound–southbound	15th Street NW	SR 516	3.70	01/2006–12/2008
60	Seattle	SR 167	Northbound–southbound	SR 516	I-405	6.10	01/2006–12/2008
61	Seattle	I-405	Northbound–southbound	I-5 Tukwila	SR 167	2.30	01/2006–12/2008
62	Seattle	I-405	Northbound–southbound	SR 167	112th Avenue SE	7.70	01/2006–12/2008
63	Seattle	I-405	Northbound–southbound	112th Avenue S.E.	I-90	2.20	01/2006–12/2008
64	Seattle	I-405	Northbound–southbound	I-90	SR 520	3.40	01/2006–12/2008
65	Seattle	I-405	Northbound–southbound	SR 520	SR 522	8.40	01/2006–12/2008
66	Seattle	I-405	Northbound–southbound	SR 522	I-5 Lynnwood	6.50	01/2006–12/2008
67	Seattle	I-5	Northbound–southbound	South 320th Street	I-405 Tukwila	10.40	01/2006–12/2008
68	Seattle	I-5	Northbound–southbound	I-405 Tukwila	Albro Place	6.60	01/2006–12/2008

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Table 3.2. Urban Freeway Study Sections (continued)

Number	City	Route	Directions Covered	Beginning Landmark	Ending Landmark	Length (mi)	Time Period Covered
69	Seattle	I-5	Northbound–southbound	Albro Place	SR 520	7.80	01/2006–12/2008
70	Seattle	I-5	Northbound–southbound	SR 520	Northgate	4.10	01/2006–12/2008
71	Seattle	I-5	Northbound–southbound	Northgate	Snohomish/King County Line	5.40	01/2006–12/2008
72	Seattle	I-5	Northbound–southbound	Snohomish–King County Line	128th SW	8.10	01/2006–12/2008
73	Seattle	I-5	Northbound–southbound	128th SW	Marine View Drive	8.40	01/2006–12/2008
74	Jacksonville	I-95	Northbound	Phillips Highway	SR 202	5.16	03/2008–12/2008
75	Jacksonville	I-95	Southbound	Phillips Highway	SR 202	5.16	03/2008–12/2008
76	Jacksonville	I-95	Northbound	SR 202	Atlantic Boulevard	4.56	03/2008–12/2008
77	Jacksonville	I-95	Southbound	SR 202	Atlantic Boulevard	4.56	03/2008–12/2008
78	Jacksonville	I-95	Northbound	U.S. 23	SR 111 (Edgewood)	3.85	03/2008–12/2008
79	Jacksonville	I-95	Southbound	U.S. 23	SR 111	3.85	03/2008–12/2008
80	Jacksonville	I-95	Northbound	SR 111	I-295	4.13	03/2008–12/2008
81	Jacksonville	I-95	Southbound	SR 111	I-295	4.13	03/2008–12/2008

Note: Houston data are based on toll tag–equipped probe vehicles and comprise direct travel time measurements. The remaining locations' data comprise roadway-based sensor measurements of volume, speed, and lane occupancy. Sections in boldface were used in the before-and-after analysis. All sections were considered by the statistical modeling.

Figure 3.1. Atlanta base map.

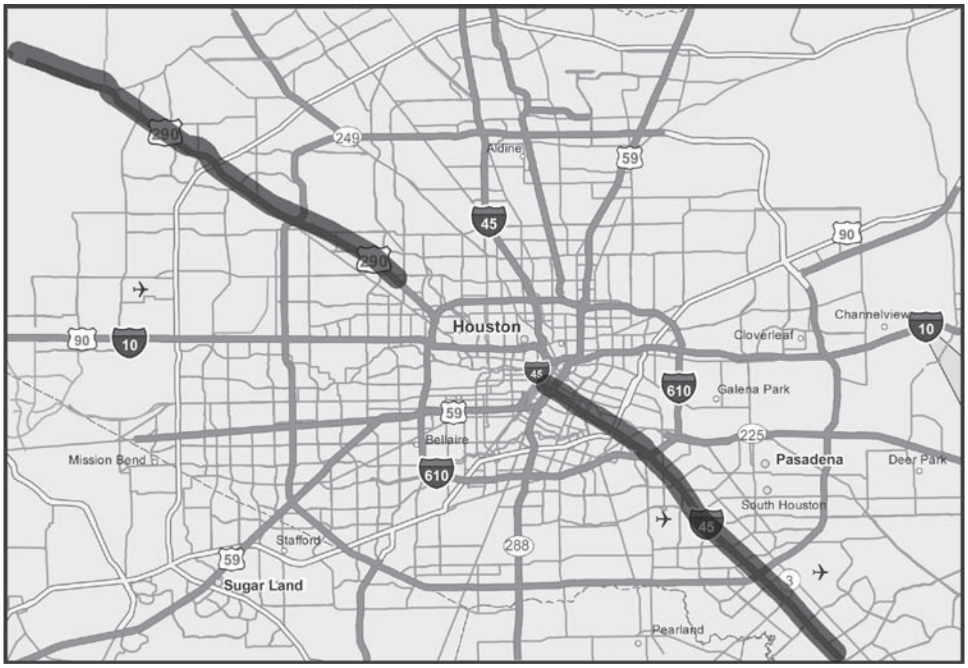

Figure 3.2. Houston base map.

Figure 3.3. Minneapolis–St. Paul base map.

Figure 3.4. San Francisco Bay Area base map.

Figure 3.5. Los Angeles base map.

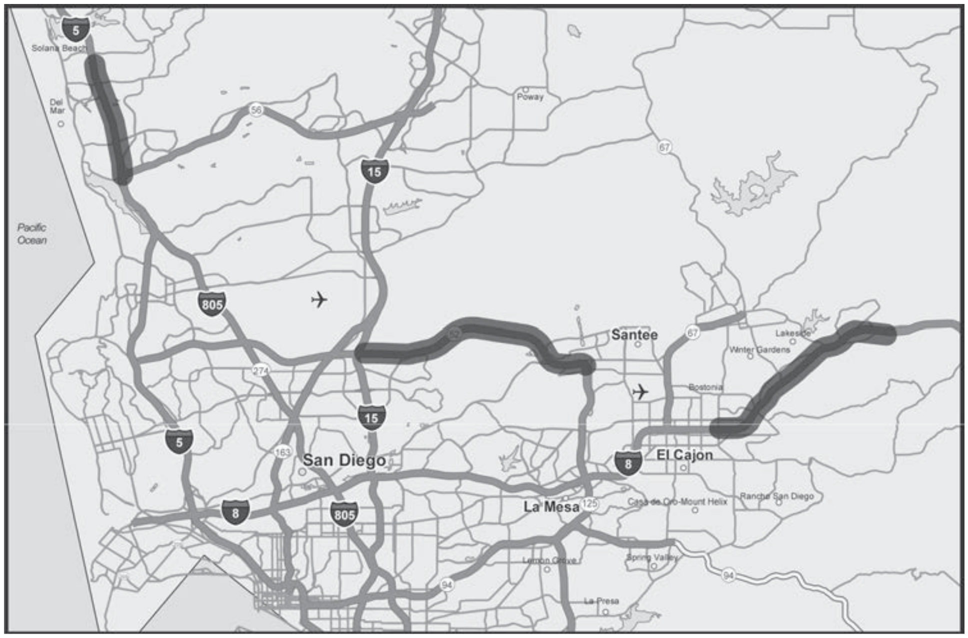

Figure 3.6. San Diego base map.

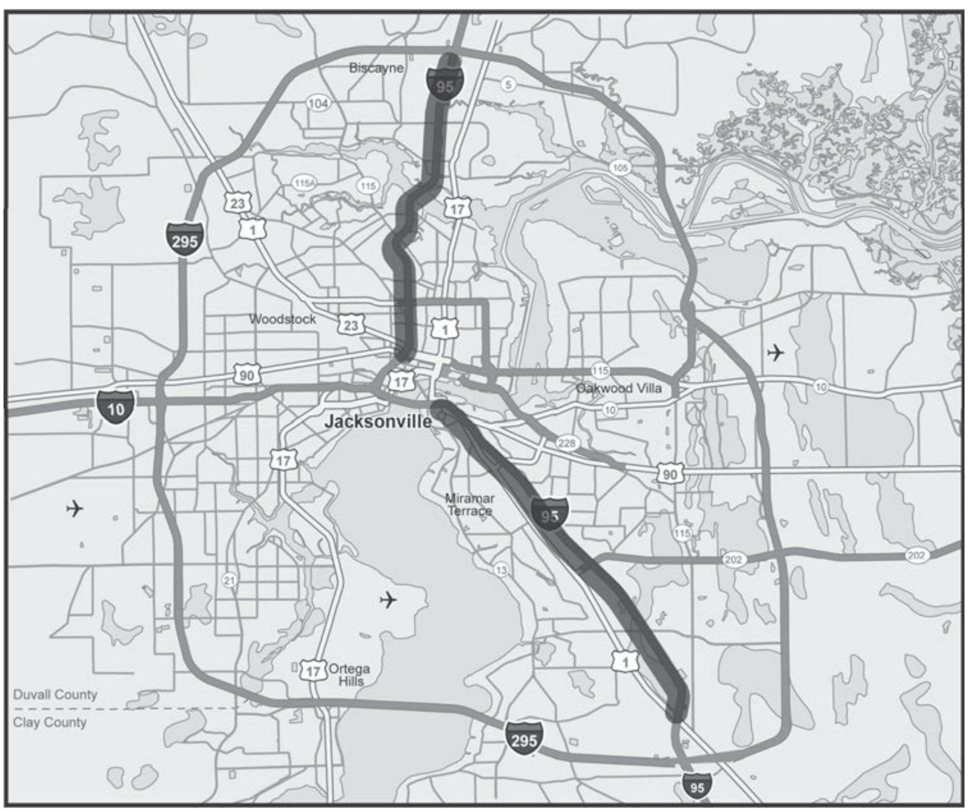

Figure 3.7. Jacksonville base map.

Table 3.3. Signalized Arterial Study Sections

City	Arterial	From	To	Length (mi)	Travel Time Data	
					Data Technology	Period
Orlando	Section 1: SR 50 eastbound	Florida Turnpike	SR 408W	6.85	Tag-based probe	March 2008+
	Section 2: SR 50 westbound	SR 408W	Florida Turnpike	6.85	Tag-based probe	March 2008+
	Section 3: U.S. 441 northbound	SR 417	SR 408	10.67	Tag-based probe	March 2008+
	Section 4: U.S. 441 southbound	SR 408	SR 417	10.67	Tag-based probe	March 2008+
	Section 5: U.S. 441 northbound	SR 408	N John Young Parkway	4.35	Tag-based probe	March 2008+
	Section 6: U.S. 441 southbound	N John Young Parkway	SR 408	4.35	Tag-based probe	March 2008+
Los Angeles	Santa Monica Boulevard	I-405	N Gardner Street	6.9	GPS probe (Inrix)	2006–2007
Phoenix	E Camelback Road	44th Street	Highway 51	4.2	GPS probe (Inrix)	2006–2007
Minneapolis–St. Paul	Washington Avenue	County Highway 153	U.S. 65	3.4	GPS probe (Inrix)	2006–2007
Miami	U.S. 1	17th Avenue	Le Jeune Road	3.8	GPS probe (Inrix)	2006–2007
Houston	Westheimer Road	W Sam Houston	I-610	6.9	GPS probe (Inrix)	2006–2007

Note: Probe-tag technology provided direct estimates of travel time over the segment. Inrix-provided data were supplied as speed estimates by link (approximately 0.5 to 1 mile long). Only the Orlando sections were used in the analysis because of sample size limitations on the other sections.

Rural Freeways

Table 3.4 presents the sections for which rural freeway travel time data were assembled. The Inrix data were deemed to have sufficient sample sizes for the two locations indicated.

Incident and Work Zone Data

Incident and Work Zone Characteristics

Data on the basic characteristics of incidents were available from three sources and were used to varying degrees, depending on the team's assessment of the data sources for each city. Incident and event data were provided at no cost to the project team by the private vendor Traffic.com from their traveler information management system (TIMS). The TIMS data provided a standardized source of information for traffic incidents, events, scheduled and unscheduled construction, and other events that could affect traffic conditions (such as severe weather or transit delays).

Incident data are gathered directly by Traffic.com observers using numerous sources of information, such as video images, aircraft, mobile units, and police and emergency communication frequencies. In some cities, Traffic.com observers are stationed on the floor of the regional TMC. In other cities, Traffic.com observers are mobile or are stationed in a connected operations center.

The incident data from Traffic.com were chosen for this study because it has several unique attributes:

- All reported incidents are entered. Traffic.com does attempt to confirm reports, and will indicate in their system when the reported incident has been confirmed. Thus, they provide both reported incidents, as well as confirmed incidents;
- Traffic.com incident data are collected by an independent entity that is not involved in the traffic or emergency management process. It was reasoned that Traffic.com staff could gather more complete and accurate data because

Table 3.4. Rural Freeway Study Sections

State	Route	From	To	Length	Travel Time Data	
					Data Technology	Period
Texas	I-45	Exit 213, Navarro County	Exit 267, Ellis County	54.1	GPS probe (Inrix)	2006–2007
South Carolina	I-95	South Carolina–Georgia Border	SR 68, Hampton County	38.2	GPS probe (Inrix)	2006–2007

information gathering and reporting were their sole focus (in contrast, public agency traffic managers typically must manage incidents and crises and record relevant information at the same time). Additionally, the Traffic.com incident data are routinely reviewed to ensure quality data entry by Traffic.com observers;

- Traffic.com incident data contain the sequence of events as an incident is reported, responded to, and cleared. For example, an incident record is updated and appended whenever the status or conditions of the incident change. This information provides more specificity about the incident; and
- Traffic.com incident data provided consistent data attributes in all of this study's cities and also used unambiguous location referencing.

The following incident attributes were used in this study:

- **Unique traffic item identifier—**A unique identifier for each record or observation;
- **Unique original traffic item identifier—**A unique identifier for the original traffic incident that did not change as information about the same incident was updated;
- **Metropolitan area—**Unique city identifier;
- **Roadway and location identifier—**Unique combination of identifiers for the location.
- **Type of traffic item—**Possible entries include:
  - Accident;
  - Alert;
  - Congestion;
  - Disabled vehicle;
  - Mass transit;
  - Miscellaneous;
  - Other news;
  - Planned event;
  - Road hazard;
  - Scheduled construction;
  - Unscheduled construction; and
  - Weather.
- **Verification—**An indication of whether the incident or event was verified;
- **Number of lanes blocked—**Numeric entry for number of travel lanes that were blocked; and
- **Start and ending times—**The combination of these attributes provided incident duration. The start time was the time when the lane or shoulder blockage began; the end time was when the blockage was cleared.

Data collected by TMC operators and entered into consoles at the TMC and/or entered by freeway service patrols were also available for some cities. The type of data collected by these entities varies, but they generally correspond to Traffic.com data; the key items of location, duration, and lane blockage are the same. The sources of incident data used in the urban freeway analysis were as follows:

- **Atlanta—**TMC data were the primary source (this included work zones and special events), checked against both Traffic.com and Georgia DOT crash data;
- **Houston—**Traffic.com data were found to match TMC (Transtar) incident data very well, and since Traffic.com contains work zones and special events, was the source of incident information;
- **Minneapolis—**Traffic.com data;
- **San Diego, Los Angeles, and San Francisco Bay Area—**Traffic.com data;
- **Seattle—**Special data set, a fusion of TMC and police computer-aided dispatch data; and
- **Jacksonville—**TMC data.

Incident Activity Data

Areas with incident management differ substantially in the institutional arrangements and policies that govern their day-to-day operations. Many of these incident management approaches are subjective and did not lend themselves to the quantification that was needed for the statistical modeling. Initially, it was thought that the approach taken in SHRP 2 Project L06, Institutional Architectures to Advance Operational Strategies, could be used. The L06 approach is based on adapting the capability maturity model developed for software engineering to operations activities in transportation agencies. The capability maturity model in software engineering is a model of the maturity of the capability of certain business processes. A maturity model can be described as a structured collection of elements that describe certain aspects of maturity in an organization; the model aids in defining and understanding an organization's processes. It was hoped that the resulting levels could be used as indicators of the degree of sophistication in policies and institutional arrangements with regard to incident management. Unfortunately, Project L06's capability maturity model was too general and nonspecific to incident management to be of use in the statistical modeling for this project. Instead, the team used the Traffic Incident Management (TIM) Self-Assessment procedure developed by FHWA to indicate the sophistication of incident management arrangements for modeling purposes. This procedure has the advantages of capturing a wide range of activities in a single numeric score and being widespread among operators to facilitate application of the final models. The TIM Self-Assessment consists of three primary assessment areas:

1. Program and institutional issues;
2. Operational issues; and
3. Communications and technology issues.

Composite scores are given for each of these areas (there are multiple attributes in each area), as well as a single overall score. The team explored using both the individual scores, as well as the overall score, in the modeling. Unfortunately, self-assessment scores were only available for three cities, which were not enough for model development. Nonetheless, preliminary (but inconclusive) results are presented.

Weather Data

Overview

Weather data were obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration. NCDC, the world's largest active archive of weather data, produces climate publications and responds to data requests from all over the world. NCDC offers a wide range of climate products and services, including a surface climate product that provides local climatological data, as well as marine and upper-air data.

The local climatological data product consists of hourly, daily, and monthly climatological summaries for approximately 1,600 U.S. locations (daily summary forms are not available for all stations). Since the end of January 2005, the local climatological data have been processed through automated quality control processing. About 480 first-order stations also undergo additional quality control after the end of the month.

Data Access

Similar to other NCDC products and services, the local climatological data are available through a variety of media, including online access, annual subscriptions, CD-ROMs, DVDs, computer tabulations, maps, and publications (*1*). Free access to NCDC data is granted to certain users, such as academic and educational users, using reverse domain lookup. The local climatological data for specific locations and specific time frames are available for download. Final data loads occur on a monthly basis, usually overnight. Data gaps may exist during the time frame of previous and current final data loads.

Data Format and Description of Hourly Data

The hourly data files used for the research contained the following basic weather elements:

- Sky condition—Cloud height and amount (clear, scattered, broken, and overcast) up to 12,000 feet;
- Visibility (to at least 10 statute miles);
- Basic present weather information—Type and intensity for rain, snow, and freezing rain;
- Obstructions to vision—Fog, haze;
- Pressure—Sea-level pressure, altimeter setting;
- Ambient temperature and dew point temperature;
- Wind—Direction, speed, and character (gusts, squalls);
- Precipitation accumulation; and
- Selected significant remarks, including variable visibility, precipitation beginning and ending times, rapid pressure changes, pressure change tendency, wind shift, and peak wind.

Geometric, Operating, and Improvement Data

Geometric data were obtained from satellite imagery (lane configurations) and the 2007 Highway Performance Monitoring data. Operating and improvement data were obtained directly from state DOTs. The most important data in this category were those elements related to calculating capacity for each individual link.

Data Processing Procedures

Urban Freeway Data Processing

Data for all urban freeway sections were centrally processed to ensure consistency. The processing began with quality control of the data as received from the TMCs. The data quality checks used were those developed for FHWA (*2*). Data were aggregated to 5-minute by-lane summaries. Aggregation rules followed those in a forthcoming ASTM standard (ASTM E2665-08). Two levels of spatial aggregation were done on the 5-minute-interval data:

1. **Station level—**Data were aggregated laterally over all lanes in a direction; and
2. **Section level—**Station-level data were aggregated longitudinally for all stations on a study section.

The aggregation process is shown in Figure 3.8. From the section-level data, a procedure for estimating the start and end times of the peak hour and peak period was applied; this procedure is detailed in Chapter 4 under the section "Defining Peak Hour and Peak Period." Analysts then reviewed the start and end times and made adjustments based on local knowledge.

Section-level statistics were computed for each time slice to be used in the analysis:

- Peak hour (weekdays only);
- Peak period (weekdays only);
- Counterpeak hour (weekdays only; the opposite time slice from the peak hour; that is, if the peak hour is in the morning, then the counterpeak is in the afternoon);

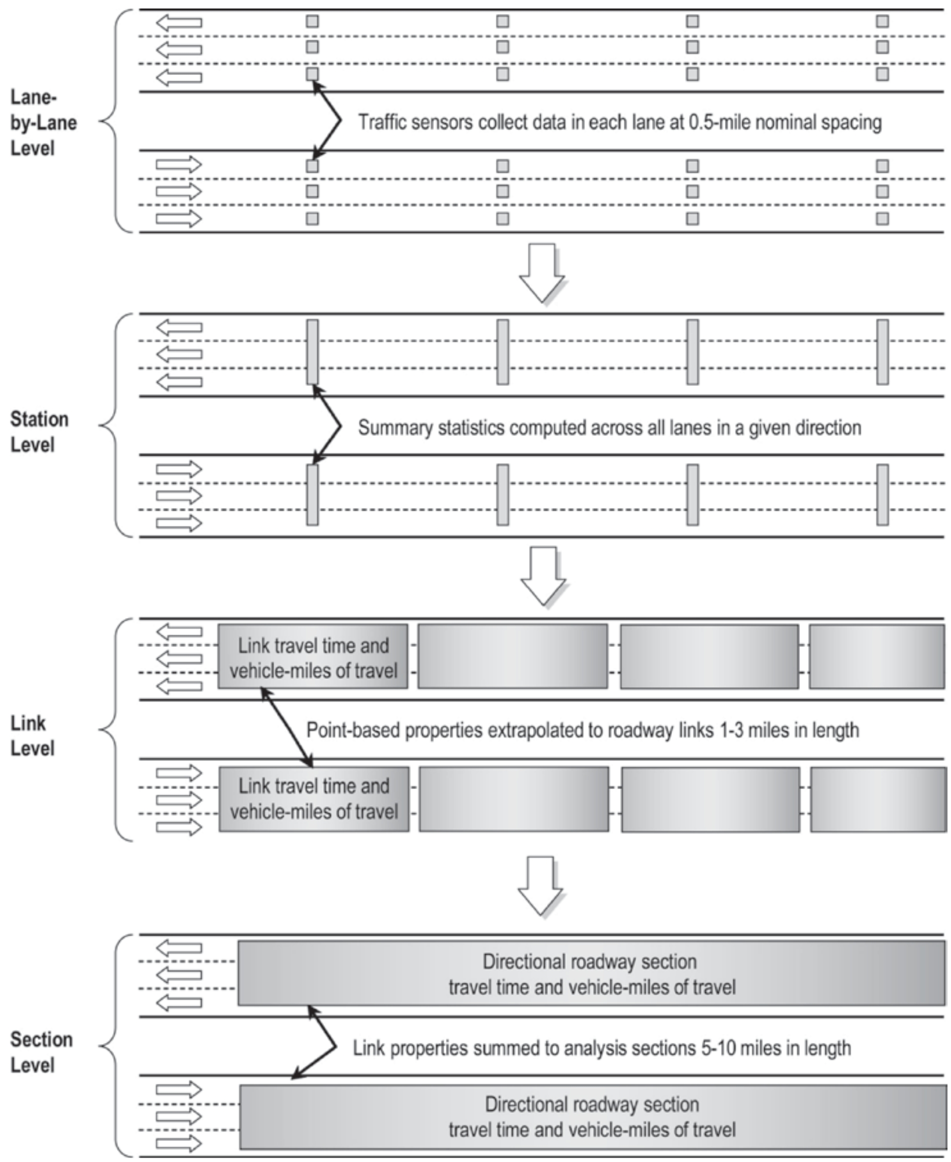

Figure 3.8. Study sections mapped to original experimental design matrix (3).

- Midday;
- Week day (all hours of the day); and
- Weekend and holiday (all hours of the day).

Signalized Arterial Data Processing

Calculating travel time and reliability statistics from toll tag–equipped probe vehicles is straightforward—travel times are measured directly so there is no need for transformations as shown in Figure 3.8. Data quality control is different, however. Because of the opportunities for vehicles to make incomplete trips through a section of arterial (such as stopping at adjacent land uses), some travel times will be detected as being excessively high. As a result, probe data quality controls have been focused on eliminating outliers. In FHWA's Mobility Monitoring and Urban Congestion Report Project (*3*), the quality control criterion for probe data states that two consecutive travel times cannot change by more than 40%. Another method proposed by researchers at the University of Washington is that a travel time cannot be more than one standard deviation above or below the moving average of the 10 previous entries.

These methods work well for freeway data, for which probe data coverage is high. However, probe data on arterials are considerably sparser. Many of the outliers in arterial data will pass through this method undetected because there are not enough immediate adjacent observations. Instead of relying on continuous observations, arterial data quality control focused more on the overall spread of the data. Examination of the arterial data led the team to develop the following quality control processing rules, all of which were applied to the data:

1. Any days with extremely low or high travel times are removed by visual inspection.
2. Rank all travel time for a section, and treat any value greater than the 75th percentile plus 1.5 times the interquartile distance, or less than the 25th percentile minus 1.5 times the interquartile distance, as an outlier. This technique is robust because it uses the quartile values instead of variance to describe the spread of the data.
3. Two consecutive travel times cannot change more than 40%.
4. A travel time cannot be more than one standard deviation above or below the moving average of the 10 previous entries. These 10 previous entries must be continuous and valid data.

Rural Freeway Data Processing

The rural freeway portion of the study relied on speed data supplied by Inrix on Traffic Message Channel links. From a processing standpoint, Inrix data were treated in the same way as detector data. However, because the Inrix data were provided by relatively short links, and many links comprised the very long rural segments used in the research, a trajectory-based method was used to estimate travel times for the entire segment. The vehicle trajectory method traces the vehicle trip in time and applies the link travel time corresponding to the precise time in which a vehicle is expected to traverse the link. For example, a section travel time that begins at 7:00 a.m. will use a link travel time for 7:00 a.m. to 7:05 a.m. at the trip origin, but could use a link travel time from 7:05 a.m. to 7:10 a.m., or from 7:10 a.m. to 7:15 a.m., at the trip destination. The vehicle trajectory method attempts to more closely model the actual link travel times experienced by motorists as they traverse the freeway system. Figure 3.9 shows how the vehicle trajectory method works compared with the snapshot method used for the much shorter urban freeway sections. In the trajectory method, the vehicle stair-steps through the time–distance matrix (rows are time and columns are distance along the route, as indicated by detector location); these are shown as the gray arrows moving up from right to left. Thus, the travel time speed at any given location depends on when the vehicle is at that location. The snapshot method simply takes all the travel times and speeds for a time slice along the entire route (black arrows moving straight across from left to right); that is, speeds are not considered to be time dependent.

Calculation of Free-Flow Speed

The distribution statistics for the Travel Time Index (TTI) depend on measuring travel time relative to an ideal or free-flow speed. Deviation from the free-flow speed indicates that congestion has occurred. For urban freeways, the research team used a constant value of 60 mph for all sections. This is a well-established threshold for measuring congestion on urban freeways. For signalized highways and rural freeways, the situation is more complex due to variations in speed limits and signal-influenced delay, even at very low volumes. For these sections, the 85th percentile speed was used as the free-flow speed. In all cases, if section speeds were higher than the free-flow speed, the TTI was set to 1.0; no credit was given for going faster than the free-flow speed.

Final Data Set for Statistical Analyses

As the preceding discussion and figures show, a large array of data sets at various levels of spatial and temporal aggregation was created. The end result of the processing and fusing was the data set used in the statistical analyses. This data set was highly summarized, which was necessary because reliability is defined over a long period of time to allow all the factors to exert influence on it. Each observation in the statistical analysis data set was for an individual section for an entire year for each of the daily time slices studied: peak hour, peak period, midday, weekday, and weekend and holiday. The data set contained the data types described in the following subsections; the data were intended to capture characteristics for an entire year on the study section. Appendix A shows the variables in the final data set.

Reliability Metrics

- Mean, standard deviation, median, mode, minimum, and percentiles (10th, 80th, 95th, and 99th) for both the travel time and the TTI;
- Buffer indices (based on mean and median), Planning Time Index, skew statistic, and Misery Index; and
- On-time percentages for thresholds of median plus 10% and median plus 25%; and average speeds of 30, 45, and 50 mph.

Operations Characteristics

- Areawide and section-level service patrol trucks (average number of patrol trucks per day);
- Areawide and section-level service patrol trucks per mile (average number of patrol trucks per day divided by centerline mile);
- Traffic Incident Management Self-Assessment scores;

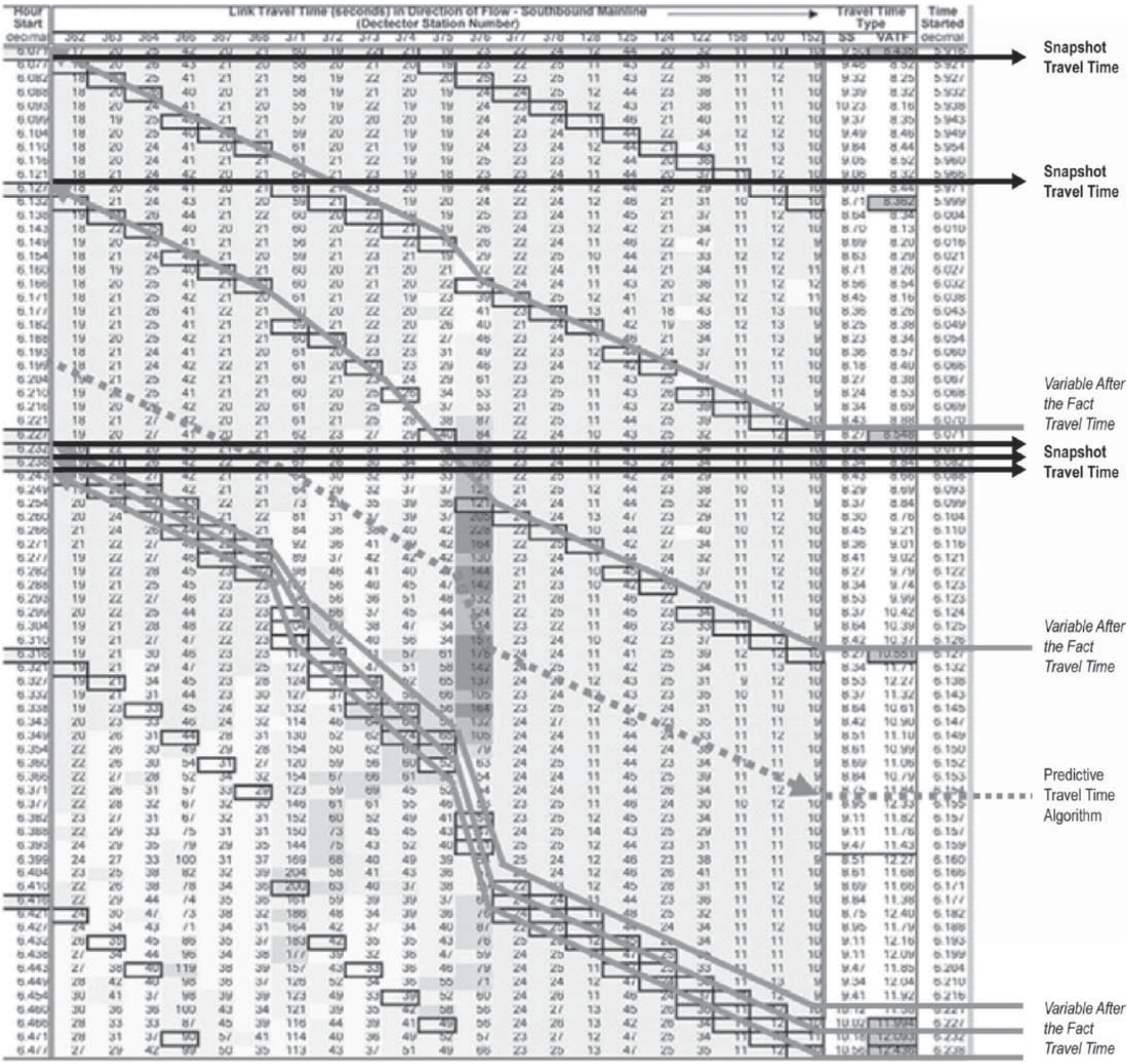

Figure 3.9. Snapshot and vehicle trajectory methods of estimating travel times from spot speeds (4).

- Quick clearance law (yes or no);
- Property damage only move-to-shoulder law (yes or no);
- Able to move fatalities without medical examiner (yes or no);
- TMC staff per mile covered; and
- Number of ramp meters, dynamic message signs, and CCTVs.

Capacity and Volume Characteristics

- Start and end times for the peak hour and peak period;
- Calculated and imputed vehicle miles traveled;
- Demand-to-capacity and annual average daily traffic-to-capacity ratios:
  - Average of all links on the section, and
  - Highest for all links on the section; and
- Annual average daily traffic-to-capacity ratios for downstream bottlenecks by ramp merge area.

Incident Characteristics

- Number of incidents (annual);
- Incident rate per 100 million vehicle miles;
- Incident lane hours lost (annual);

- Incident shoulder hours lost (annual); and
- Mean, standard deviation, and 95th percentile of incident duration.

Work Zone Characteristics

- Number of work zones (annual);
- Work zone lane hours lost (annual);
- Work zone shoulder hours lost (annual);
- Mean, standard deviation, and 95th percentile of work zone duration.

Weather Characteristics

- Number of (annual) hours with precipitation amounts greater than or equal to 0.01, 0.05, 0.10, 0.25, and 0.50 inches;
- Number of (annual) hours with measurable snow;
- Number of (annual) hours with frozen precipitation; and
- Number of (annual) hours with fog present.

Assigning Incidents to Study Sections

Incidents were assigned spatially to the study sections based on the linear referencing in the traffic and incident data sets. Only incidents that actually occurred on the section were included. Flow on a study section is influenced by incidents that occur immediately downstream of that section, and incidents that occur just beyond the extreme upstream end of the study section will influence the downstream study section. The decision to include only on-section incidents was based on the application of the statistical models: it is far easier for practitioners to develop section-specific data than to have to compile off-section data, as well. Also, the goal of the statistical modeling is not to build a deterministic model of traffic flow but to try to capture the cumulative, annual flow characteristics of a section.

For the peak hour, peak period, and midday time slices, an incident was assigned to the time slice if it began in the time slice, ended in the time slice, or spanned the time slice. To capture the effect of incidents that occurred immediately before the start of a time slice, a 15-minute window was allowed. The lane hours lost calculation was based on those that were lost solely within the period. For example, consider a peak hour of 7:30 to 8:30 a.m. If an incident began at 8:00 a.m. and lasted until 9:15 a.m. (a total of 75 minutes), only the lane blockages from 8:00 to 8:30 a.m. would count.

Description of Seattle Study Area

This section briefly describes the portions of the Seattle freeway system included in the congestion by source analyses; more detail is provided in Appendices C and D. Figure 3.10 illustrates the 21 study sections. Each of these roadway segments was studied by direction, leading to an analysis of 42 study sections.

Five freeways were included in the analysis: I-5, I-405, I-90, SR 167, and SR 520. They were broken into multiple segments based on a combination of geometric and travel patterns. The segmentation of each roadway is described briefly below.

Freeway I-5

I-5 was divided into six segments, named (from south to north) South, Tukwila, Seattle central business district (CBD), Seattle North, North King, Lynnwood, and Everett. The basic attributes of these six segments are discussed below.

South is the longest segment. It is primarily four lanes wide, with a high-occupancy vehicle (HOV) lane on the left side, and travels from the southern edge of WSDOT's instrumented roadway system to the southern I-5/I-405/SR 518 interchange. Its traffic is heavily directional (relative to its capacity). It contains a very large hill located at the northern end of the segment. The hill can affect congestion southbound in the evening peak period due to the slow speeds of buses and trucks climbing the grade, especially those entering I-5 from I-405 and SR 518. Both directions of traffic can be affected by downstream congestion.

Tukwila, the next segment to the north, goes from the southern I-5/I-405 interchange to just north of Boeing Field; it is also mostly four general-purpose (GP) lanes wide, with one inside HOV lane. The northern end of Boeing Field is the approximate end of the backup from much of the recurring congestion that occurs in the a.m. and many p.m. peak periods. Much of that congestion stems from bottlenecks occurring in the next roadway section to the south. In the southbound direction of travel this segment tends to be relatively congestion free (the congestion tends to be bottlenecked to the north in the downtown sections). It occasionally suffers from backups in the downstream segment, when very severe congestion entering I-405 northbound combined with queuing on the South Center Hill can interfere with traffic flow. Otherwise, most congestion is commonly caused by disruptions of some kind.

The Seattle CBD section, the next section to the north, contains a significant number of bottlenecks in closely spaced succession. Unfortunately, they are so closely spaced that it was not practical to divide them into separate roadway sections. At its southern end, this is a four-lane GP, one-lane HOV roadway. One of the GP lanes is dropped at the West Seattle freeway interchange. This is followed by the interchange with I-90, which includes a collector–distributor lane that also serves as a mechanism for separating downtown ramps from some of the mainline traffic flows. Immediately north of the I-90 interchange is the southern terminus of the I-5 express lanes, a reversible roadway that operates primarily

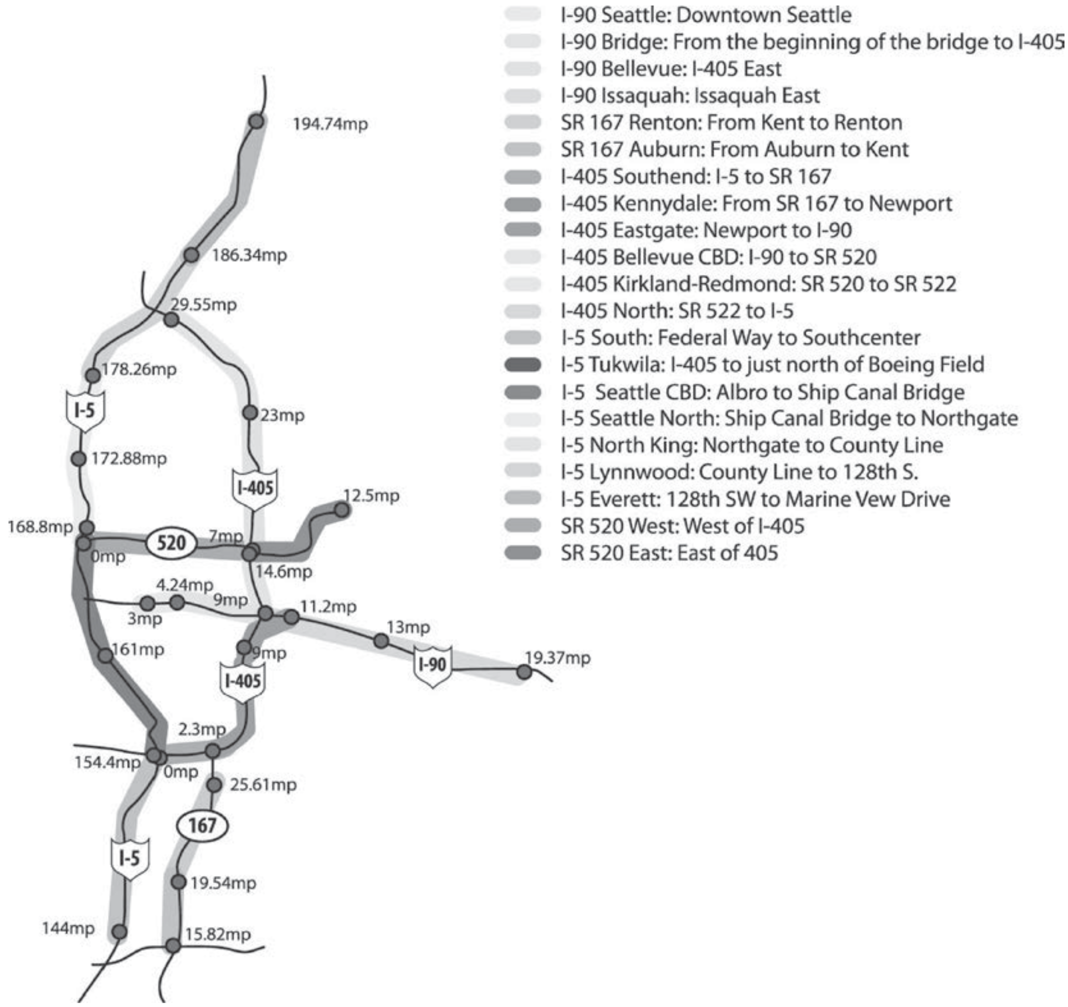

Figure 3.10. Map illustrating Seattle study sections.

southbound in the a.m. and northbound in the p.m. In this stretch of highway, the left-hand HOV lane first becomes a GP lane, and then becomes an exit-only lane to the northbound express lanes. When the express lanes are operating southbound, these lanes become part of a left-hand exit to downtown. Another of the through lanes also becomes an exit-only ramp to downtown, leaving only two GP through lanes. (One additional lane exists as part of the collector–distributor to I-90 and other downtown ramps.) This is another bottleneck location. This area is followed by a series of on- and off-ramps, including the on-ramp from the collector–distributor, which provides the on-ramps from I-90, to downtown. This section of the freeway also moves underneath the Washington State Convention Center, as part of a short tunnel segment, with modest visibility and sight distances. The collector–distributor becomes the third lane when it rejoins the main roadway underneath the convention center, and then a fourth lane is added part way through downtown as an add lane from one of the downtown ramps. No HOV lane exists on this stretch of freeway. Finally, as the roadway exits the downtown Seattle area, it reaches the end of this roadway segment at the SR 520 interchange. The right two lanes become exit-only lanes to SR 520. These lanes are often stop-and-go during both peak periods due to congestion on SR 520. One final bottleneck appears in the last ramp from downtown (Mercer Street), a left-hand on-ramp that sets up a C-class weave, as many vehicles entering at Mercer wish to be in the right-hand lanes in order to exit to SR 520.

All these features exist in the southbound direction. The only difference is that the express lanes terminus is an add lane located just south of the downtown core. Consequently, it has less impact on the overall freeway performance than the northbound terminus does. However, the C-class weave from SR 520 to Mercer (again, a left-hand on-ramp followed by a right-hand exit lane) is a bottleneck, as are the effects of the downtown exit- and on-ramps.

The North Seattle roadway section is the next section to the north. This section starts at the I-5/SR 520 interchange, goes across the Ship Canal Bridge, and continues to the northern terminus of the express lanes. This section of roadway has only modest routine northbound congestion. However, southbound, it is affected by a C-class weave from the NE 45th Street and NE 50th Street entrances to the SR 520 interchange. In addition, the Ship Canal Bridge is exposed to wind, adding to the factors that affect throughput on this roadway. This roadway is four GP lanes wide in the southern section, and becomes three lanes wide with an add–drop lane to Lake City Way (about half way through the study segment). No HOV lane exists in this section of the roadway. Note that this study does not include the express lanes themselves, which serve as the HOV facility (and as additional GP capacity) during the peak directional movements.

The North King section of the roadway starts with the northern entrance of the express lanes and continues to the King County–Snohomish County line. It is four lanes wide, with an HOV lane on the left. The HOV lane starts (ends) at the express lanes terminus. This roadway experiences routine congestion associated with that terminus in both directions. When the express lanes are operating northbound, considerable weaving takes place into and out of the left-hand HOV lane. Northbound, modest volumes of vehicles move from the left-hand entrance to the GP exits on the right side of the freeway. Southbound, this section of roadway has minor merge-related slowdowns, both when vehicles enter the express lanes, and when the express lanes are closed, as I-5 loses two lanes of capacity at that time (one GP lane and the HOV lane).

Lynnwood is the next section of I-5 to the north. This section of roadway goes from the King County–Snohomish County line to SE 128th Street, and it includes the northern I-5/I-405 interchange. This section of roadway has four GP lanes and one HOV lane. Additional lanes exist at the I-405 interchange to smooth flow between the freeways.

Everett, the final I-5 section, is primarily three GP lanes wide with an HOV lane on the left side. Of greatest significance for this study is that in 2006, north of the instrumented roadway, a major construction project was underway. This project included the extension of the HOV lanes and significant redesign of the ramps in the city of Everett. These construction activities created some backups that extended back onto the Everett study section, mostly late at night, but occasionally on weekends.

Freeway I-405

The I-405 freeway was divided into six sections. From the south they are

- South;
- Kennydale;
- Eastlake;
- Bellevue CBD;
- Kirkland–Redmond; and
- North.

The South section contains two GP lanes and one left-hand HOV lane. This section extends from the I-405/I-5 interchange to the SR 167 interchange. Bottlenecks occur at both of these interchanges, with the most significant of those being the northbound movement. The southern end of this study segment is also significantly affected by on- and off-ramps leading to and from the South Center Mall. (Short ramp lengths and the narrow freeway lead to difficulty merging and the commensurate increase in traffic disruption from these ramps.)

The Kennydale section is among the most routinely congested sections in the region. It stretches from the SR 167 interchange to 2 miles south of the I-90 interchange. This stretch of road includes the merge (northbound) from SR 167 and diverge (southbound) from I-405 to SR 167. Both of these movements cause major bottlenecks because they are routinely over capacity. North of the SR 167 interchange on I-405 are a series of ramps to and from the city of Renton, which creates considerable ramp disruptions. The freeway then goes up and over a major hill (the Kennydale Hill) which can slow heavy trucks, and there is significant heavy truck traffic on this route as it is the primary route for travel from the region's major distribution centers to I-90 and all points east. Because the roadway is only two GP lanes and one HOV lane through most of this entire section (there are some add–drop lanes), any slow-moving vehicle is likely to create minor congestion. The roadway is severely over capacity, especially northbound in the morning and southbound in the evening.

The Eastlake section of the freeway is a short 2-mile segment designed to examine the effects of I-90 interchange congestion. In the peak directions, this segment is very congested; in the off-peak directions it flows well.

The Bellevue CBD section stretches from the I-90 interchange just south of the Bellevue CBD to the SR 520 interchange just north of the Bellevue CBD. Bellevue is the second largest city in the region and a significant urban center. Considerable traffic uses I-405 to reach Bellevue, and the freeway serves a considerable pass-through movement, as well. For traffic coming from the north (including SR 520, which serves the Microsoft headquarters complex), I-405 is the primary connection to I-90 and the other bridge across Lake Washington. As a result of the combination of through movements, large Bellevue-based ramp movements, and the congestion that occurs at the I-90 and SR 520 interchanges, this section of roadway is routinely congested during peak periods.

The Kirkland–Redmond roadway section has a southern boundary at the SR 520 interchange and travels north to the SR 522 interchange. Unlike I-405 south of Bellevue (which although directional has a strong reverse direction movement), the Kirkland–Redmond section is very directional, southbound in the morning, northbound in the evening. The roadway changes width from three GP lanes and one HOV lane north of the NE 80th Street interchange to four GP lanes and one HOV lane between SR 520 and Kirkland. In addition to severe demand-related congestion at most of the major on-ramps, the roadway study segment has a very steep hill (uphill southbound) just south of the SR 522 interchange.

The North study segment is the last of the I-405 roadway segments. It is a two-GP, one-HOV lane section that extends from SR 522 to the northern I-5/I-405 interchange. This section has no significant bottleneck points, but it does have some simple capacity issues, primarily southbound in the morning.

Freeway I-90

The I-90 roadway was divided into four segments from Issaquah to downtown Seattle. These are (moving from west to east) Issaquah, Bellevue, Bridge, and Seattle.

The Issaquah segment is a three-GP-, one-HOV-lane roadway section that travels 6 miles from the city of Issaquah toward Bellevue. While there are no significant geometric bottlenecks on this study segment, it does contain three very-high-volume ramps. The result is routine a.m. congestion westbound. In the evening, some off-ramp queuing can cause delays in the right-hand lanes of the roadway eastbound.

The Bellevue study segment covers the remaining distance between Issaquah and the I-405 interchange. Two additional on-ramps add traffic, although an additional lane is added in this section, before becoming a drop lane at the I-90 interchange. As with the Issaquah eastbound p.m. movement, this roadway section can be affected by significant off-ramp queuing to I-405, in this case, in the westbound a.m. peak period. On very bad days queues on I-90 from the downstream section of I-90 can also reach the western portions of this segment during the a.m. peak period.

The Bridge study section contains both I-90's Lake Washington floating bridge and the stretch of I-90 that crosses Mercer Island, which also contains a short tunnel. A reversible express lane also sits in the middle of this study section. (The express lane section is not included in this analysis.) The eastern end of the express lane is located just to the west of I-405. The eastbound exits from the express lanes cause little disruption because of direct ramps from that facility to the I-405 interchange and an add lane to the I-90 mainline. Westbound it causes congestion only when the express lane is eastbound, in which case the HOV lane must merge into the three GP lanes, causing a merge bottleneck. In addition to the ramps from Mercer Island to I-90, several other locations on this section of roadway can become bottlenecks under specific conditions. The most significant are the exit from the tunnel section (which leads to the bridge, and creates some visibility issues when the sun is at certain angles) and the bridge itself (where drivers can also suffer from considerable visual distraction).

The Seattle section is the last section on I-90. It covers from the western end of the I-90 floating bridge, through tunnels underneath Capitol Hill, and to I-5, where I-90 ends. Westbound travelers can exit to downtown Seattle or turn north or south on I-5. All three of these ramps can experience queues that extend back onto I-90 depending on the time of day, the types of events occurring in downtown Seattle, and the congestion found on I-5. Eastbound, this roadway section has only one entrance ramp, other than the ramps from I-5 or downtown. Merge congestion is therefore modest. However, backups from the Bridge section of I-90 can easily extend back onto this section, creating congestion.

Freeway SR 167

This roadway is east of I-5, and travels in a north–south direction through the region's primary warehouse and distribution centers. It also serves manufacturing areas and a growing residential population, especially to the far south. This roadway was divided into two study sections for this project, Auburn and Renton. The entire roadway contains two GP lanes and one HOV lane. The HOV lane is now a high-occupancy toll lane, but in 2006 it was still a traditional HOV lane.

The Auburn section extends from the SR 18 interchange (the southern end of the surveillance equipment, although not the end of the SR 167 freeway), to the city of Kent. This stretch of roadway has no major geometric bottlenecks northbound, but it does suffer from on-ramp merge congestion due to high traffic volumes northbound in the a.m. Southbound in the p.m., it has a bottleneck at the southern terminus to the study section, where the HOV lane ends (becoming a GP lane), and one of the GP lanes becomes an exit-only lane to SR 18. In addition, due to the restricted number of lanes, traffic south of this bottleneck can move very slowly in the p.m. peak, further worsening the queues observed southbound on the study section.

The Renton study section travels from Kent to the I-405 interchange, which is a significant bottleneck. The ramp queues from northbound SR 167 to I-405 frequently back up onto SR 167 in both peak periods (although the a.m. peak is the primary movement), as I-405 simply does not have the capacity to accept the SR 167 traffic volumes. Southbound the SR 167 section also congests because of very high traffic volumes. There are no significant geometric causes for those delays.

Freeway SR 520

The final roadway in the study section, SR 520, was divided into two sections, called Seattle and Redmond.

The Seattle section goes from I-5 across the Lake Washington floating bridge to I-405. This section is two GP lanes. There is an HOV lane only in the westbound direction; that HOV lane ends in a lane drop at the approach to the bridge itself. The bridge has no shoulders. The lack of shoulders means any incident occurring on the bridge approaches or on the bridge itself blocks a lane. On the western end of the study section are two ramps, one of which leads to the University of Washington. This roadway operates near capacity in both directions over 13 hours each weekday. Because both directions are capacity constrained, the directional volumes are roughly equal throughout the day. The primary difference in the measured performance of the two directions for this roadway is the location of the bridge relative to the entire study section. Eastbound, the study section travels a little over 1 mile from I-5 to the bridge itself, and all of this distance is a two-lane roadway. This means that the measured queue eastbound is never larger than roughly 1 mile. Once the queue grows larger than 1 mile, it extends onto I-5, where its effects are felt in the southbound Seattle North study section or the northbound Seattle CBD study section. Conversely, in the westbound direction, the study section allows for the measured queue from the bridge deck to extend for more than 3 miles. In the heart of the p.m. peak period, this entire roadway section is routinely stop-and-go congestion.

The Redmond study section includes that section of SR 520 from I-405 east to the end of the freeway, a signalized intersection with SR 202 and other local roads. The freeway branches into two parts as it ends, each of which ends at a signal. The freeway passes by the Microsoft headquarters campus. Consequently, significant traffic volumes move toward the center of this study section in the a.m. peak period and away from the center of the study section in the p.m. peak period. In addition, the eastern end of the roadway serves a large residential population that travels to both Bellevue and Seattle. Thus the a.m. peak also contains a large westbound home-to-work movement that extends the length of the study section, while the p.m. peak contains a large work-to-home movement. The signalized intersections at the eastern end of the facility create this section's only major bottleneck. The signals cause significant congestion to extend back from the eastern end of the facility during the p.m. peak period. In the morning, these lights simply serve to meter traffic entering the roadway, allowing the roadway to operate fairly well. The only other bottlenecks that occur are minor ramp delays leading to Microsoft (these can add considerable delay to travelers headed to Microsoft, but they do not significantly affect the main freeway lanes) and queues that originate on the Seattle section of SR 520 but extend back onto the Redmond section. This happens, on average, at least once a week, usually as a result of crashes or other major traffic incidents on the Seattle section of the roadway.

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CHAPTER 4

Empirical Measurement of Reliability

Overview

As discussed in Chapter 3, the research team took an empirical approach to the problem of reliability estimation. Before conducting the three main analyses (congestion by source, before-and-after studies of reliability improvements, and statistically based predictive relationships for reliability), exploratory analyses were conducted to (*a*) explore the basic characteristics of reliability and (*b*) establish basic parameters and principles for measuring and analyzing reliability. These analyses formed the basis for the more detailed analyses that followed, but they also offer valuable guidance on their own for others interested in measuring and studying reliability.

Recommended Reliability Metrics for the Research and General Practice

The research team concluded that all potentially useful reliability metrics communicate information about the size and shape of the underlying travel time distribution: that is, the history of travel times on a facility, corridor, or network. (The Phase 1 report more completely describes the wide range of possible reliability metrics.) As shown in Figure 4.1, travel times can be developed using a variety of methods, from direct measurement (top left) to purely synthetic means (top right). Although a wide variety of other performance metrics can be developed from travel times, is travel time the best primary metric to use? Travel times are not normalized and clearly will vary according to the length of the segment or trip being studied.

The original candidate reliability measures were the ones in use throughout the United States. However, during the study, research in Europe suggested other potentially useful measures. To examine how these concepts related to those specified in the work plan, an analysis using 2006 freeway data from the Atlanta NaviGAtor system was conducted. The first concept tested was the notion that in a skewed distribution, the median is a better descriptor of central tendency than the mean. Table 4.1 shows that for all the highway sections studied, the mean and the median are very close. This is true for relatively uncongested sections (Travel Time Index [TTI] <1.1) and congested sections (TTI >1.4).

Further confirmation that using the mean in the Buffer Index calculation provides the same information as using the width statistic is found in Figure 4.2. The strong positive relationship indicates that both measures are closely related and can be used interchangeably.

The team considered including the skew of the travel time distribution to be useful in the research. Use of this measure would largely be limited to researchers and technical personnel as its communication to laypersons is problematic, but having a way of characterizing the travel time distributions of different facilities and time periods would be valuable.

As a further empirical test of reliability performance measures, an additional analysis using data from the Seattle area was conducted. The data for this research were obtained from the loop sensors maintained by WSDOT along SR 520, an urban limited-access freeway running from Seattle to Redmond. The corridor was divided into westbound and eastbound segments and segments west of I-405 (Bellevue to Seattle) and east of I-405 (Redmond to Bellevue). This particular data set was an excellent example for the study of reliability data because each of the four segments has a very different level and pattern of congestion. SR 520 westbound from Bellevue to Seattle experiences the highest level of congestion. Volumes are typically heavy throughout the day with congestion peaks in the a.m. and p.m. A 2-mile-long floating bridge with no shoulders on the western end of the corridor is highly susceptible to incident-induced congestion, adding to the existing volume saturation–related delays. On the eastbound section of this roadway from Seattle to Bellevue, volumes are similar to those found in the westbound direction, but because the bridge bottleneck is located at the beginning

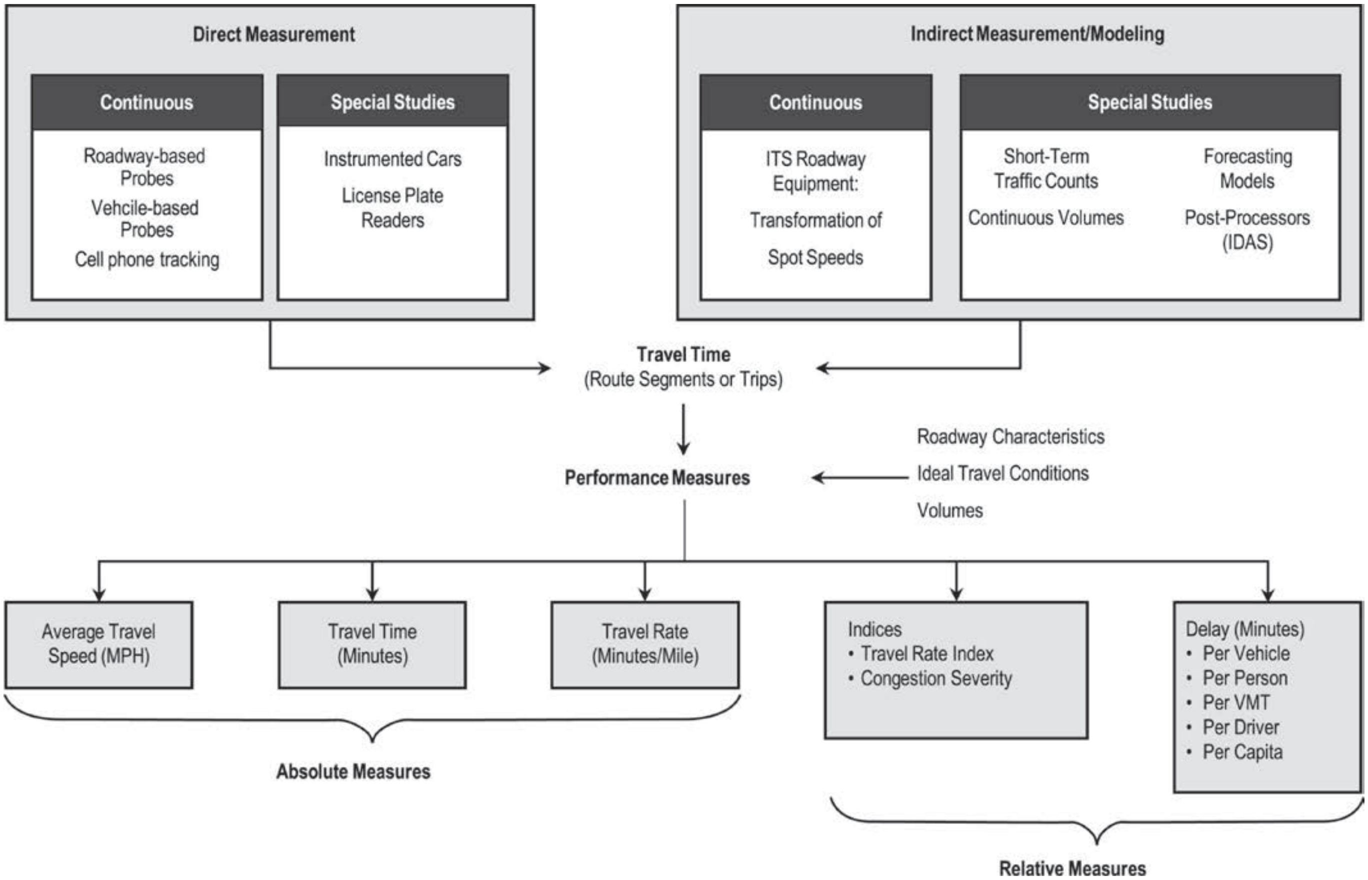

Figure 4.1. Travel time is the basis for defining mobility-based performance measures.

Table 4.1. Travel Time Distribution Statistics: Atlanta Freeways, 2006 (4:00 to 7:00 p.m.)

Section	Section Length (mi)	TTI	Travel Time (min)		
			Mean	Median	95th Percentile
I-75 northbound: south of Hudson Road to I-85 split	12.980	1.065	13.8	13.3	15.671
I-75 northbound: south of I-85 split to Brookwood Interchange	6.250	1.334	8.3	7.3	13.409
I-75 northbound: Brookwood Interchange to Wade Green Road	18.290	1.619	29.6	28.8	42.803
I-75 southbound: south of Hudson Road to I-85 split	12.610	1.560	19.7	18.5	30.418
I-75 southbound: south of I-85 split to Brookwood Interchange	6.570	1.665	10.9	10.7	14.089
I-75 southbound: north of Wade Green to Brookwood	16.760	1.056	17.7	17.1	20.140
I-85 northbound: Camp Creek Parkway to I-75	2.590	1.171	3.0	2.7	5.439
I-85 northbound: Brookwood Interchange to SR 316	17.430	1.570	27.4	27.0	36.305
I-85 southbound: I-75 to Camp Creek Parkway	2.670	1.055	2.8	2.7	3.291
I-85 southbound: SR 316 to Brookwood Interchange	18.690	1.248	23.3	23.0	28.537
I-285 eastbound: Cobb Parkway to Chamblee Tucker	13.400	1.673	22.4	21.9	32.365
I-285 westbound: Chamblee Tucker to Cobb Parkway	13.190	1.565	20.6	19.4	32.929
I-20 eastbound: I-285 Westside to I-75/I-85	3.680	1.036	3.8	3.7	4.496
I-20 westbound: I-75/I-85 to I-285 Westside	3.410	1.093	3.7	3.5	4.788
I-20 eastbound: I-75/I-85 to Wesley Chapel	8.590	1.345	11.6	11.3	16.234
I-20 westbound: Wesley Chapel to I-75–I-85	8.560	1.046	9.0	8.7	10.244

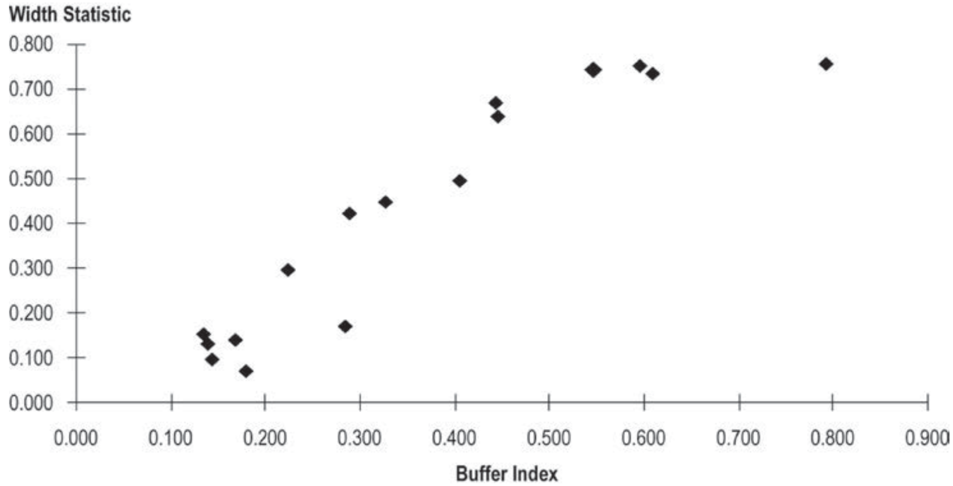

Figure 4.2. Buffer Index versus width statistic on Atlanta freeways, 2006 (4:00 to 7:00 p.m.).

of the study corridor, the average travel times tend to be higher than those measured in the westbound direction. The eastbound traffic is frequently congested throughout the day, with substantial peaks in both a.m. and p.m.

Table 4.2 shows the number of observations and minimum, maximum, mean, standard deviation, and skewness statistics for the travel time in the p.m. peak period (3:00 to 7:00 p.m.) for each section of SR 520. Using skewness and the standard error of skewness, a z-value can be calculated. If skewness divided by the standard error of skewness is greater than 1.96, then one can be 95% confident that the distribution is skewed. (The standard error of skewness is calculated as the square root of 6/n, where "n" is the number of observations.) The standard error of skewness values for the four sections in Table 4.2 are all roughly 0.02, since the sample sizes (number of observations) are the same. The skewness ranges from 10 to 100 times the standard error of skewness, indicating that the distributions are skewed.

Although a few extreme values affected the mean and the maximum, a few extreme values did not affect the 80th, 90th, and 95th percentile calculations, and therefore the difference between the mean and these percentiles was not as robust a measure as it would have been using the median. Because travel time data are by nature skewed, a travel time reliability–based comparison to the median would be more appropriate (e.g., the Buffer Index).

A test was performed in which all travel times affected by incidents and accidents were removed from the SR 520 data set for the western portion of the corridor from Bellevue to Seattle. This simulated the benefits that could be gained if vehicle improvements eliminated all vehicle accidents and breakdowns. Table 4.3 shows the statistics that reflect these two conditions.

While improvements are seen in all direct measures of travel time, both indices report a worsening of reliability. This outcome is caused by the central condition having improved more than the extreme portions of the distribution. Thus the corridor is less reliable. But from both a motorist's standpoint and a highway agency's standpoint, this outcome would be a significant improvement in performance. Because both the central tendency and the actual extreme travel times improved, the traveler would experience an improvement in the corridor operation. Consequently, the team was unconvinced that either of these indices effectively reported the changes illustrated by this experiment.

Essentially the issue with choosing one number to explain a reliability distribution is that one number cannot explain the

Table 4.2. Travel Time Statistics for P.M. Peak Period on SR 520

SR 520 Section	Number	Minimum	Maximum	Mean	Standard Deviation	Skewness
Westbound Bellevue to Seattle	12,350	409	2,975	1,088.8	441.3	0.27
Eastbound Seattle to Bellevue	12,095	409	2,861	598.8	203.8	2.26
Westbound Redmond to Bellevue	12,385	330	2,365	492.4	364.6	2.58
Eastbound Bellevue to Redmond	12,371	330	3,354	604.9	264.2	3.13

Table 4.3. Effect on Travel Times of Removing All Incidents and Accidents on SR 520, Bellevue to Seattle, P.M. Peak Period (3:00 to 7:00 p.m.)

	Travel Times for Weekdays (s)	Travel Times for Days with No Incident Effects (s)	Difference (s)
Mean	1,089	1,026	63
Median	1,063	1,006	57
80th Percentile	1,560	1,467	93
90th Percentile	1,687	1,651	36
95th Percentile	1,780	1,748	32
Misery Index	0.59	0.66	–0.07
Unreliability skew	1.08	1.2	–0.12

entire distribution. Rather than relying on only one percentile calculation or one index, several must be documented to effectively track travel times. By noting the 80th, 90th, and 95th percentile values in comparison to the median (50th percentile) value, the range in travel time changes can be demonstrated from year to year. Each statistic can illustrate the change in a particular problem.

An example of the use of these statistics is given in Figure 4.3, which shows the westbound segment of SR 520 from Bellevue to Seattle. The gray lines are weekday travel times in the p.m. peak period from 3:00 to 8:00 p.m. The black lines are the weekday travel times during the same time period, except that travel times during incident or accident conditions have been removed; that is, the black lines represent the travel time percentiles if no incidents or accidents occurred. This case is an excellent example of the shifting of the travel time percentile lines. The median travel time improves from 1,500 to 1,300 seconds at 5:30 p.m., the peak 5-minute time period. The shift in the 95th percentile is more pronounced at the onset of the peak period congestion from 3:00 to 4:00 p.m. The 50th, 80th, and 95th percentile travel times all have noticeable improvement over the before condition. At the same time, on this badly oversaturated roadway, it is quickly apparent that although incidents and accidents make travel both worse and more unreliable, they are by no means the primary cause of either congestion, nor are they the only cause of unreliable travel.

It was concluded from this analysis that a few additions to the list of reliability metrics originally developed in Phase 1

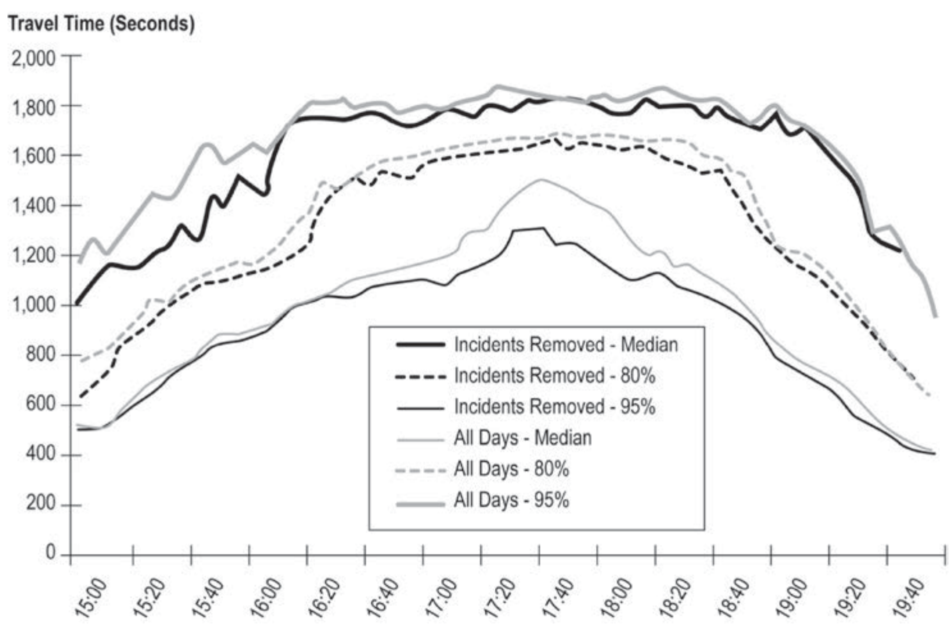

Figure 4.3. Travel time distributions on SR 520.

were in order. Based on the skewness of the travel time distributions, the median is a better central tendency statistic to use as a base value for travel time for indices. Therefore, the following adjustments were made:

- The two Buffer Indices were defined using both the mean and median as the reference value (note that the skew statistic already uses the median as its reference value);
- The 80th percentile travel time was added as a reliability metric;
- The skew statistic was added; and
- Some on-time measures were defined by using the median rather than the mean.

The final set of reliability metrics appears in Table 4.4. Note that TTI rather than pure travel time is used as the primary measurement for the percentiles of the distribution. As a unitless index, TTI is normalized for distance so that sections of different lengths can be compared. An alternative would have been to use the travel rate (minutes per mile, the inverse of space mean speed). All the reliability measures used in this report were derived from the distribution of TTIs rather than raw travel time.

Travel Time Distributions and Reliability Performance Metrics

The Introduction presents several perspectives for defining reliability. For the purpose of the L03 research, *reliability* was defined as the variability of travel times on an extended highway section over the course of 6 months to 1 year for different time slices of the day. This definition allowed direct measurement with the available data and is consistent with the current state of the practice in performance measurement and economic analyses.

A simple way to visualize reliability is to develop travel time distributions and superimpose reliability metrics on them. Figures 4.4 through 4.8 show an example of this process for a 5.19-mile section in Atlanta during 2007 for multiple time slices: peak hour, peak period, midday, weekday (all hours), and weekend and holiday (all hours). Throughout the analysis, holidays were defined as the major federal holidays: New Year's Day, Martin Luther King Day, President's Day, Independence Day, Labor Day, Veteran's Day, Thanksgiving, and Christmas Day. This is a highly congested section in peak periods, with an average TTI over 2.0, which means that trips take over twice as long as they would under free-flow conditions. During the course of the research the team found that several observations on these plots can be generalized to other locations:

- The shape of the travel time distribution for congested peak times (nonholiday weekdays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad shoulder of travel times decreases as congestion levels decrease;
- Similarly, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, note that the highest travel times occur during the peaks; and
- Despite the fact that peaks have been defined, there are still a number of trips that occur at close to free flow; there are more of these trips in the peak period than in the peak hour. This is probably because peak times actually shift slightly from day to day, as traffic demand can be shifted by events. Also, there are probably some days when overall demand is lower than other days.

Table 4.4. Final Set of Reliability Metrics Used in the Research

Reliability Performance Metric	Definition	Units
Buffer Index	Difference between 95th percentile TTI and average TTI, normalized by average TTI. Difference between 95th percentile TTI and median TTI, normalized by median TTI.	%
Failure and on-time measures	Percentage of trips with travel times <1.1 median travel time (MTT) and <1.25 MTT. Percentage of trips with space mean speed less than 50, 45, and 30 mph.	%
Planning Time Index	95th percentile TTI.	None
80th percentile TTI	Self-explanatory.	None
Skew statistic	(90th percentile TTI – median)/(median – 10th percentile TTI).	None
Misery Index (modified)	Average of highest 5% of travel times divided by free-flow travel time.	None

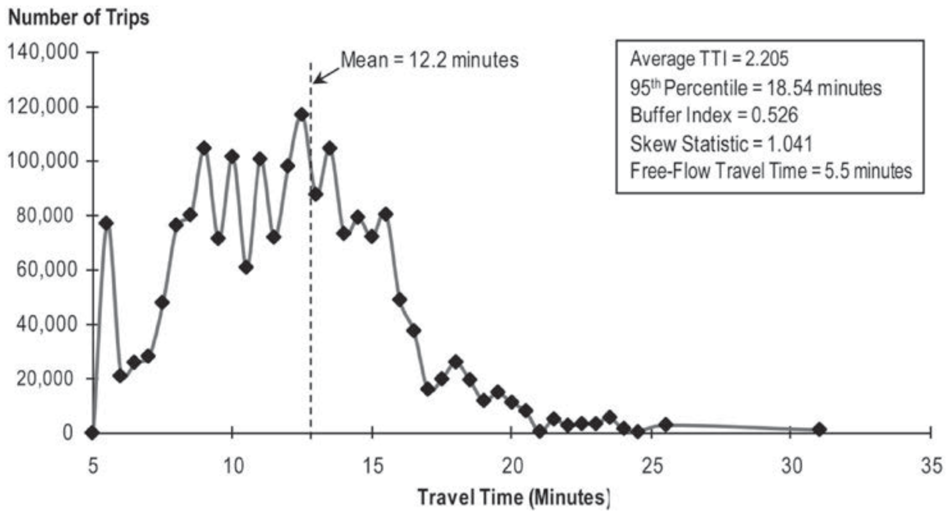

Figure 4.4. Peak hour travel time distribution, Atlanta, I-75 northbound, I-285 to SR 120 (2007).

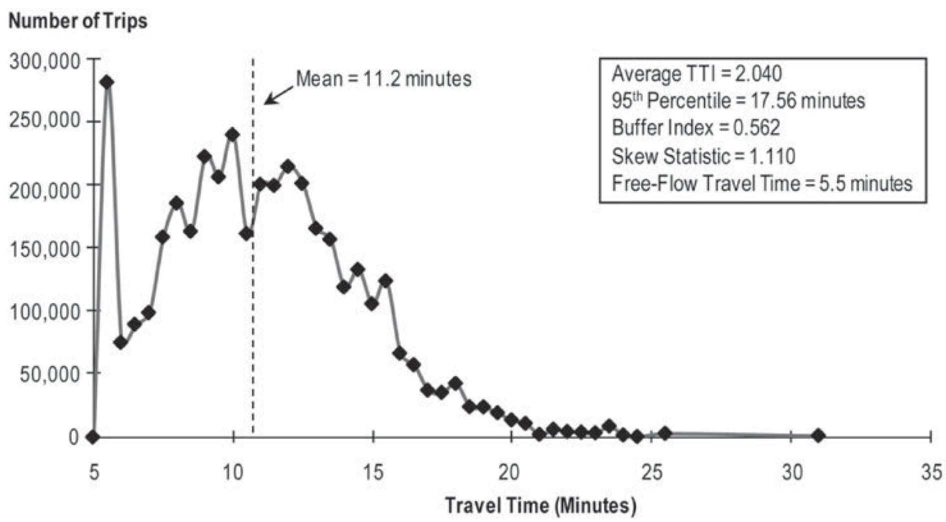

Figure 4.5. Peak period travel time distribution, Atlanta, I-75 northbound, I-285 to SR 120 (2007).

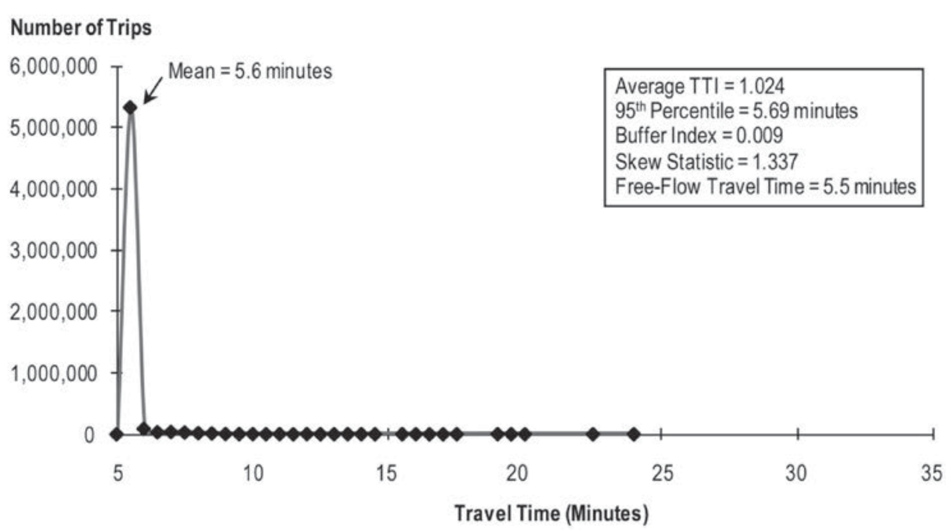

Figure 4.6. Midday travel time distribution, Atlanta, I-75 northbound, I-285 to SR 120 (2007).

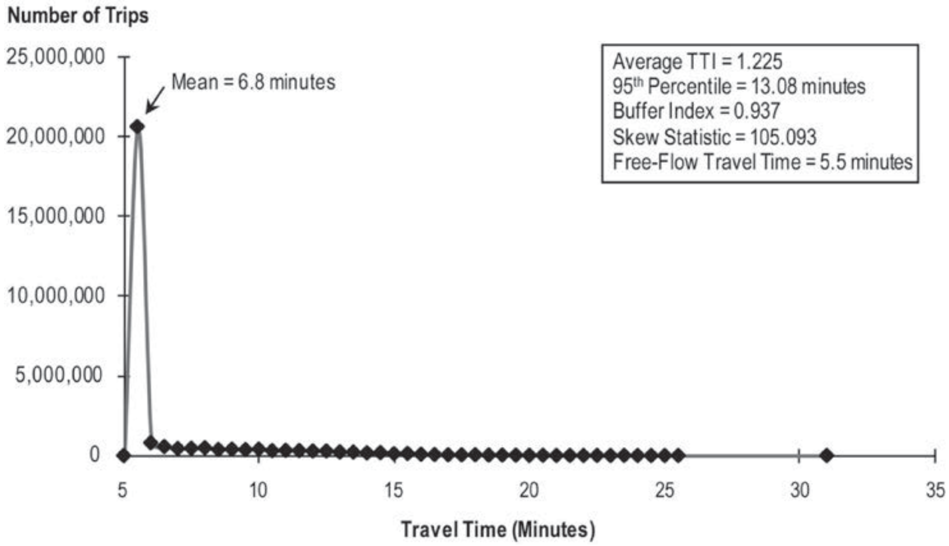

Figure 4.7. Weekday travel time distribution, Atlanta, I-75 northbound, I-285 to SR 120 (2007).

Data Requirements for Establishing Reliability

To allow sufficient time for the occurrence of the myriad of events (e.g., incidents, bad weather) that can affect travel times, reliability requires a fairly long history of travel times. The question is, how much data are needed to make a reasonable estimate of a section's reliability? The study team worked with the assumption that a year's worth of data was desirable.

The research team conducted tests with urban freeway (detector-based) data from Atlanta and the San Francisco Bay Area. These tests were conducted by selecting multiple samples from several time durations, computing the TTI and Buffer Index for the samples, comparing them with the annual value, and noting the error. Table 4.5 shows the results of using 2007 freeway data from Atlanta for the peak period on each section. It is apparent from these results that a month's worth of data provides reasonable estimates of average travel time, but it is insufficient to establish reliability.

Longer time periods also were tested; the results for the Buffer Index appear in Figure 4.9. For this analysis, all possible month combinations for each sampling rate were tested. With 6 months of data, the error rate for the Buffer Index was about the same as it was with 1 month of data for estimating TTI.

Incidents are relatively infrequent in terms of the number of minutes each year that they are present on a facility.

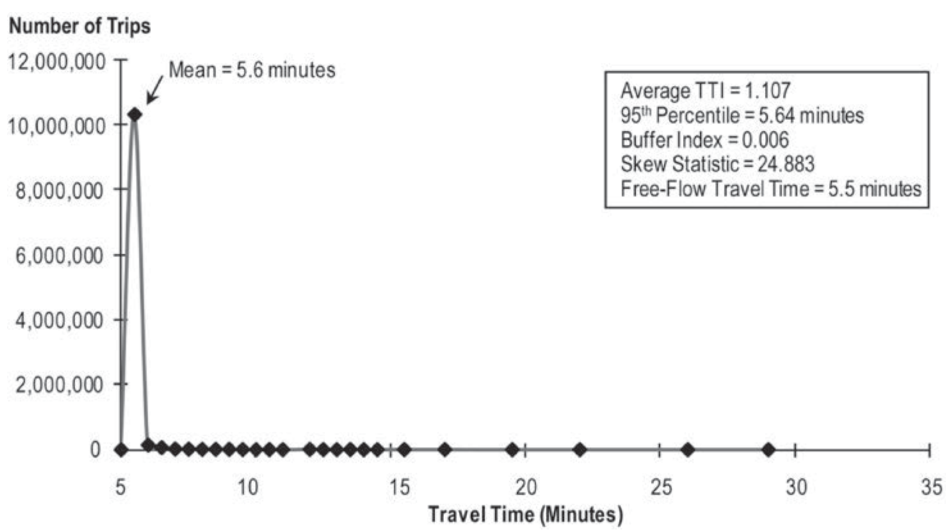

Figure 4.8. Weekend and holiday travel time distribution, Atlanta, I-75 northbound, I-285 to SR 120 (2007).

Table 4.5. Error Rates for Using 1 Month of Data to Estimate Annual Average Travel Time and Reliability During Peak Periods in Atlanta (2006)

Section	Mean Absolute Error	
	Travel Time	Buffer Index
I-285 eastbound from GA 400 to I-75	8.1%	25.4%
I-285 eastbound from GA 400 to I-85	7.0%	24.9%
I-285 westbound from GA 400 to I-75	5.8%	26.9%
I-285 westbound from GA 400 to I-85	5.1%	26.4%
I-75 northbound from I-20 to Brookwood	4.0%	46.2%
I-75 northbound from I-285 to Roswell Road	7.1%	26.1%
I-75 northbound from Roswell Road to Barrett Parkway	4.3%	42.1%
I-75 southbound from I-20 to Brookwood	6.0%	33.5%
I-75 southbound from I-285 to Roswell Road	5.2%	25.0%
I-75 southbound from Roswell Road to Barrett Parkway	8.2%	19.3%
Overall	**6.1%**	**23.1%**

Table 4.6 shows annual incident minutes on an 11-mile stretch of U.S. 101 southbound in California. All incidents of any type were present only 17% of the time on U.S. 101 southbound. One must, therefore, simulate a relatively long time to hope to be able to capture a single incident.

The exploratory research found that the travel time variance and the mean travel time for any facility are highly correlated. Figure 4.10 shows how the standard deviation of the travel time rate for U.S. 101 southbound varies according to the mean travel time rate. As the Atlanta data above also show, many fewer samples are required to estimate the mean travel time than to estimate its variance (or standard deviation).

The research team concluded from these analyses that a minimum of 6 months of data is required to estimate travel time reliability. In areas where snow and ice are frequent events, this requirement would be expected to increase to a full year. It may be possible in winter weather–affected locations to use 6 months of data if the data represent every other month. However, the team proceeded with the idea that a year's worth of data would provide more sound results and strove to achieve the 1-year minimum.

Trends in Reliability

An examination of congestion and reliability trends from 2006 to 2008 on the 10 Atlanta study sections was undertaken. Anecdotal information suggested that congestion had decreased in 2008 after a midyear spike in gas prices and the economic downturn. Table 4.7 presents the results for the peak period. Note that the peak period was fixed and was determined using the procedure given in this chapter using 2006 data. On all 10 sections, TTI increased between 2006 and 2007 and decreased between 2007 and 2008. In nine cases, the 2008 TTIs were below those of 2006. Note that eight of the 10 sections had ramp meters installed in 2008.

On seven of the 10 study sections, the Buffer Index actually increased in 2008 over 2007 levels, yet overall congestion was better (i.e., TTI went down). The two components of the Buffer Index (95th percentile and mean travel time) decreased in all cases. However, when the Buffer Index increased, it can be seen that the drop in the 95th percentile was proportionately lower than the drop in the mean travel time, leading to a higher index value. The 80th percentile travel time decreased in 2008 on all sections, and the skew statistic exhibited a similar pattern as the Buffer Index. The Planning Time Index (not shown in

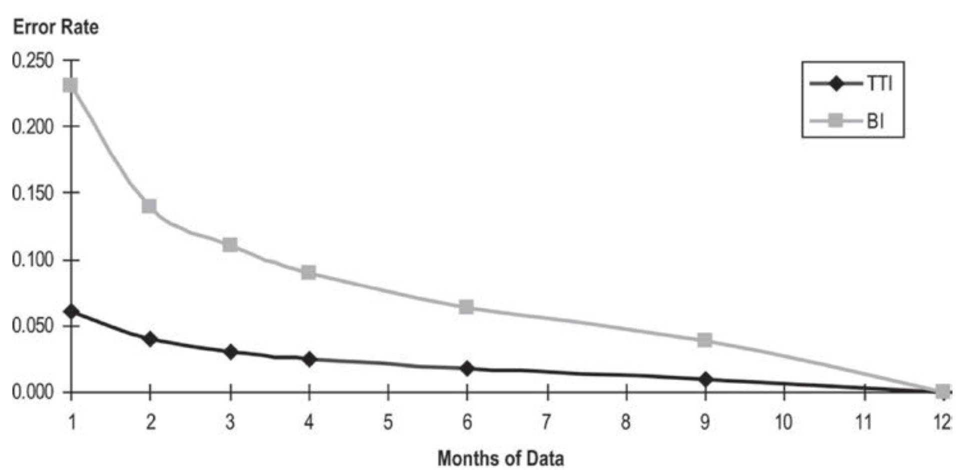

Figure 4.9. Error rates for samples to estimate TTI and Buffer Index in study sections during peak periods in Atlanta (2008).

Table 4.6. Annual Incident Minutes on U.S. 101 Southbound in Marin County

Incident Type	Logged Incidents	Estimated Logged (%)	Estimated Number of Incidents	Duration (min) Mean	Duration (min) Standard Deviation	Total Incident Minutes	Annual Probability
Accident, injury	19	100%	19	42.8	40.3	813	0.87%
Accident, noninjury	84	99%	85	22.6	22.2	1,915	2.05%
Accident, other	76	99%	77	19.7	17.0	1,513	1.62%
Breakdown	88	60%	147	17.9	19.8	2,620	2.80%
Other	15	60%	25	32.5	73.4	812	0.87%
Traffic hazard	274	60%	457	19.0	14.9	8,662	9.25%
Subtotal incidents	556	69%	809	20.2	22.2	16,335	17.45%
Nonincidents	NA	NA	NA	NA	NA	77,265	82.55%
Total year	NA	NA	NA	NA	NA	**93,600**	**100.00%**

Note: Estimated Logged accounts for the typical underreporting of less severe incidents. NA = not applicable.

Table 4.7) exhibited the same characteristics as the 95th percentile since its base is free-flow speed, which does not change.

Figures 4.11 and 4.12 show the travel time distributions for two sections where the Buffer Index and skew statistic increased:

- The I-75 section had ramp meters turned on in mid-October 2008 and saw a decrease in demand of 5.5% from 2007 to 2008; and
- The I-285 section had ramp meters turned on by July 1, 2008, and saw a decrease in demand of 1.8%.

Note that for the same fixed peak period, there was more free-flow travel in 2008 on both sections. On the I-75 section the increase in free-flow travel was due primarily to the decrease in demand, but on the I-85 section the improved flow was probably due to a combination of reduced demand and ramp meters. Both the Buffer Index and the skew statistic indicate there was more spread in the distribution, but the worst travel times (the 80th and 95th percentiles) were decreased.

What can be concluded from these seemingly conflicting results on the seven segments about reliability trends? In other words, does reliability get better or worse at these locations?

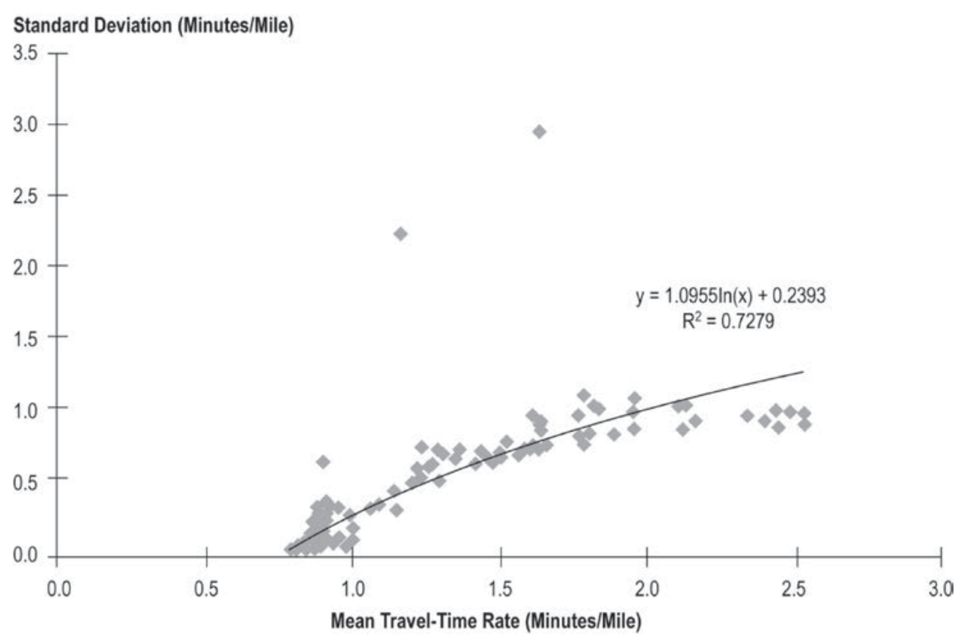

Figure 4.10. Standard deviation of travel time rates for U.S. 101 Southbound.

Table 4.7. Trends in Reliability, Atlanta Freeways (2006–2008)

	Year				Year		
	2006	2007	2008		2006	2007	2008
Section I-75 NB from I-285 to Roswell Road[a]				**Section I-285 WB from GA 400 to I-75[c]**			
TTI	2.046	2.026	1.665	TTI	1.826	1.893	1.672
Average TTI	11.271	11.162	9.177	Average TTI	12.564	13.026	11.504
95th Percentile TTI	16.934	17.507	14.800	95th Percentile TTI	19.053	19.754	19.543
Buffer Index	0.502	0.568	0.613	Buffer Index	0.517	0.516	0.699
80th Percentile TTI	13.974	14.191	11.458	80th Percentile TTI	15.632	16.140	14.699
Skew statistic	0.942	1.087	1.514	Skew statistic	1.202	1.043	1.779
Daily VMT[b]	691,399	689,628	N/A	Daily VMT	584,487	588,442	572,211
Section I-75 SB from I-285 to Roswell Road[a]				**Section I-285 EB from GA 400 to I-85[c]**			
TTI	1.312	1.369	1.293	TTI	2.247	2.314	1.797
Average TTI	7.665	7.994	7.552	Average TTI	14.495	14.926	11.593
95th Percentile TTI	10.139	10.517	9.868	95th Percentile TTI	23.353	24.724	21.084
Buffer Index	0.323	0.316	0.307	Buffer Index	0.611	0.656	0.819
80th Percentile TTI	8.353	8.719	8.306	80th Percentile TTI	19.336	19.945	15.256
Skew statistic	1.524	1.515	1.461	Skew statistic	1.285	1.248	2.347
Daily VMT	691,399	689,628	N/A	Daily VMT	588,597	580,629	567,497
Section I-75 NB from I-20 to Brookwood				**Section I-285 WB from GA 400 to I-85[c]**			
TTI	1.350	1.542	1.339	TTI	1.621	1.681	1.511
Average TTI	6.710	7.664	6.656	Average TTI	10.424	10.809	9.713
95th Percentile TTI	8.120	10.755	8.031	95th Percentile TTI	13.740	13.707	12.612
Buffer Index	0.210	0.403	0.207	Buffer Index	0.318	0.268	0.299
80th Percentile TTI	7.097	8.112	7.015	80th Percentile TTI	11.622	11.957	11.082
Skew statistic	1.283	1.923	0.771	Skew statistic	0.790	0.763	0.656
Daily VMT	616,038	620,959	595,034	Daily VMT	588,597	580,629	567,497
Section I-75 SB from I-20 to Brookwood				**Section I-75 NB from Roswell Road to Barrett Parkway[a]**			
TTI	2.052	2.171	2.067	TTI	1.579	1.652	1.514
Average TTI	9.336	9.877	9.404	Average TTI	8.762	9.170	8.405
95th Percentile TTI	13.110	14.270	12.389	95th Percentile TTI	11.827	12.823	12.357
Buffer Index	0.404	0.445	0.317	Buffer Index	0.350	0.398	0.470
80th Percentile TTI	10.805	11.416	11.042	80th Percentile TTI	10.206	10.560	9.656
Skew statistic	1.324	1.120	0.956	Skew statistic	1.513	1.348	1.586
Daily VMT	616,038	620,959	595,034	Daily VMT	669,568	675,274	N/A
Section I-285 EB from GA 400 to I-75[c]				**Section I-75 SB from Roswell Road to Barrett Parkway[a]**			
TTI	1.359	1.481	1.380	TTI	1.809	1.872	1.614
Average TTI	9.322	10.162	9.469	Average TTI	9.785	10.129	8.730
95th Percentile TTI	12.548	13.150	12.493	95th Percentile TTI	13.835	14.301	12.791
Buffer Index	0.346	0.294	0.319	Buffer Index	0.414	0.412	0.465
80th Percentile TTI	10.505	11.382	10.849	80th Percentile TTI	11.208	11.575	10.529
Skew statistic	1.148	0.996	1.070	Skew statistic	0.849	0.920	0.945
Daily VMT	584,487	588,442	572,211	Daily VMT	669,568	675,274	N/A

(continued on next page)

Table 4.7. Trends in Reliability, Atlanta Freeways (2006–2008) (continued)

	Year				Year		
	2006	**2007**	**2008**		**2006**	**2007**	**2008**
All Sections				80th Percentile TTI	11.874	12.400	10.989
TTI	1.720	1.800	1.585	Skew statistic	1.186	1.196	1.308
Average travel time	10.033	10.492	9.220	Daily VMT	3,150,088	3,154,932	2,878,074
95th Percentile TTI	14.266	15.151	13.597	Daily VMT without I-75 (I-285 to Barrett Pkwy)	1,789,122	1,790,030	1,734,742
Buffer Index	0.399	0.428	0.451				

[a] Ramp meters were turned on mid-October 2008.
[b] VMT (vehicle miles traveled) was calculated for both directions combined, then divided by two for each directional section.
[c] Ramp meters were turned on July 1, 2008.
Note: NB = northbound; SB = southbound; EB = eastbound; WB = westbound.

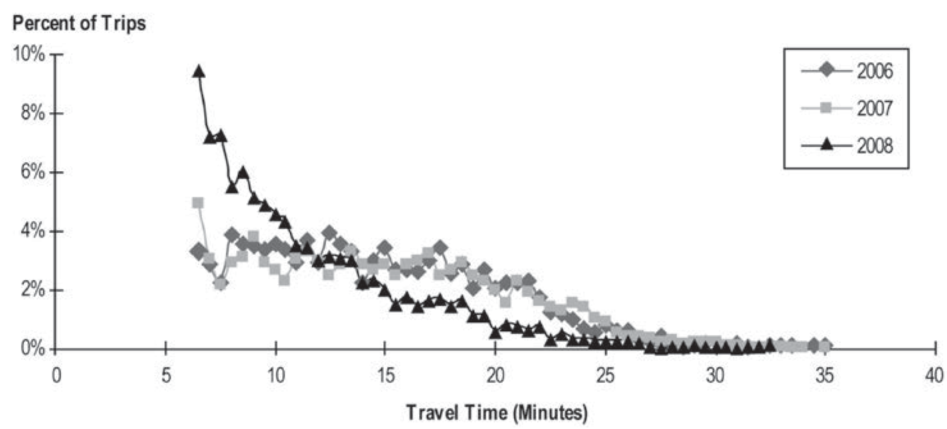

Figure 4.11. I-285 eastbound, GA 400 to I-85, peak period.

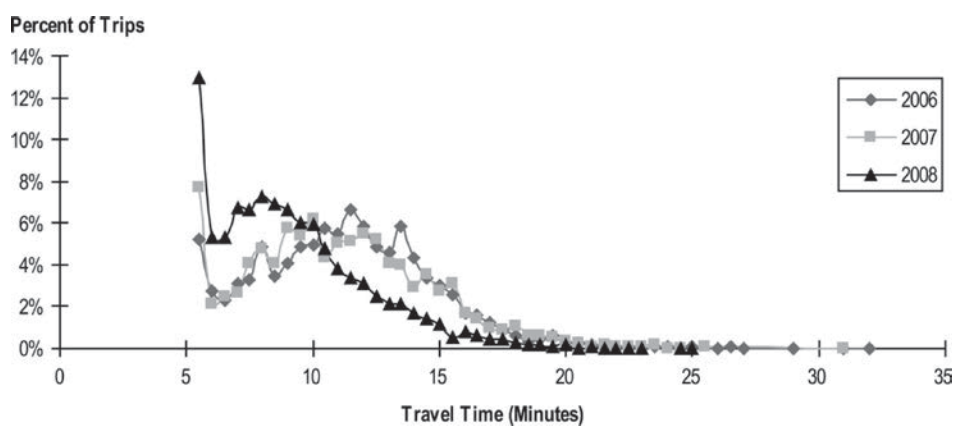

Figure 4.12. I-75 northbound, I-285 to Roswell Road, peak period.

Both the Buffer Index and the skew statistic indicate there was more spread in the distribution, but the worst travel times (the 80th and 95th percentiles) were decreased. That the drop in the 95th percentile was not as great as the drop in the mean indicates that although base (typical) conditions improved, the variation around the new base was higher (as indicated by the Buffer Index and skew statistic). So, for a traveler in 2008, the worst days are better than they were in 2007, but compared with a typical trip, the worst days are proportionately worse. Whether reliability got better or worse depends on whether the traveler perceives the extra time in absolute or relative terms. In absolute terms, the buffer time (95th percentile minus the mean) improved in 2008.

Assume for the moment that the decreases in the metrics are due solely to the decreased demand in 2008, which would have reduced the base (recurring) congestion. Also assume that the worst travel times are influenced by roadway events such as incidents. The decreases in the 80th and 95th percentiles in 2008 are another indication of the interaction between base congestion and events; that is, assuming event characteristics are equivalent, less base congestion leads to lower event-related congestion. However, the lessened impact is somewhat marginal: the drop in the worst travel times was not as big as for base congestion.

There are two implications of these results for future research and existing practice. First, the Buffer Index may not be the most appropriate metric for tracking trends. In the Atlanta analysis, it can be seen that the mean travel times had a proportionately higher decrease than the 95th percentile. Presumably, this trend occurred because the major factor was decreased demand, which would tend to decrease all travel times, and not primarily affect the extremes as some operational treatments do. So, because of the way the Buffer Index is normalized by the mean, it can produce a counterintuitive result; that is, it can produce worsened reliability and decreased average congestion. Although this nuance means that the Buffer Index might not be the best metric for measuring trends, it still gives useful information about conditions. In the new reality of 2008, the size of the buffer did indeed increase, even if the increase was primarily the result of a large decrease in the mean travel time.

The second implication is that demand can have a significant effect on both average congestion level and reliability. As shown in Figure 2.2 (Chapter 2), conceptually, demand and base capacity interact with events to produce total congestion patterns. Overall, analysis shows just how important volume is to congestion and reliability when capacity is improved.

Defining Peak Hour and Peak Period

The length of peak times for conducting congestion and reliability analyses can be defined by either (*a*) determining fixed times for all locations, based on subjective local knowledge; or (*b*) determining the start and end times empirically. The research team decided on the latter method and defined peak hour and peak period as follows:

- **Peak hour** is the continuous 60-minute period during which the space mean speed is less than 45 mph. As this period can be much longer than an hour, the selection of the actual peak hour within this period is based on examining alternative 60-minute periods based on three criteria:
  - Low space mean speed,
  - High vehicle hours of travel, and
  - High vehicle miles of travel.

The analyst must decide which 60-minute period is the actual peak hour based on comparing this information with local knowledge. Note that for routinely congested sections, the highest VMT will occur either right before the actual peak (high flow right before breakdown conditions) or after the peak (high flow during queue release); and

- **Peak period** is a continuous time period of at least 75 minutes during which the space mean speed is less than 45 mph.

The peaks for the urban freeway study sections are shown in Table 4.8.

Estimating Demand in Oversaturated Conditions on Freeways

When traffic flow breaks down on freeways, the observed volume of vehicles moving past a point drops due to slower speeds and the onset of queuing. Roadway detectors count only volume (the number of vehicles that pass a given point), not demand (the number of vehicles that want to pass the point). The simultaneous volume–speed plots in Figures 4.13 and 4.14 are typical of congested freeways everywhere. This loss in capacity after flow breakdown is often referred to as lost productivity or lost efficiency because it means that under such conditions, throughput is actually lost.

The actual demand that wants to pass a given point is stored upstream in the queue. The applications that are likely to use the L03 results (e.g., the *Highway Capacity Manual* [HCM], travel forecasting and simulation models) need to know that demand in order to predict traffic conditions. To address this need, the research team developed a procedure for allocating queued demand to the time period when that demand is trying to use a section of highway. The steps are as follows:

1. A congestion threshold speed of 35 to 45 mph is set by the analyst (40 mph is used in the examples presented here). For each 5-minute observation
   a. If the mean observed speed is ≥40 mph, then the observed volume is equal to the demand.

Table 4.8. Peak Hour and Peak Period Definitions for L03 Study Sections

City	Section	Peak Hour	Peak Period		
		Start	Start	End	Length (h)
Houston	1	6:20	6:00	8:15	2:15
	2	6:35	6:15	8:40	2:25
	3	7:35	6:40	9:20	2:40
	4	16:40	15:15	18:55	3:40
	5	16:50	16:20	19:10	2:50
	6	16:50	16:20	19:10	2:50
	7	6:05	6:15	7:50	1:35
	8	6:45	6:15	9:10	2:55
	9	6:45	6:15	9:10	2:55
	10	7:00	7:20	8:55	1:35
	11	16:35	16:15	18:30	2:15
	12	16:50	16:40	18:30	1:50
	13	16:55	16:45	19:00	2:15
Minneapolis–St. Paul	14	7:00	6:25	8:55	2:30
	15	15:19	15:10	17:35	2:25
	16	16:35	15:10	18:05	2:55
	17	16:20	16:20	18:10	1:50
	18	16:05	15:05	18:25	3:20
	19	16:15	16:15	18:20	2:05
	20	7:55	7:55	9:25	1:30
	21	16:15	16:15	17:55	1:40
	22	16:10	14:45	17:55	3:10
	23	7:00	7:00	8:35	1:35
	24	16:20	16:10	18:20	2:10
	25	6:55	6:55	8:55	2:00
	26	16:00	15:25	17:55	2:30
	27	16:15	16:15	18:05	1:50
	28	7:05	7:05	8:55	1:50
	29	16:20	16:20	18:15	1:55

City	Section	Peak Hour	Peak Period		
		Start	Start	End	Length (h)
Los Angeles	30	7:10	6:45	9:30	2:45
	31	7:15	6:35	9:00	2:25
	32	16:45	16:50	19:00	2:10
San Francisco Bay Area	35	16:25	15:45	18:50	3:05
San Diego	37	15:45	15:25	18:40	3:15
	38	16:55	16:55	18:30	1:35
	39	6:45	6:45	8:20	1:35
	40	16:40	15:00	19:05	4:05
	41	16:25	15:45	18:25	2:40
	42	6:30	6:25	8:55	2:30
Atlanta	43	17:00	16:30	18:30	2:00
	44	7:45	7:15	8:30	1:15
	45	17:15	7:15	9:00	1:45
	46	17:00	15:30	18:30	3:00
	47	7:15	7:15	8:45	1:30
	48	17:15	16:30	18:30	2:00
	49	17:00	16:00	18:30	2:30
	50	7:45	7:15	9:00	1:45
	51	17:00	16:30	18:30	2:00
	52	7:30	7:15	9:00	1:45
Jacksonville	74	7:30	7:15	8:40	1:25
	75	17:00	16:45	18:10	1:25
	76	7:25	7:10	8:30	1:20
	77	17:00	16:45	18:10	1:25
	78	17:00	16:45	18:10	1:25
	79	7:20	7:10	8:35	1:25
	80	17:00	16:45	18:10	1:25
	81	16:45	16:35	17:55	1:20

Note: Sections are keyed to Table 3.2.

b. If the mean speed is <40 mph, then the observed volume is not equal to demand, and a demand estimate is required.

2. The congested period is then the set of consecutive 5-minute observations with speeds <40 mph. If a single 5-minute period is uncongested, but it is surrounded by congested 5-minute observations, then this single 5-minute observation is considered to be congested, as well.
3. The congested period is split into two halves. The queue is assumed to be building during the first half of the congested period and dissipating during the second half.
4. The cumulative demand is computed for about half an hour before the onset of congestion and for half an hour after the termination of congestion.
   a. During the first half of the congested period, the demand rate (vehicles per 5-minute period) is assumed to be equal

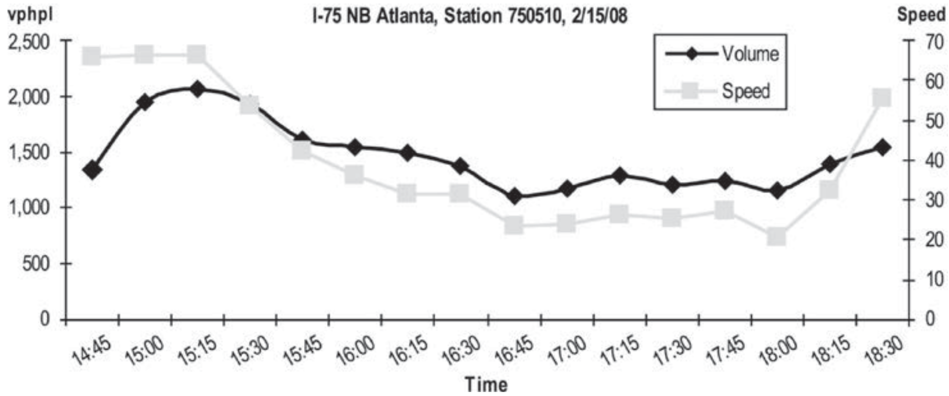

Figure 4.13. Volume drop after onset of congestion: Example 1.

to the average of the demand rates observed in the last two 5-minute periods just before the onset of congestion. This demand rate is assumed to be fixed for the first half of the congested period, and it is used to compute the cumulative demand for this half of the congested period.

b. Once the cumulative demand at the midpoint of the congested period is computed, then the analyst calculates a second demand rate to be used during the second half of the congested period. This second demand rate is set so that the cumulative demand will equal the cumulative observed volume by the end of the congested period.
c. The second-half demand rate then is added to the cumulative demand at the midpoint of the congested period until the end of the congested period is reached, at which point the estimated demand should be equal to the observed cumulative volume.
d. The two 5-minute periods after the termination of the congested period are checked to see if the estimated demand curve smoothly fits to the observed cumulative volume curve. The observed 5-minute volume for the first 5-minute period following the end of the congested period should not be sharply higher than the estimated demand rate for the second half of the congested period. It is sometimes necessary to smooth out the transition by assuming the congested period extends an additional 5-minute period.

Figure 4.15 illustrates the application of this approach to a congested period for U.S. 101 in Marin County, California.

Reliability Breakpoints on Freeways

After reviewing the urban freeway data, it became apparent to the research team that the data could be used in creative ways to answer basic questions about reliability and to provide insight into the complex statistical modeling ahead. One of these questions was, at what volume (demand) levels does reliability radically change? The issue this question addresses is similar to establishing basic capacity values for when flow breakdown occurs, except that here the concern is with the volume level that causes reliability to rapidly deteriorate. A

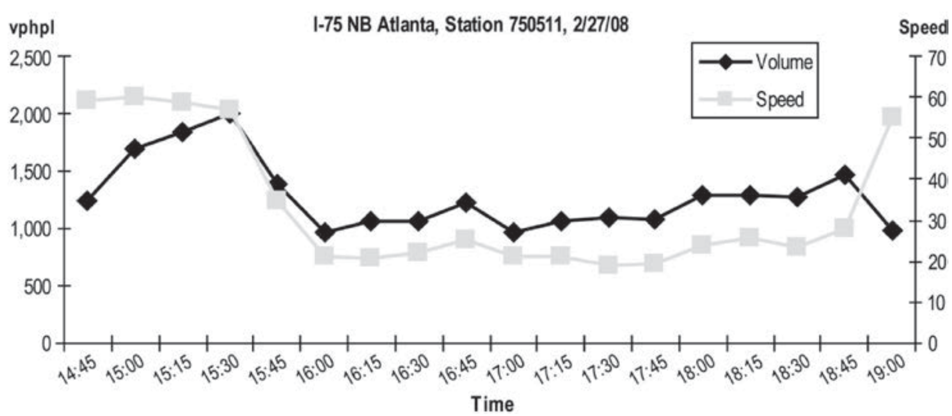

Figure 4.14. Volume drop after onset of congestion: Example 2.

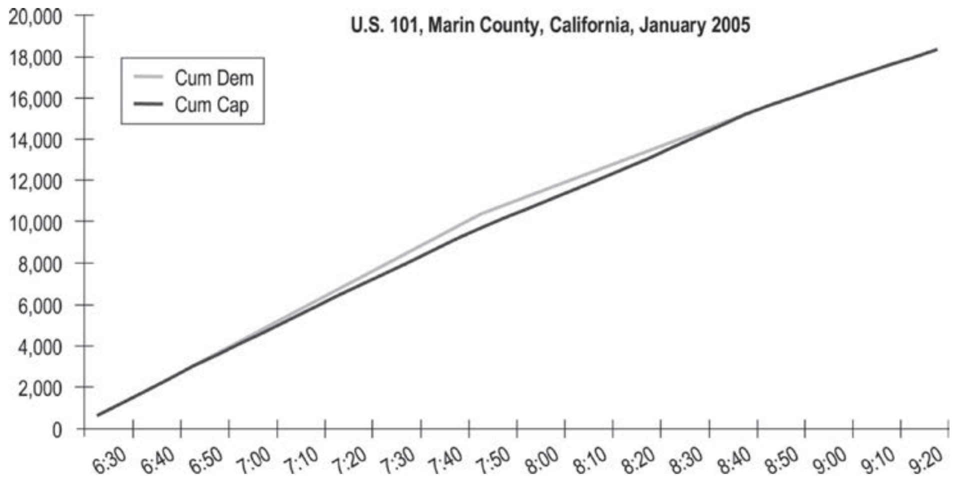

Figure 4.15. Example of demand estimation during oversaturated conditions.

complete description of this effort is provided in the Phase 2 report; a summary is provided below.

Various measures of travel time reliability were investigated, and the standard deviation of the measured travel time rate per mile was selected as an appropriate indicator of travel time reliability for the purpose of establishing reliability breakpoints. The team chose the standard deviation in order to examine both sides of the mean volume that lead to breakdown.

Two methods for measuring the standard deviation of the travel time rate were evaluated. Loop detectors provide excellent temporal coverage for limited geographic locations, and vehicle probes provide excellent geographic coverage of a facility for limited time periods. A method was developed for calibrating loop detector estimates of travel time reliability to probe vehicle measurements of travel time reliability so that the annual travel time reliability for the freeway could be estimated.

A year's worth of loop detector station data for four stations (located on two freeways in the San Francisco Bay Area) was evaluated to determine how traffic volumes and incidents affected the observed travel time reliability on a freeway for the morning peak, afternoon peak, and off-peak periods over the course of a year.

Three weeks of travel time rate data were evaluated from 13 loop detector stations on eastbound I-580. The mean and standard deviation of the travel time rate (minutes per mile) were computed for each of three time periods (a.m. peak, p.m. peak, off-peak) for each day of the week.

As shown in Figure 4.16, both the mean travel time rate and the standard deviation were relatively constant until the counted mean volume (across all detectors) for a peak period reached between 1,250 and 1,350 vehicles per hour per lane (vphpl). Somewhere in this range, the mean and standard deviation of the travel time rate starts to soar almost vertically. This breaking point, when there are strong indications of congestion on the freeway, is quite a bit lower than the theoretical 2,000 vphpl capacity of the freeway (after converting from passenger car capacity to mixed-flow capacity). But note that the volumes in Figure 4.16 are the average across the peak period. Peak 15-minute demands within the peak period may be significantly higher than the average volume across the entire peak period.

Figure 4.17 shows similar computations and results for the five detectors in the westbound direction of I-580. Both the mean and the standard deviation in the travel time rate for each peak period tended to rise almost vertically in the range of 1,600 to 1,700 vphpl averaged across the peak period. The breakpoint volumes for freeway reliability varied by detector location, even for the same facility.

Figures 4.18 and 4.19 show the volume–reliability relationships for one year's worth of peak and off-peak time periods for a single detector in each direction on I-580. The breakpoint volume for this detector was in the 1,200 to 1,300 vphpl range for the eastbound direction and 1,100 to 1,200 vphpl westbound. For the eastbound direction, the relationship appeared to be precisely vertical once the breakpoint volume was reached for the peak period. The westbound direction appeared to have a few nonrecurrent incidents that caused some reliability problems before the breakpoint volume was reached.

Figure 4.20, computed from a year's worth of loop detector data for U.S. 101 southbound, shows that a similar flat relationship between mean volume and standard deviation of travel time existed on this freeway until the breakpoint volume of between 1,050 and 1,150 vphpl was reached. After this point, both the mean and the standard deviation of the travel time rate increased steeply, but not precisely vertically.

The analysis above shows that travel time reliability on a freeway is not a function of counted traffic volumes until a breakpoint volume is reached. At that breakpoint, travel time

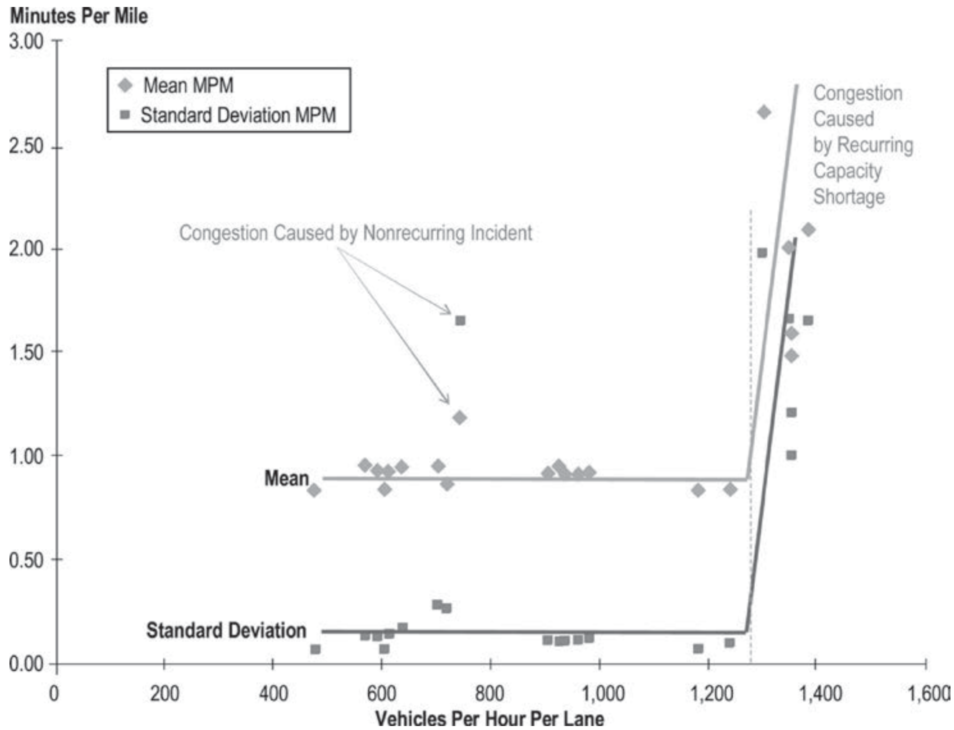

Figure 4.16. Volume and reliability on I-580 eastbound at multiple detectors.

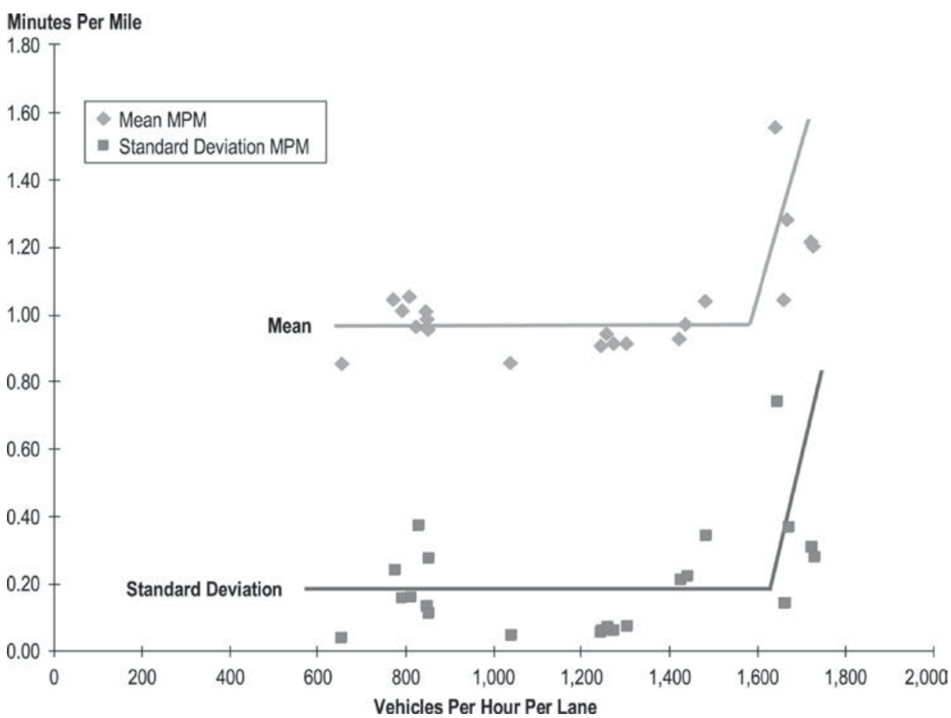

Figure 4.17. Volume and reliability on I-580 westbound at multiple detectors.

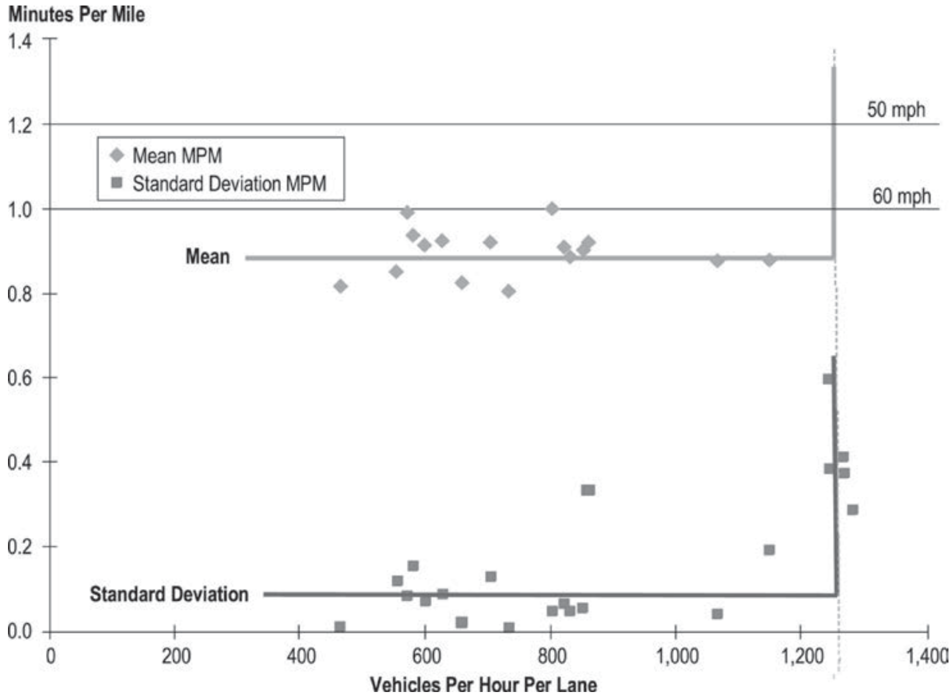

Figure 4.18. Volume and reliability for a single detector on I-580 eastbound.

reliability decreases abruptly. Once the breakpoint volume is exceeded, the decrease in travel time reliability (increase in variance) is extreme and so abrupt as to suggest it is asymptotic, with a nonsingular relationship to further volume increases.

The breakpoint volume varies significantly between facilities and even (by location and direction of travel) within the same freeway facility. In other words, the breakpoint volume does not appear to be a fixed ratio of the theoretical capacity of the subject section of the facility.

The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed according to HCM procedures. This difference is partly because the breakpoint volume computed in

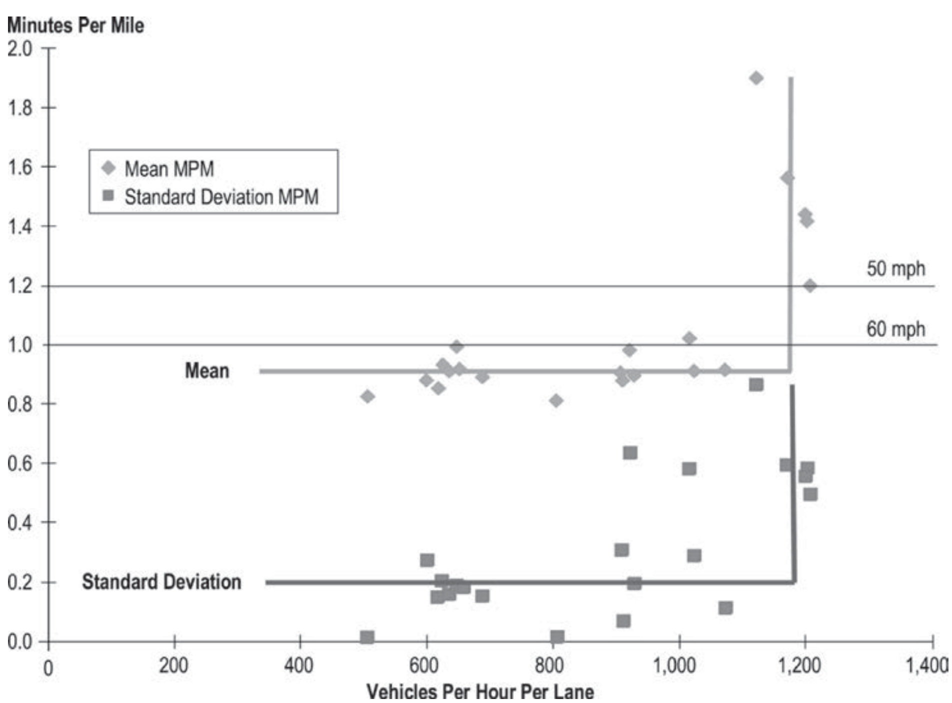

Figure 4.19. Volume and reliability for a single detector on I-580 westbound.

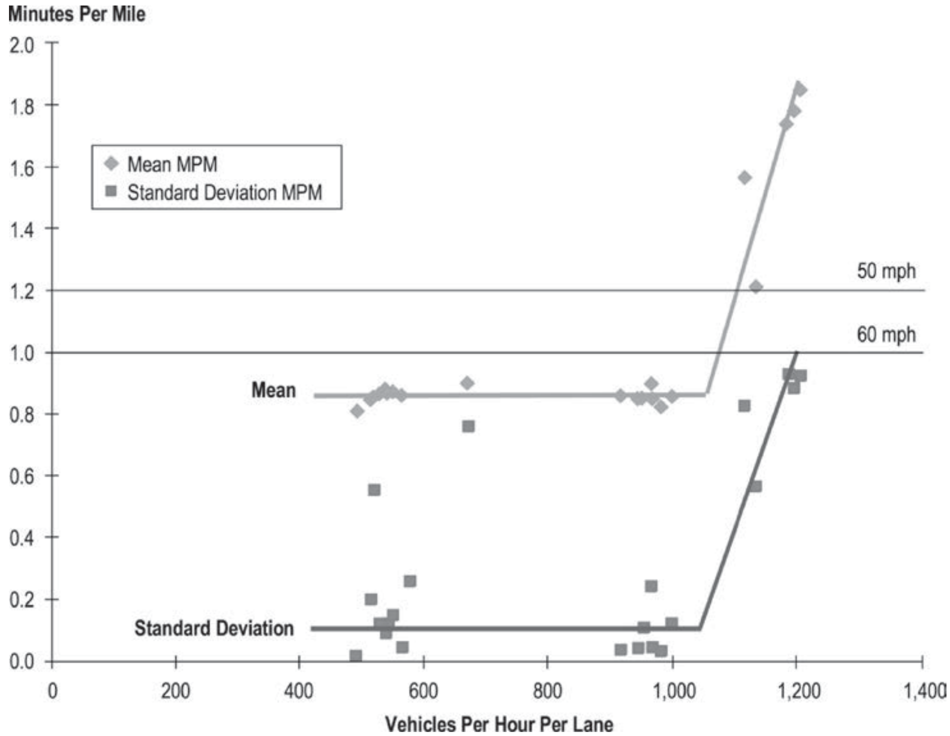

Figure 4.20. Volume and reliability on U.S. 101 southbound.

this analysis is the average hourly volume counted over a peak period as opposed to the peak 15-minute demand used in the HCM capacity computation.

But this peaking effect does not entirely explain the difference in volumes. Part of the reason that the breakpoint volume is significantly lower than the theoretical capacity is that most sections of freeway are upstream of a bottleneck; thus, they are affected by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, traffic-influencing events, especially incidents, effectively lower capacity when they occur, and over time they degrade reliability. This effect manifests itself in lower breakpoint volumes than for capacity (volumes) related strictly to physical features. Finally, even for bottlenecks, the data suggest that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

Sustainable Service Rates on Freeways

The concepts presented in the previous section can be extended to the idea of a *sustained service rate* (SSR), which is defined as the highest flow rate that can be sustained over a peak demand period with a low probability of breakdown. Brilon et al. proposed calling this broader capacity the whole-year capacity of the facility (*1*). They focused on capacity just before breakdown, but the L03 team sought to quantify the probability of breakdown for different flow rates.

An analysis was undertaken using data from the study sections in Seattle and Atlanta. For comparison with HCM terminology, the team defined SSR in terms of vehicles per hour per lane:

- Data were available at 5-minute intervals in the two locations, so the first step was to aggregate the data to 15-minute time intervals;
- For each 15-minute interval, an estimate of the corresponding vehicles per hour per lane value was made by multiplying the 15-minute volume by four and applying a peak hour factor of 0.95 (a more sophisticated version of this method would compute the peak hour factor directly from the data); and
- The data for a detector location were scanned in time sequence, looking for points when flow broke down (i.e., when congestion or queuing began). Speeds less than 45 mph was used in this analysis. When two consecutive 15-minute periods registered speeds less than the threshold, the flow that occurred immediately before breakdown was assigned as the SSR.

The results are shown in Table 4.9. The results are in vehicles per hour per lane, which includes both automobiles and trucks. One way to look at the results is that they represent how capacity varies over the course of a year. The theoretical maximum capacity is probably somewhere close to the 99th percentile, allowing for the fact the actual maximum SSR may be an outlier.

Table 4.9. Distribution of SSR at Selected Locations (2007)

Route	Station	SSR (vphpl)										
		Mean	Standard Deviation	Maximum	P99	P95	P90	P75	Median	P10	P5	P1
Atlanta												
I-75 northbound, Northside	10068	1,390	482	1,975	1,921	1,848	1,739	1,663	1,560	543	132	87
I-75 northbound, Northside	10070	1,922	288	2,407	2,386	2,236	2,125	2,050	1,967	1,750	1,430	621
I-75 northbound, Northside	750510	1,825	264	2,561	2,449	2,295	2,157	1,954	1,809	1,579	1,357	985
I-75 northbound, downtown connector	10026	1,631	357	2,169	2,169	2,082	2,036	1,900	1,654	1,205	929	316
I-75 northbound, downtown connector	10033	1,597	475	2,245	2,240	2,170	2,121	1,944	1,686	915	684	174
I-75 northbound, downtown connector	10037	1,581	366	2,553	2,199	2,016	1,936	1,806	1,682	1,152	840	287
I-75 northbound, downtown connector	10038	1,567	367	2,412	2,153	1,961	1,879	1,804	1,696	1,058	892	272
I-75 southbound, downtown connector	10130	1,270	306	2,110	1,776	1,658	1,599	1,493	1,295	902	575	291
I-75 southbound, downtown connector	10131	1,666	334	2,381	2,181	2,017	1,955	1,853	1,733	1,321	1,031	305
I-285 eastbound, North Arc	2850010	1,675	328	2,091	2,082	1,984	1,950	1,889	1,789	1,174	966	536
I-285 eastbound, North Arc	2850014	1,843	457	2,444	2,434	2,360	2,305	2,206	1,933	1,248	838	448
I-285 eastbound, North Arc	2850017	1,347	495	2,175	2,130	1,905	1,852	1,721	1,419	507	209	42
I-285 westbound, North Arc	2851033	1,634	307	2,230	2,126	1,917	1,849	1,797	1,728	1,306	911	527
Seattle												
I-405	614DN	1,668	202	1,991	1,953	1,904	1,851	1,782	1,708	1,463	1,326	817
I-405	614DS	1,766	233	2,212	2,082	2,018	1,976	1,896	1,809	1,562	1,265	680
I-405	672DN	1,749	348	2,101	2,094	2,041	2,018	1,953	1,854	1,250	775	486
I-405	677DN	2,145	358	2,595	2,557	2,493	2,462	2,371	2,219	1,790	1,649	574
I-405	678DN	1,839	315	2,265	2,253	2,151	2,105	2,044	1,910	1,497	1,117	650
I-405	678DS	1,554	268	1,976	1,961	1,881	1,839	1,725	1,596	1,250	1,072	547
I-405	681RS	2,027	266	2,398	2,356	2,291	2,240	2,170	2,081	1,826	1,687	635
I-405	684DN	1,687	169	2,094	2,044	1,896	1,862	1,782	1,706	1,505	1,429	1,197
I-405	684DS	1,616	198	1,961	1,896	1,828	1,775	1,725	1,659	1,433	1,303	673
I-405	687RN	1,531	200	1,961	1,832	1,775	1,729	1,649	1,558	1,341	1,227	597
I-405	689RS	1,516	173	1,961	1,786	1,718	1,664	1,611	1,543	1,334	1,224	836

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Table 4.9. Distribution of SSR at Selected Locations (2007) (continued)

Route	Station	SSR (vphpl)										
		Mean	Standard Deviation	Maximum	P99	P95	P90	P75	Median	P10	P5	P1
I-405	693RN	1,599	167	1,961	1,851	1,794	1,767	1,702	1,630	1,417	1,349	992
I-405	694RN	1,574	178	1,961	1,889	1,820	1,763	1,687	1,596	1,368	1,296	961
I-405	696DN	1,927	48	1,961	1,961	1,961	1,961	1,961	1,927	1,892	1,892	1,892
I-405	696DS	1,615	221	1,961	1,953	1,866	1,835	1,769	1,674	1,349	1,186	920
I-405	698DN	1,586	151	1,961	1,961	1,805	1,771	1,693	1,571	1,414	1,349	1,091
I-405	698DS	1,607	185	1,999	1,938	1,866	1,813	1,721	1,630	1,383	1,292	1,087
I-405	704DN	2,032	276	2,398	2,383	2,337	2,272	2,204	2,105	1,714	1,497	992
I-405	706DN	1,615	541	1,961	1,961	1,961	1,961	1,961	1,892	992	992	992
I-405	708DN	1,811	175	2,124	2,105	2,010	1,995	1,919	1,843	1,630	1,467	1,201
I-405	708DS	1,788	222	2,117	2,094	2,048	2,003	1,934	1,839	1,528	1,440	954
I-405	709DN	1,930	222	2,322	2,208	2,158	2,139	2,060	1,961	1,740	1,550	866
I-405	709DS	1,933	293	2,379	2,364	2,223	2,174	2,117	1,995	1,588	1,307	783
I-405	710RN	1,778	229	2,132	2,086	1,999	1,961	1,904	1,824	1,592	1,292	714
I-405	710RS	1,926	239	2,318	2,288	2,177	2,124	2,056	1,951	1,786	1,600	673
I-405	711RN	1,776	179	2,060	1,999	1,959	1,934	1,877	1,820	1,617	1,427	946
I-405	711RS	1,877	427	2,504	2,402	2,310	2,250	2,174	2,048	1,205	920	688
I-405	716RN	1,891	256	2,291	2,227	2,139	2,098	2,041	1,930	1,661	1,349	817
I-405	716RS	1,979	291	2,409	2,345	2,280	2,200	2,128	2,025	1,775	1,455	509
I-405	717RN	1,830	246	2,284	2,124	2,067	2,041	1,972	1,877	1,581	1,330	692
I-405	717RS	1,940	215	2,333	2,307	2,236	2,147	2,060	1,959	1,754	1,653	1,068
I-405	720DS	1,498	272	1,961	1,923	1,820	1,775	1,695	1,554	1,180	984	540
I-405	722DS	1,512	209	1,961	1,892	1,744	1,710	1,642	1,539	1,296	1,060	817
I-405	726RS	1,629	334	2,333	2,291	2,128	2,029	1,900	1,585	1,345	1,007	638
I-405	730RN	1,572	313	2,044	2,044	1,961	1,923	1,843	1,568	1,243	882	585
I-405	730RS	1,641	218	1,961	1,961	1,892	1,851	1,744	1,661	1,490	1,258	570
I-405	731RN	1,564	309	1,972	1,972	1,921	1,870	1,816	1,695	1,094	1,056	654
I-405	731RS	1,459	220	1,961	1,961	1,824	1,718	1,623	1,482	1,224	1,140	654

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Table 4.9. Distribution of SSR at Selected Locations (2007) (continued)

Route	Station	SSR (vphpl)										
		Mean	Standard Deviation	Maximum	P99	P95	P90	P75	Median	P10	P5	P1
Seattle												
I-405	734DN	1,781	251	2,200	2,200	2,071	2,006	1,921	1,832	1,493	1,224	654
I-405	734DS	1,736	281	2,170	2,170	2,105	2,067	1,955	1,721	1,493	1,391	570
I-405	736DN	1,951	248	2,470	2,345	2,253	2,181	2,092	1,982	1,752	1,391	897
I-405	736DS	1,942	285	2,424	2,333	2,242	2,212	2,117	2,006	1,634	1,455	654
I-405	738DN	1,888	255	2,223	2,200	2,139	2,094	2,014	1,934	1,733	1,486	665
I-405	738DS	1,894	265	2,409	2,265	2,200	2,155	2,056	1,946	1,596	1,509	752
I-405	739DN	1,816	240	2,147	2,120	2,037	2,003	1,946	1,858	1,661	1,277	718
I-405	739DS	1,790	238	2,272	2,196	2,120	2,048	1,915	1,813	1,566	1,440	654
I-405	740RN	1,772	251	2,101	2,075	2,014	1,987	1,927	1,835	1,471	1,307	673
I-405	740RS	1,846	227	2,379	2,307	2,139	2,075	2,003	1,866	1,611	1,497	1,037
I-405	741RN	1,624	386	2,082	2,044	1,984	1,946	1,873	1,790	950	756	498
I-405	741RS	1,795	214	2,307	2,212	2,143	2,014	1,904	1,801	1,626	1,566	965
I-405	742DN	1,783	281	2,120	2,098	2,044	2,016	1,949	1,877	1,429	1,144	661
I-405	742DS	1,606	556	1,961	1,961	1,961	1,961	1,961	1,892	965	965	965
I-405	763DS	1,644	226	2,044	2,003	1,927	1,873	1,794	1,695	1,372	1,262	806
I-405	764DS	1,927	48	1,961	1,961	1,961	1,961	1,961	1,927	1,892	1,892	1,892

Note: P99, P95, P90, P75, P10, P5, and P1 = 99th, 95th, 90th, 75th, 10th, 5th, and 1st percentile, respectively.

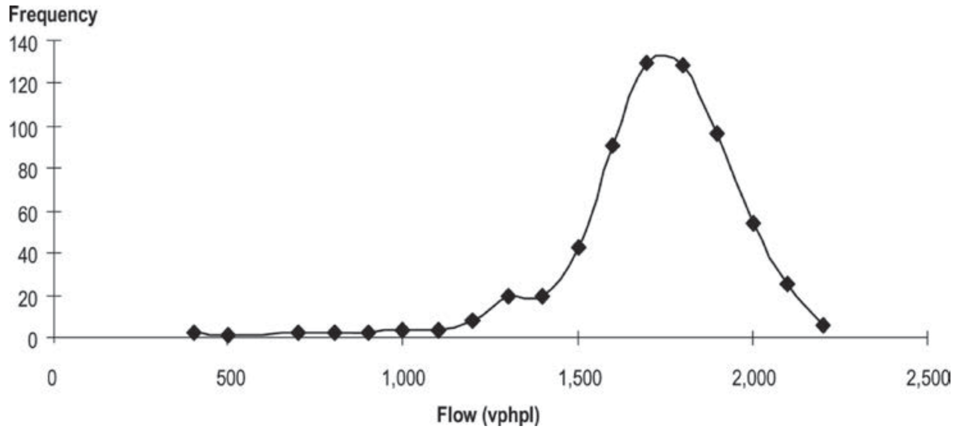

Figure 4.21. Distribution of SSR on I-405 in Seattle at Station 651DN.

Further examination of the shape of the SSR distributions revealed some interesting results. Two distinct patterns emerged: a unimodal and a bimodal distribution. The unimodal SSR distribution is exhibited in Figures 4.21 and 4.22. As with travel times, the distribution is skewed, but to the left as opposed to the right.

A typical bimodal distribution is shown in Figure 4.23. A crude analysis of congestion levels indicates that the unimodal distribution is most common on slightly to moderately congested sites, but the bimodal distribution is more characteristic of highly congested locations.

A possible explanation for the occurrence of two distribution types is that the bimodal distribution shows both a recurring (close to 2,000 vphpl) and a nonrecurring (around 1,000 vphpl) SSR. Locations with high base congestion are more vulnerable to traffic-influencing events such as incidents, and this sensitivity may be reflected in the SSRs. These locations also may be more prone to lane-blocking incidents because of higher incident rates or lack of shoulders, or both. Incidents in less congested locations have less effect because there is more excess capacity to buffer their effect, which is shown by the long tail to the left but no second peak for nonrecurring events.

Sites with a bimodal distribution may also be upstream of a bottleneck. Thus, flow will be observed to break down under low-volume conditions when actually it is queue spillback from the downstream bottleneck.

Reliability of Signalized Arterials

Data from the Orlando signalized arterial study sections were analyzed after undergoing the quality control checks discussed in Chapter 3. Figures 4.24 through 4.29 show the travel time distributions and selected performance measures. (These are the first *continuous* travel time distributions for signalized arterials that the team has seen.) As with urban freeway travel time distributions, the distribution is skewed to the right (toward higher travel times), but the extent of the skew does not appear to be as great, possibly because

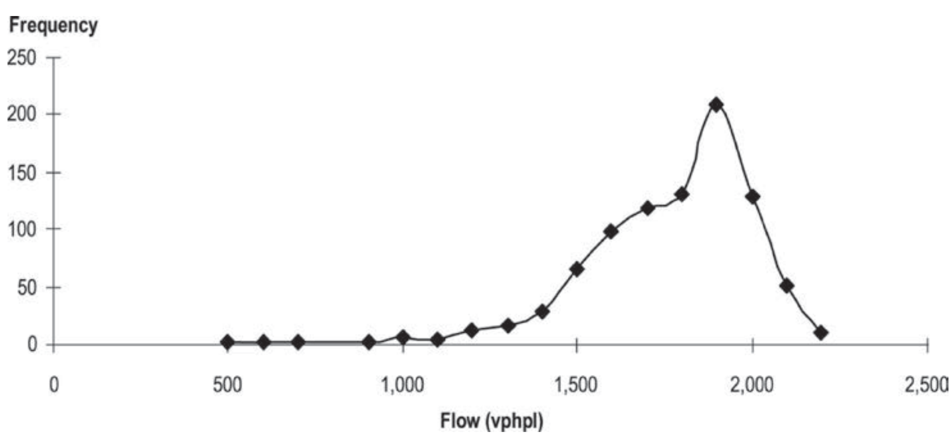

Figure 4.22. Distribution of SSR on I-405 in Seattle at Station 708DS.

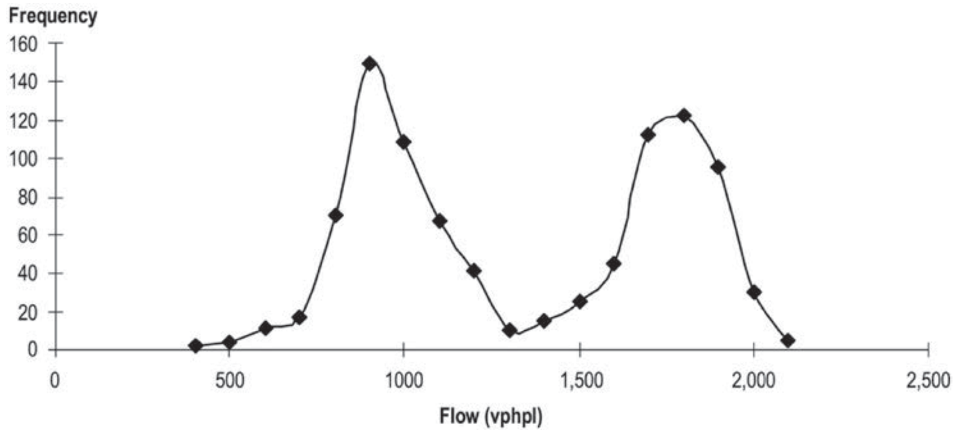

Figure 4.23. Distribution of SSR on I-405 in Seattle at Station 612DN.

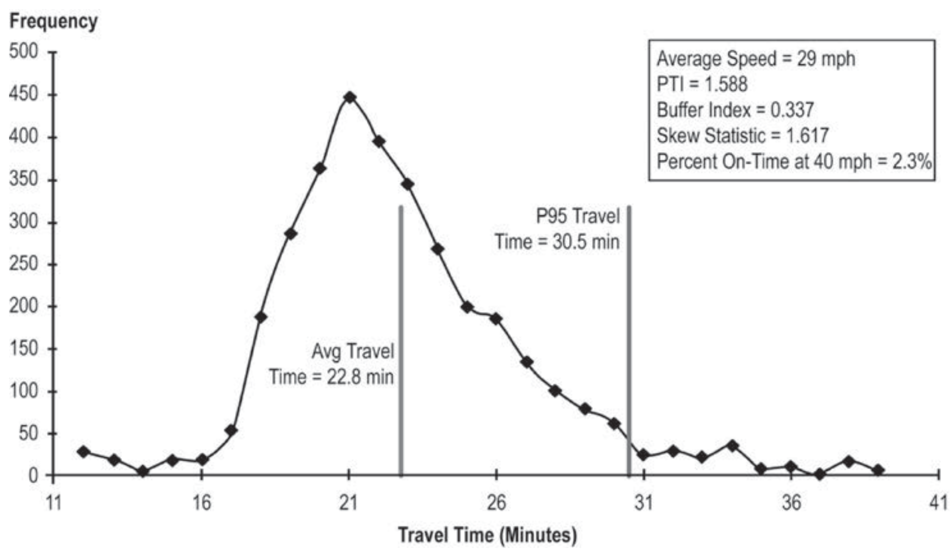

Figure 4.24. Orlando, Section 3, a.m. peak.

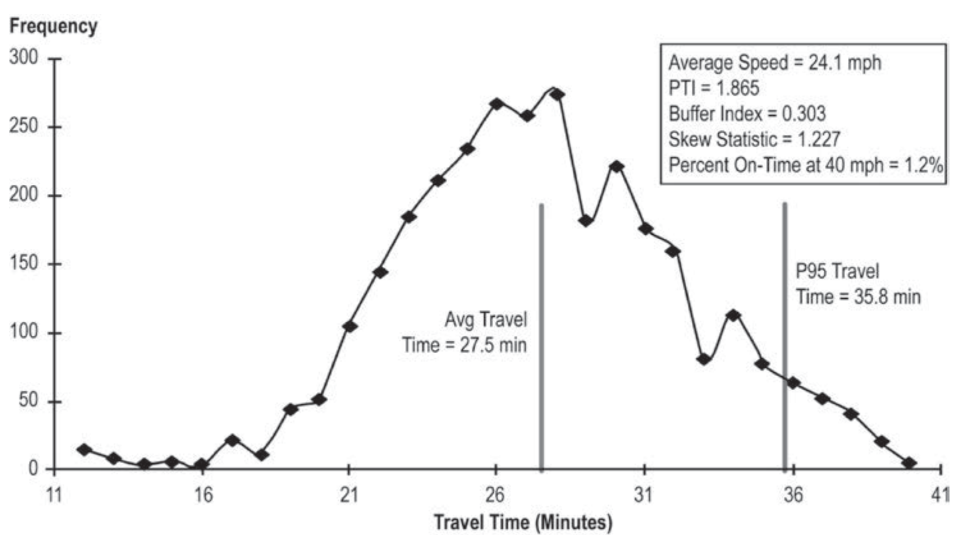

Figure 4.25. Orlando, Section 3, p.m. peak.

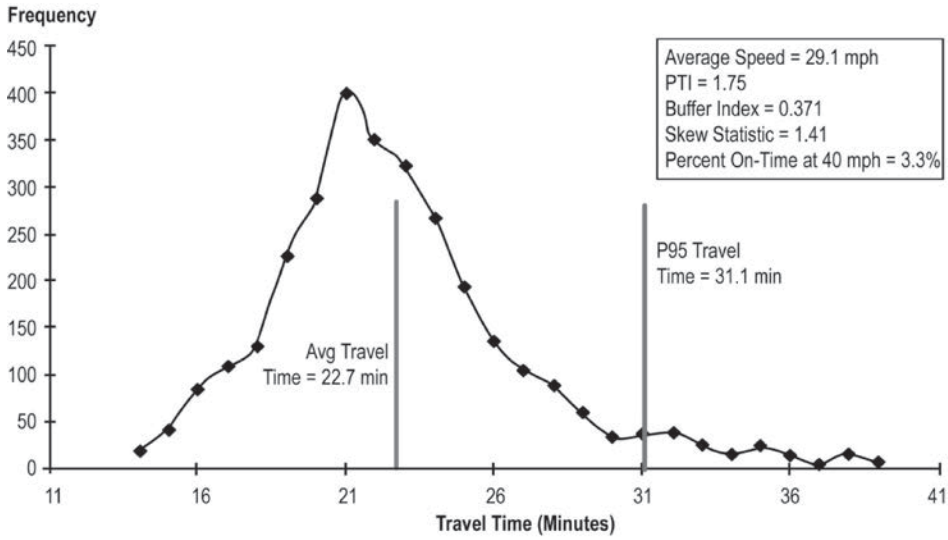

Figure 4.26. Orlando, Section 4, a.m. peak.

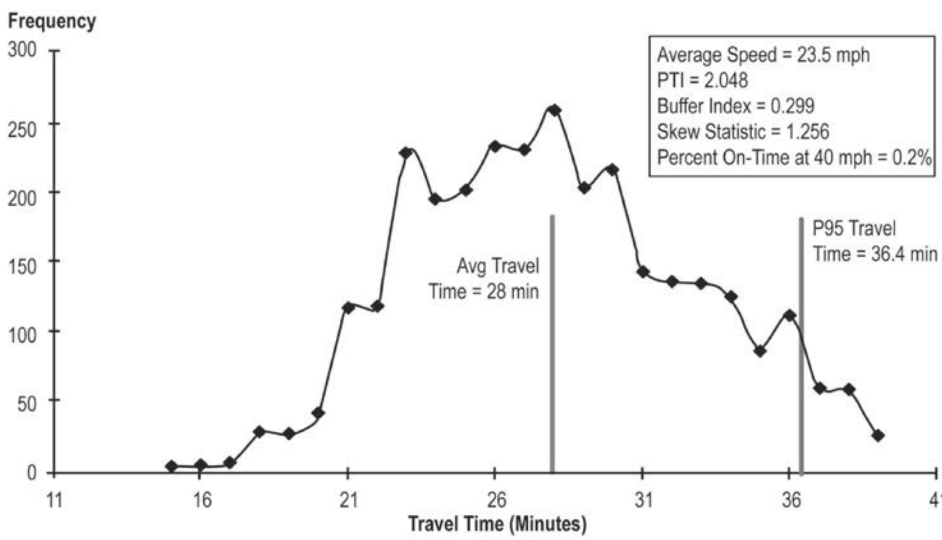

Figure 4.27. Orlando, Section 4, p.m. peak.

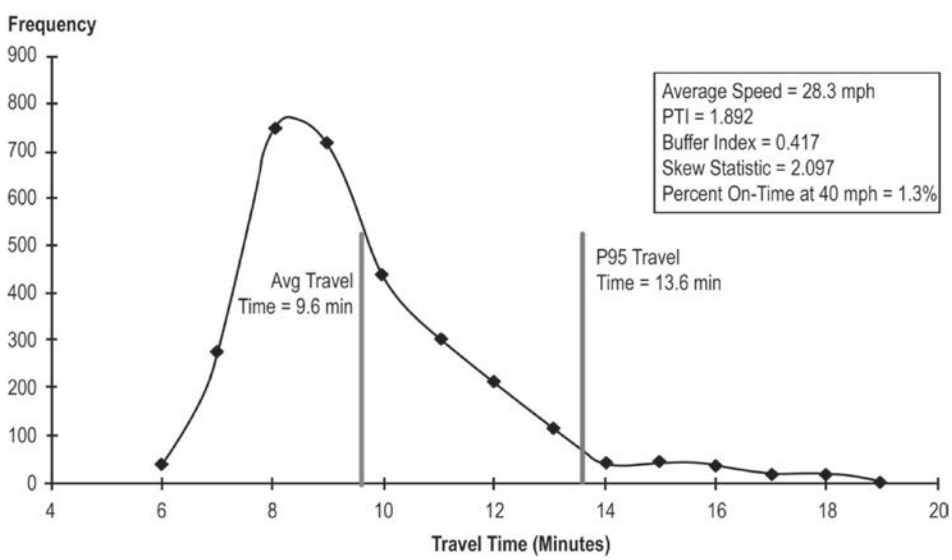

Figure 4.28. Orlando, Section 5, a.m. peak.

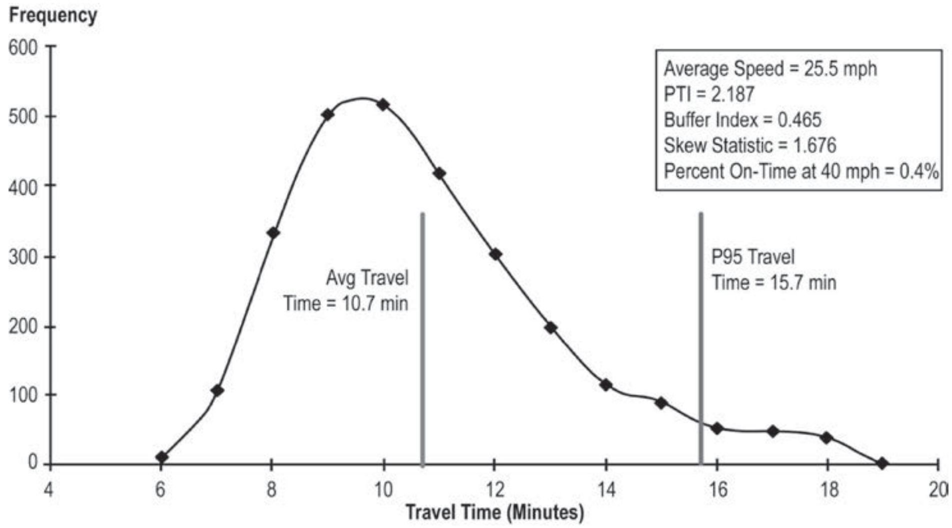

Figure 4.29. Orlando, Section 5, p.m. peak.

incidents on arterials do not have the same effect as on freeways. Since midblock flows of signalized arterials are largely controlled by the metering of upstream signals, the flows are well below what the midblock capacity would be without the signals. This excess capacity absorbs the effect of single-lane or shoulder blockages at midblock locations. Some midblock incidents have little or no effect and do not produce the extreme travel times observed on freeways. However, if an incident occurs at the signal, where capacity already is restricted, there will be a major impact on traffic flow.

The morning distributions appear to be more compact and peaked than the afternoon distributions, which tend to be broader. This difference may be a function of higher congestion levels in the afternoon; the team noticed a similar pattern on congested urban freeways.

Reliability of Rural Freeway Trips

Figures 4.30 through 4.33 show the reliability of trips on the two study sections for 2006 and 2007 combined. The plots show the distribution of the actual travel times. However, in calculating TTI and associated statistics, travel times faster than the free-flow travel time were set to the free-flow travel time to be consistent with how these statistics were calculated on urban freeways.

Vulnerability to Flow Breakdown

An alternative way to view travel time reliability is in terms of a facility's vulnerability or susceptibility to disruptions that lead to congestion. That is, in the absence of recurring

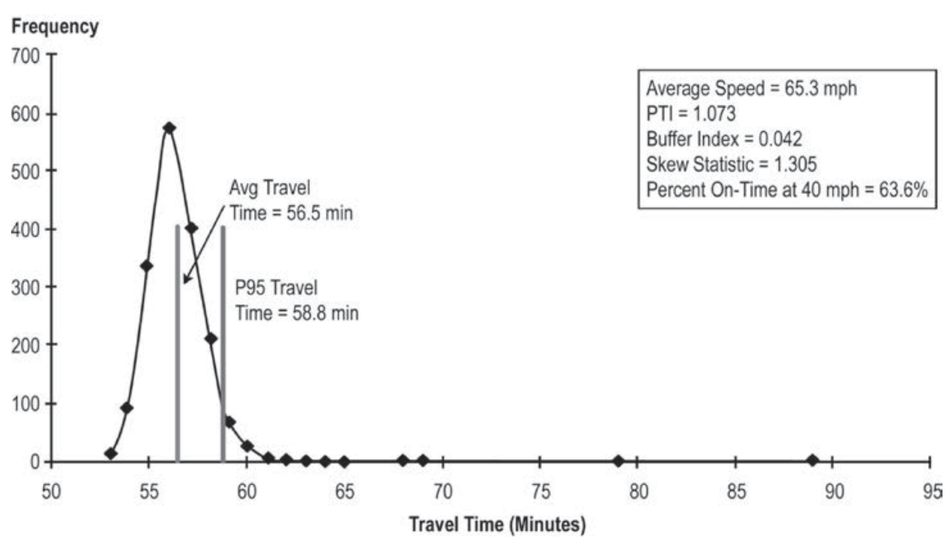

Figure 4.30. I-45 northbound, Texas (length = 61.4 miles).

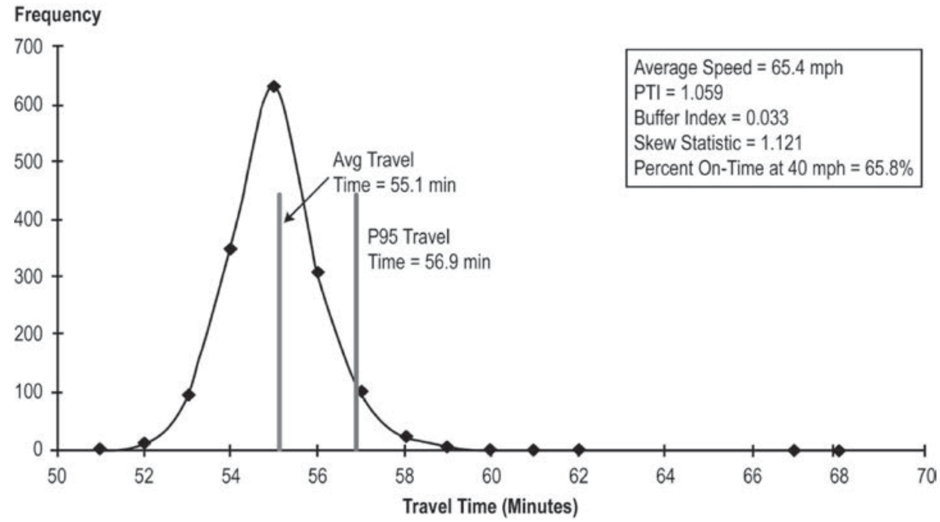

Figure 4.31. I-45 southbound, Texas (length = 60.0 miles).

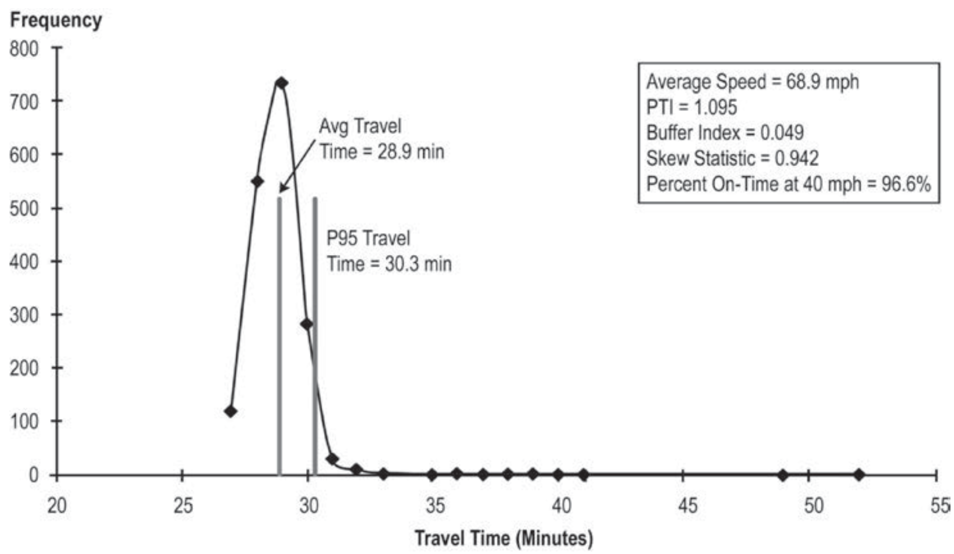

Figure 4.32. I-95 northbound, South Carolina (length = 33.1 miles).

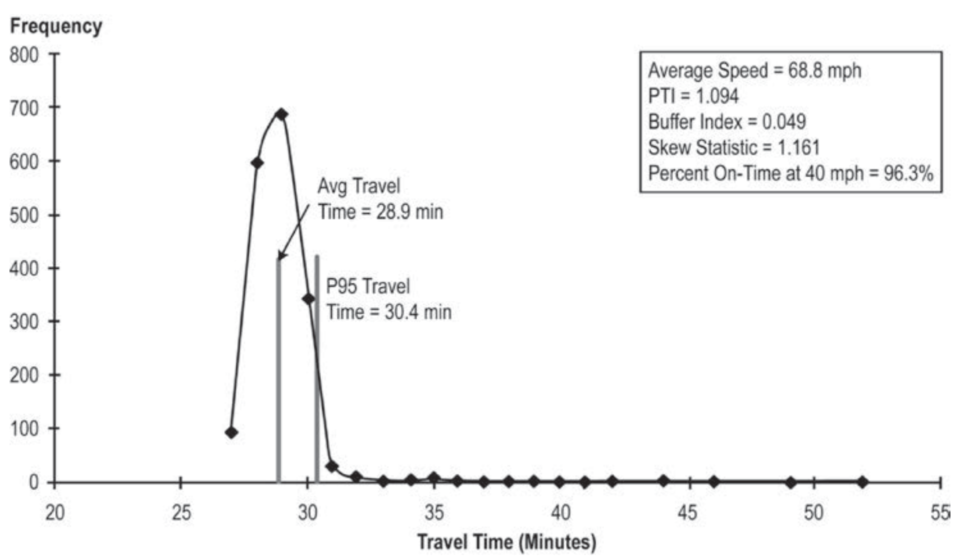

Figure 4.33. I-95 southbound, South Carolina (length = 33.1 miles).

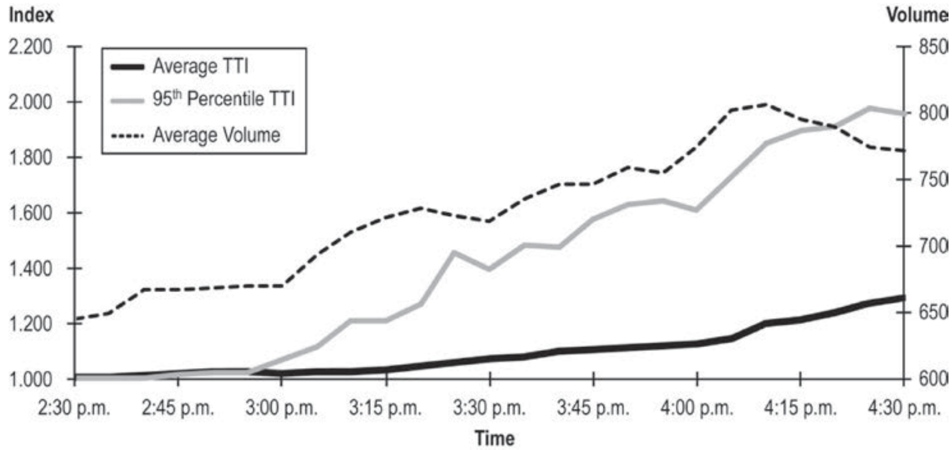

Figure 4.34. Beginning of weekday peak on I-75 in Atlanta at Station 750502 (2008).

congestion, there is a likelihood that a disruption (e.g., an incident) may cause congestion to form. Whether congestion will materialize is a function of how severe the disruption is and how much traffic volume is present.

An analysis was undertaken to understand this effect using data from Atlanta. Figure 4.34 shows volumes and TTIs for individual stations (detectors in all lanes at a roadway location) measured at 5-minute intervals for nonholiday weekdays. The transition from uncongested midday conditions to prepeak conditions can be seen around 2:50 p.m. Volumes started to increase quickly at about this time, and the 95th percentile TTI increased even more sharply. However, average TTI stayed almost unchanged until after 3:15 p.m. The point at which the 95th percentile and average TTIs diverged (i.e., 2:50 p.m.) can be thought of as the point at which the facility began to be highly vulnerable to breakdown. On average days, there is little noticeable congestion, but on the worst days, congestion builds rapidly. This period between TTI divergence and the uptick in average congestion is therefore extremely important from a traffic management standpoint.

Figure 4.35 shows the corresponding probability of congestion (when speeds are less than 50 mph, identified in the HCM as the approximate point of breakdown flow) for the entire afternoon time period for the same location shown in Figure 4.34. Figure 4.36 shows two characteristics of congestion at point locations. First, there appears to be a nonlinear relationship between average TTI and 95th percentile TTI, as seen in the steeper growth of the curves up to the peak. Second, average volume peaked early (around 4:10 p.m.) and stayed relatively flat throughout the peak, indicating that

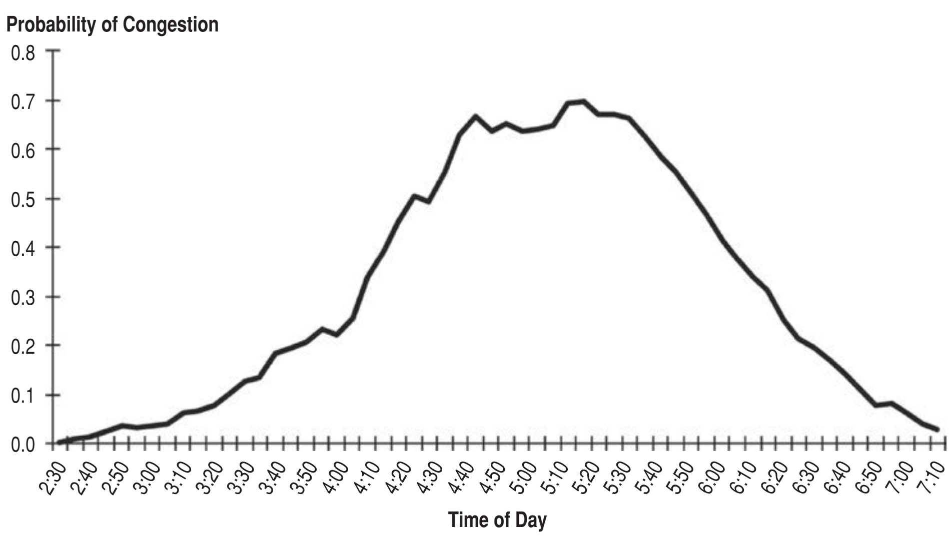

Figure 4.35. I-75 in Atlanta at Station 750502 (2008).

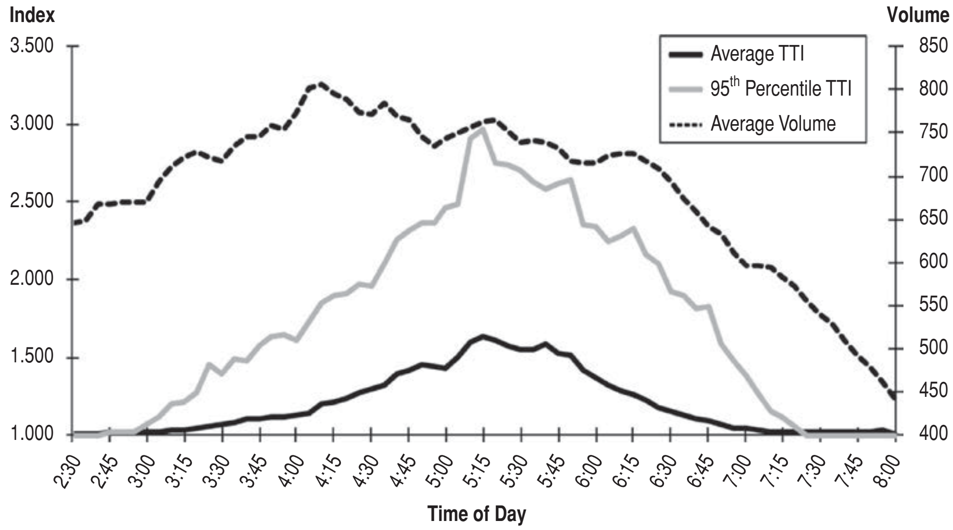

Figure 4.36. Complete weekday peak, I-75 in Atlanta at Station 750502 (2008).

congestion suppressed volumes, as discussed earlier in this chapter under "Estimating Demand in Oversaturated Conditions on Freeways."

Reliability of Urban Trips Based on Reliability of Links

The approach taken in this research for urban conditions was to define travel time reliability over a section of highway, typically 4 to 5 miles in length, with relatively homogenous geometric and traffic conditions. In many transportation modeling applications, it is desirable to know the travel time of entire trips, and by extension, the reliability of trips. The data sources used in this study precluded studying entire trips (from origin to destination) because they were collected at the roadway level.

However, an experiment was conducted with urban freeway data from Atlanta in an attempt to develop trip-based reliability. Specifically, the team was interested in seeing if the reliability of a trip could be predicted from the reliability of the individual links comprising the trip. Here *trip* means travel occurring solely on the freeway, as data for access to and egress from the freeway were not available. The term *links* refers to stations (detectors for all lanes at a specific location).

From the Atlanta section data, extended sections were developed by combining two adjacent sections. These combinations resulted in four one-way trips (one in each direction):

- I-75 North, from I-285 to Barrett Parkway (12.53 miles)
  - 25 links northbound, and
  - 20 links southbound; and
- I-285 Northern Arc, from I-75 to I-85 (10.37 miles)
  - 36 links eastbound, and
  - 34 links westbound.

The number of links is different for the directions because of station placement. For each directional section, morning and afternoon peak times were considered. The analysis proceeded as follows.

First, reliability metrics for the individual links were calculated for each direction and time slice. After this, reliability for the entire trip was calculated. A simple method of combining the link reliability metrics was then used: all the metrics for the links were averaged to see if the resulting average was correlated with the trip metrics. Figures 4.37 through 4.39 demonstrate that the metrics are very highly correlated. Simple nonlinear functions were then fit to the data. All coefficients were significant at an alpha level of 0.001 (most at an alpha level of 0.0001). Root mean squared error (RMSE) was used as a measure of goodness of fit when no intercept term was specified in the regression analyses.

$$\text{95th percentile TTI}_{\text{trip}} = X_1^{0.8014}\left(\text{RMSE} = 3.2\%\right) \tag{4.1}$$

$$\text{80th percentile TTI}_{\text{trip}} = X_2^{0.8702}\left(\text{RMSE} = 1.8\%\right) \tag{4.2}$$

$$\text{MeanTTI}_{\text{trip}} = X_3^{0.9020}\left(\text{RMSE} = 0.1\%\right) \tag{4.3}$$

$$\text{MedianTTI}_{\text{trip}} = X_4^{1.0600}\left(\text{RMSE} = 2.6\%\right) \tag{4.4}$$

$$\text{StandardDeviation}_{\text{trip}} = 0.6195 * X_5^{1.1163}\left(\text{RMSE} = 13.3\%,\ R^2 = .976\right) \tag{4.5}$$

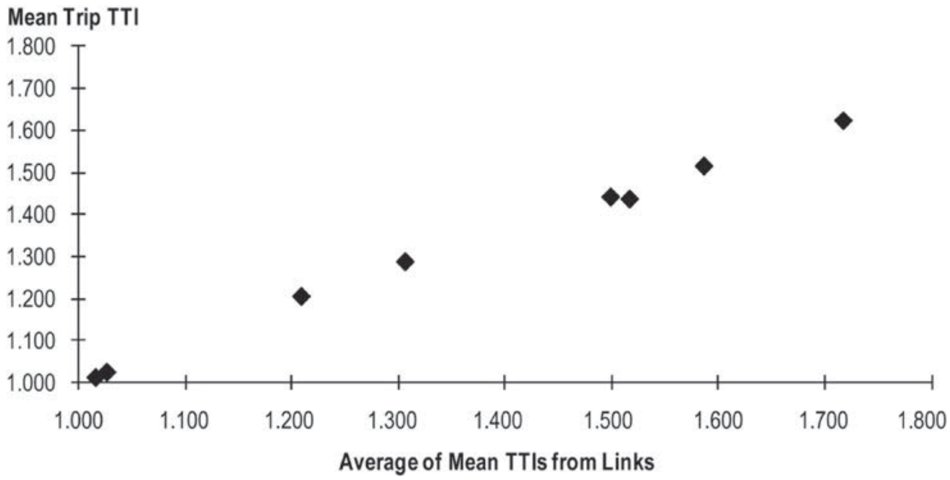

Figure 4.37. Trip versus link reliability: mean TTI.

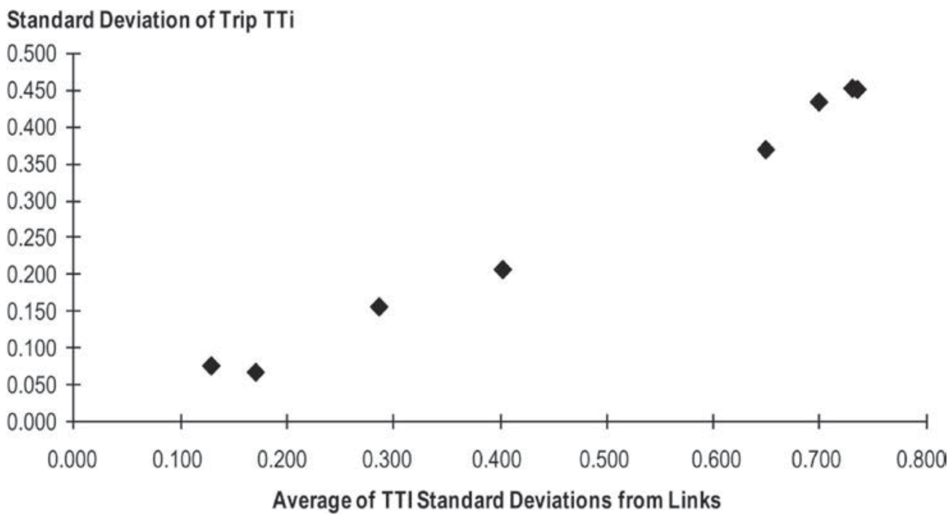

Figure 4.38. Trip versus link reliability: standard deviation.

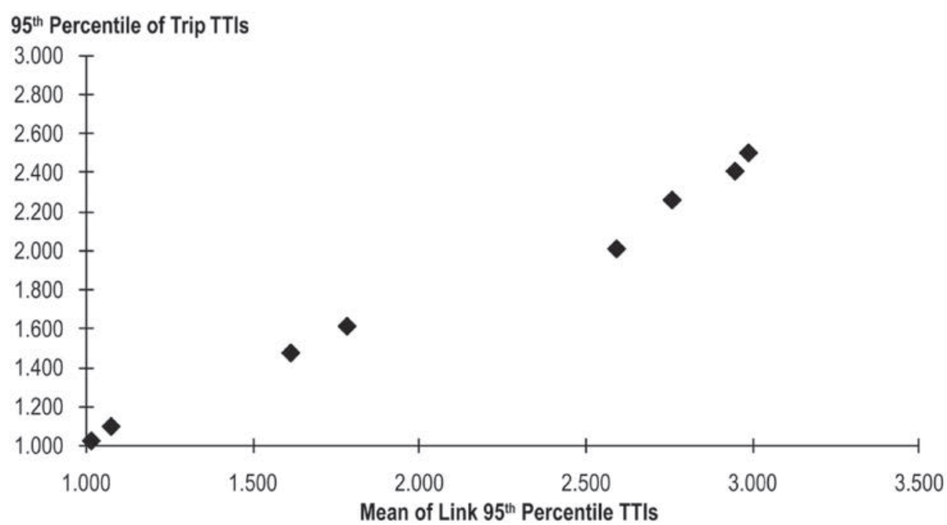

Figure 4.39. Trip versus link reliability: 95th percentile TTI.

where

X_1 = average of 95th percentile TTIs for all the links in the trip,

X_2 = average of 80th percentile TTIs for all the links in the trip,

X_3 = average of mean TTIs for all the links in the trip,

X_4 = average of median TTIs for all the links in the trip, and

X_5 = average of standard deviations of TTIs for all the links in the trip.

It should be pointed out that the strong correlation is probably due to the trip-based measures using travel times from individual links. However, in travel demand forecasting models, trip travel times are calculated this way. Although the analysis was restricted to freeway sections, the team does not see why nonfreeway links could not be added to the trip, and their reliability metrics treated in the same way; that is, the reliability statistics of the nonfreeway links could be combined with the freeway links' reliability statistics. Finally, the trips used here were relatively short, even for urban conditions. Longer trips may run into the same time dependency noted for long-distance trips in this chapter's discussion of the Reliability of Rural Freeway Trips.

Reference

1. Brilon, W., J. Geistefeldt, and H. Zurlinden. Implementing the Concept of Reliability for Highway Capacity Analysis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2027,* Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 1–8. http://trb.metapress.com/content/u700713ur834410r/fulltext.pdf.

CHAPTER 5

Estimating Congestion by Source: The Cause of Congestion

Introduction

The objective of this chapter is to describe in detail the factors that cause congestion, with the specific intent of helping agencies respond cost-effectively to reduce the formation of congestion. The results of a series of analyses that examined the causes of freeway congestion, first in Atlanta, then in greater detail in the Seattle metropolitan region, are discussed. The analyses were based on an entire year's worth of freeway operations data that covered a significant portion of freeways in the two regions. The freeway performance information was combined with data that described when incidents, accidents, and construction activity occurred and tracked the effects of weather. The effects of a variety of special events in Seattle were also tracked. The analyses did not include an examination of ramp delays, either entering (ramp meters) or exiting (queuing due to inadequate ramp intersection capacity) the roadway.

Many analyses have been performed over the years to examine the causes of roadway delay (Table 2.5). Traditionally those studies have been based on (*a*) queuing analysis of specific incidents; (*b*) simulation of specific roadway corridors, given a limited set of volume conditions and incident and nonincident conditions; and (*c*) national scale estimates based on base roadway volumes and reported incident and crash rates.

Preliminary Look at Congestion by Source: Atlanta

A simple analysis was undertaken in Atlanta to develop a point of comparison for the detailed Seattle analysis. The times and locations of incidents and weather conditions during the Atlanta study section peak periods were merged with the traffic data. Any incident that started 15 minutes before the peak start or lane-blocking incidents that started an hour before the peak start were assumed to influence the traffic flow and were counted. Each peak period was assigned an influencing cause: incidents, weather, or both. No attempt was made to track incident-caused queues in time and space; if an incident occurred at any time or location during the peak, the entire peak was described as incident influenced. This assumption will overstate the importance of incidents as a contributor to total congestion.

Overall, the recurring–nonrecurring split was roughly 50–50 (Table 5.1). A breakdown of nonrecurring incidents appears in Table 5.2; the significance of incidents is clear, as roughly a third of the congestion occurred on days when incidents occurred.

Figure 5.1 examines congestion causes for the 50 worst congestion peak periods on these sections (i.e., those with the highest Travel Time Index [TTI]). Another potential source of congestion, high demand, was added to incidents and weather (high demand was defined as days with demand volumes higher than the average, plus 5%). For simplicity, the three sources were placed in a hierarchy, and only one source was assigned responsibility: incident, weather, or high volume, in that order. For example, if a day had at least one incident and high volumes, the cause was assigned as incident. Even with the addition of high demand, 21% of the days could not be assigned to a source. Several potential sources may explain these conditions:

- Congestion that forms off section and spills back into the study section, which could be from a downstream section or an exit ramp to either a surface street or an intersecting freeway; and
- Minor perturbations in traffic flow at a microlevel, which could be brief surges in demand or variations in driver behavior that cause flow breakdown when volumes are operating very near to physical capacity.

Table 5.1. Recurring Versus Nonrecurring Congestion During Peak Period in Atlanta (2008)

Section	Congestion Type			
	Nonrecurring		Recurring	
	No. of Incidents	Congestion (%)	No. of Incidents	Congestion (%)
I-75 northbound from I-285 to Roswell Road	128	52.0	118	48.0
I-75 southbound from I-285 to Roswell Road	81	41.8	113	58.2
I-285 eastbound from GA 400 to I-75	89	46.8	101	53.2
I-285 westbound from GA 400 to I-75	126	56.5	97	43.5
I-285 eastbound from GA 400 to I-85	159	64.6	87	35.4
I-285 westbound from GA 400 to I-85	134	56.5	103	43.5
I-75 northbound from Roswell Road to Barrett Parkway	121	49.2	125	50.8
I-75 southbound from Roswell Road to Barrett Parkway	100	42.3	136	57.6
Total	**938**	**51.6**	**880**	**48.4**

A Closer Look at Congestion by Source: Seattle

Background

Analysis Overview

To examine some of the issues raised in the preliminary Atlanta analysis, a detailed analysis was conducted using data from Seattle. This effort used measured roadway performance data (volumes and travel times taken every 5 minutes) for an entire year on approximately 120 centerline miles of urban freeway. These data included all crashes that occurred on those roadway segments, all noncrash incidents to which Washington State Department of Transportation (WSDOT) personnel responded, and National Oceanic and Atmospheric Administration (NOAA) weather data for the region. Based on these data, the analysis examined how a wide variety of factors affected travel times experienced by travelers on different freeway sections throughout the Seattle metropolitan region. Unlike traditional queuing analysis, using segment-based travel times over defined roadway segments as the dependent variable allowed the research team to explore the upstream and downstream impacts of a wide variety of disruptions, as well as to examine the effect of those disruptions on travel time reliability.

The primary intent of this section is to explore the causes of congestion on the instrumented Seattle freeway system and summarize those findings in a generalized manner so that the results are applicable elsewhere.

Table 5.2. Congestion by Source During Peak Period in Atlanta (2008)

Source	Congestion (%)
Recurring (bottleneck)	48.4
Incidents	32.8
Weather	11.1
Incidents and weather	7.7

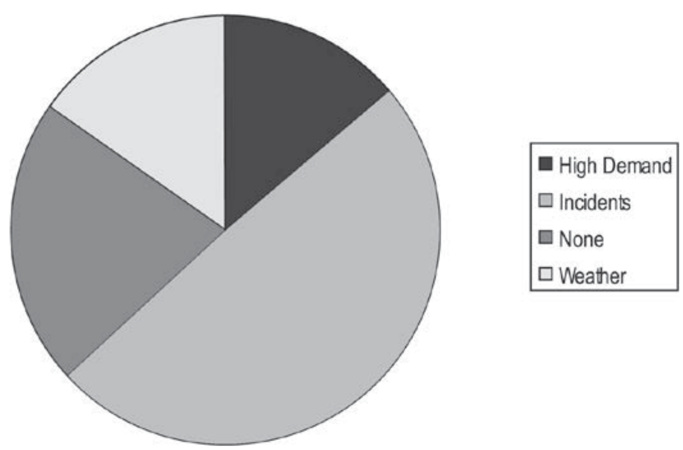

Figure 5.1. Congestion causes for the 50 worst congested peak periods in Atlanta (2008).

Factors Affecting Congestion

Given that congestion occurs when there is too much volume and too little roadway capacity, it can be said that all congestion is caused by having too much traffic volume. In some cases, too much volume is associated with routine temporal fluctuations in demand, such as peak period commute congestion in urban areas. In other cases, congestion is associated with demand associated with special events, such as sports or cultural activities. In still other cases, analysis suggests that microscale variations in demand during periods of already high demand can cause congestion even when hourly volumes would not indicate that capacity has been reached.

However, traffic engineers know that roadway capacity is not a constant. A variety of factors reduce effective or operational roadway capacity from the normal capacity figures that are computed with *Highway Capacity Manual* procedures. These factors can cause congestion even when volumes are lower than normal, theoretical roadway capacity.

It is commonly accepted that there are a limited number of basic factors that cause congestion to form; these are usually referred to as the seven sources of congestion:

1. Traffic incidents;
2. Weather;
3. Work zones;
4. Fluctuations in demand;
5. Special events;
6. Traffic control devices; and
7. Bottlenecks or inadequate base capacity.

Traffic incidents (including crashes, debris on the roadway, and other types of incidents) decrease effective capacity either by physically blocking lanes or by producing visual distractions that cause motorists to slow, resulting in lowered roadway throughput.

Weather has similar effects on effective roadway capacity. Poor weather causes drivers to drive more cautiously, slowing down and leaving more space between vehicles to maintain safety, thus reducing effective roadway throughput.

Work zones narrow lanes or reduce the total number of lanes available. They also can reduce speed limits and frequently include right- or left-lane shifts. All these physical changes decrease available or effective roadway capacity.

Fluctuations in demand cause congestion because demand that exceeds roadway capacity causes queuing to occur, and that queuing reduces effective vehicle throughput. Thus, the arrival rates (timing) with which vehicles access a roadway segment is another cause of congestion. In a simple example, a two-lane (one-direction) freeway has a capacity of 4,000 vehicles per hour (vph). In a 3-hour period, 11,000 vehicles need to use that facility. If that demand is uniformly distributed, no congestion occurs, as volume never exceeds 4,000 vph. However, if demand arrives at the roadway section in the form of 2,200 vehicles in the first hour, 5,000 in the second hour, and 3,800 in the third hour, congestion will occur in the second hour. That congestion will cause queuing that will, effectively, further reduce roadway capacity, creating delays even in the third hour, despite the fact that demand is then lower than theoretical capacity.

Special events cause congestion because they create significant fluctuations in demand. The starting and ending times of major events create surges in traffic demand that overwhelm roadway capacity near the event venue, causing congestion.

Traffic control devices (e.g., traffic signals) delay some vehicles to allow other vehicles to move safely. Therefore, by definition, traffic control devices create (control) delay. When optimally timed, traffic control delays minimize congestion. When not optimally timed, traffic control devices create unnecessary delays to vehicles.

Inadequate base capacity and bottlenecks create delay in the same way that traffic volume fluctuations cause delay. Inadequate base capacity (i.e., not enough roadway capacity for normal traffic flows) most frequently manifests itself at points along a segment of roadway where effective capacity is routinely lowest—a bottleneck. Bottlenecks are a decrease in effective roadway capacity that occur as a result of some physical change in roadway geometry or environment (e.g., a lane drop, a weaving section). That geographic location becomes the initial point at which traffic demand first exceeds effective capacity, causing queuing, which further decreases effective capacity.

As the above discussion indicates, two of the causes of congestion (fluctuations in demand and special events) influence the demand side of the volume–capacity relationship, which ultimately determines formation of congestion, and the other five influence the actual volume-carrying capacity of the roadway. The cause of congestion has significance to transportation agencies, in part, because it describes the level of control the agency has over that measure, and consequently the level to which it can anticipate and mitigate congestion formation. For example, the agency has no control over weather; it can only react to weather events. But the agency can directly influence other causes, such as the operation of traffic control devices or the design and timing of work zones.

Data Description

Traffic Incidents

Data on traffic incidents were obtained from WITS, the WSDOT incident response program resource management system database, and the State of Washington's accident reports.

The more detailed and useful data source is the WITS database, which was created to track the work performed by WSDOT's freeway service patrol personnel. Key variables for each task performed by WITS field staff are recorded, giving

WSDOT a record of when an incident was reported (used as an estimate of when that event occurred), as well as when the incident respondent declared the site of the incident cleared. The location (route, milepost, and direction) of the incident and whether a lane of traffic was blocked by the incident are also reported. Although these data allow detailed analysis of different incident types, this project limited the analysis to (*a*) when and where an incident occurred, (*b*) how long that incident lasted (in seconds), and (*c*) whether that incident closed a lane.

In 2006 WITS reported only WSDOT's incident response team actions, so no records exist for incidents to which WITS personnel did not respond. Because most WITS staff work during the peak commute periods, many incidents occurring on weekends or at night are not reported in WITS. This is a limitation of this analysis database.

Accident records were used to supplement the WITS data. Accident records should be present for all significant accidents that occurred within the study area. During peak periods, accident records generally match with WITS records, as WITS members are usually called to the scene of accidents when they are on duty. In a number of instances accident records and WITS records appeared to reference the same event but listed slightly different starting times. This project did not try to identify which of these times were correct, but kept both, and used the time related to a particular kind of event. That is, for an analysis of crash effects, the time from the accident record was used. If the analysis concerned the effects of all incidents, then the time noted in the WITS database was used.

During times when WITS was not actively patrolling or on the rare occasions when WITS staff were busy on other calls and did not respond to an accident scene, the accident records indicate the occurrence of the accident but not the duration of the disruption. This is another limitation of this analysis database.

Weather

The weather data used for these analyses were obtained from publicly available records collected from the NOAA weather station at Sea-Tac International Airport. The analytic database created for this study tracked the major statistics reported by NOAA, including the following weather information:

- Visibility
  - Up to 10 miles;
- Temperature
  - Dry bulb;
- Wind speed
  - Average speed, and
  - Gust speed (highest gust speed that hour);
- Precipitation
  - Inches; and
- Weather type
  - Rain,
  - Mist,
  - Thunderstorm,
  - Drizzle,
  - Haze,
  - Snow,
  - Freezing,
  - Small hail,
  - Hail,
  - Ice pellets,
  - Squall, and
  - Fog.

These data were too detailed for the basic analyses intended for this study. Consequently, the project team performed an extensive analysis to determine the types of summary weather statistics that would effectively indicate whether weather conditions contributed to congestion. A summary of these tests is given in Appendix E, and findings from the most important tests are presented later in this chapter. The outcome of the analysis was to define the indicator of *bad weather* as any time period in which any measurable precipitation had fallen at some time in the previous hour. Importantly, the use of this indicator discounts several weather effects, including wind, fog, snow, and rainfall intensity.

An analysis of the effects of wind on roadway performance indicated that on the two roadways (I-90 and SR 520) that cross Lake Washington on floating bridges, high winds (gusts above 20 mph) had an observable effect in moderate volume conditions, especially eastbound when the winds caused waves to crash against the bridge, creating significant spray. (Winds are generally from the south, so the spray affects the eastbound traffic more than westbound traffic.) However, wind appeared to have little observable effect on the other freeway corridors in the region.

The analysis of the effects of fog was problematic, as fog tends to be localized. Thus, while the airport could be very foggy (to the point that landings and take-offs are restricted for lack of visibility), at the same time I-5, passing within 2 miles of Sea-Tac, could have clear visibility. As a result, a fog variable was not useful in identifying specific fog-related delays.

The examination of fog as a weather variable highlighted the problems associated with using weather data from a single point to represent weather experienced around a fairly large geographic region. That is, although the Sea-Tac weather records accurately reflect conditions at the airport, the weather experienced simultaneously in other areas of the metropolitan region can be different. For example, a storm moving south to north that affects Sea-Tac at 5:00 p.m. will have occurred in the southernmost roadway sections before 5:00 p.m. and in the northern part of the city some time after 5:00 p.m. In addition, that storm may have dropped exactly 0.25 inch of rain at the airport, but it may have deposited only 0.1 inch south of the airport, and 0.5 inch in areas north of the airport. Although these rain data provide a reasonable estimate of weather conditions, they cannot be used as a precise, highly accurate measure of the actual weather occurring on any given segment of roadway during a specific 5-minute interval.

In addition to the basic time and geographic problems noted above, the snow and rainfall intensity variables presented a second problem in that many of the effects of heavy rain (i.e., heavy rain short of intense thundershowers, which rarely happen in Seattle) occur after the precipitation has fallen. This is especially true for snowfall, as the effects of falling snow are not nearly as significant as the effects of snow accumulations on the ground, depending on the amount remaining on the roadway. For example, snow flurries have little effect on driving, but 4 inches of snow on the ground 2 hours after the snow has stopped falling has a major impact on roadway performance.

Another issue associated with snowfall in the Seattle area arose from the combination of how rarely snow falls in the region and how travel times are computed. When snow falls (and sticks), Seattleites tend to avoid driving whenever possible. The region does not use salt; agencies do not clear snow as effectively as those in regions of the country that routinely experience snowfall; and snow is frequently turned into sheet ice on the roadways by cars that do travel, making the area's hilly terrain dangerous. The result is that a large percentage of travelers simply avoid going out. Therefore, after snow falls, volume and lane occupancy are frequently low on the freeways despite the slow speed of those cars that are present. However, the loop detector system only sees low volumes and occupancy values, and can thus overestimate the speeds at which the vehicles are moving. Fortunately for this study, the number of days on which snow fell during the analysis year was small.

Work Zones

To identify work zones, variable messages sign (VMS) logs were examined. From the VMS logs, it was possible to identify where, when, and for what period work zone messages were posted. It also was possible to determine from the logs when lanes were closed, but the number of lanes closed for a given construction lane closure was not incorporated into the analysis database. The closure times recorded in the VMS logs are approximate (e.g., 9:00 p.m. to 5:00 a.m.) and do not represent the exact time when lanes were actually closed or open to traffic.

Long-term construction changes (e.g., narrowed lanes during lengthy construction projects or the presence of construction barrels on shoulders in and approaching a work zone) that are likely to also cause minor disruptions in normal traffic flows are not included in the VMS database. However, because the freeways examined were major urban highways, all work zones had nighttime and weekend closures. No lanes were closed during normal weekday business hours.

Fluctuations in Demand

Volume data for the study were obtained from FLOW, the WSDOT Northwest Region's traffic management center database system. All traffic volume data used in the study were collected with permanent inductive loops that are part of that system. Loops are located roughly every half mile on the freeways analyzed. Each loop reports total volume every 5 minutes, as well as average lane occupancy for that location.

Because 5 minutes is the basic WSDOT data-reporting period, the analyses for this report were based on these 5-minute periods. Traffic volumes were available every 5 minutes, for every roadway study segment, for all 365 days for 2006. Some corridors were missing specific days or times of data because of equipment malfunction.

Because volumes varied over the course of the roadway study segments, several volume statistics were used to describe each 5-minute period for each roadway segment. These are

- The maximum volume observed for the roadway segment in that 5-minute interval;
- The minimum volume observed for the roadway segment in that 5-minute interval;
- The average volume over the length of the segment;
- The vehicle miles traveled for the segment; and
- The vehicle hours traveled for the segment.

Volumes were reported in units of vehicles per hour.

Special Events

Some special event data were collected by manually reviewing calendars for major regional venues (e.g., the Seattle Mariners' game schedule allowed the researchers to identify the dates and start times of Mariner baseball games in 2006). However, it quickly became apparent that collecting uniform special event data would not be possible. In part, this was because there is no uniform definition of how big an event must be to be classified as a special event. Major league baseball games with 30,000 people attending undoubtedly qualify, but do major college basketball games with 8,000 people attending? What about games with 2,500 people? Although all major sporting events have known start times, many (e.g., baseball) do not have consistent durations, and their ending times are not easily determined. The lack of a definite duration complicated the analysis of postevent traffic, in many cases beyond what could be addressed in this project.

Although there is little argument that major sporting events are special events, what about community events? Large events such as July 4 fireworks displays are obviously special events from a traffic perspective, but what about parades or conventions? Not only are the sizes of these events difficult to obtain, but their start and end times are far less consistent, especially in terms of when traffic volumes going to and from those events affect roadway performance.

A final consideration in developing the analysis data set was that special event traffic generally only affects roadway performance near the event venue. That is, when a major college or professional football game takes place, traffic near the stadium is bad, but traffic farther from the stadium is often light (because a large percentage of the population is at the game or watching it on television). Previous work for WSDOT showed that while special event (professional baseball and basketball) traffic had statistically significant effects on major freeways leading to the event locations, roadway performance in the opposite direction before the game began was generally not statistically significantly different (*1*).

Consequently, special event data need to be applied on a site-specific basis; descriptive information (time, location, and size) and local knowledge of the likely routes of travel affected by the event are required. These site-specific requirements made attempting to analyze 21 roadway corridors on five freeways covering approximately 120 centerline miles of roadway problematic. In the end, the project team decided to simply use the volume data from the freeway and to analyze the effects of special events as case studies to illustrate the relative size and significance of their impacts.

Traffic Control Devices

This study did not collect data on traffic control devices. All sections of freeway under study operate under ramp metering control. The fuzzy, neutral ramp-metering algorithm used by WSDOT changes ramp metering rates dynamically in response to a combination of inputs, including mainline volumes and lane occupancy values at the ramp, upstream of the ramp, and downstream from the ramp, as well as the presence of ramp queues and the determination of whether those queues are long enough to affect arterial operations.

Ramps are metered whenever congestion routinely forms. This includes all commute periods and most weekend afternoons for freeways near the downtown core areas. Metering is only applied in the direction in which congestion is (or has) formed.

Because only 1 year of data were analyzed in this study, it was not possible to determine the effects of the ramp-metering algorithm on congestion. A case study is presented below that describes the benefits obtained from meters. Other than that case study, traffic control devices are not examined in this report.

Bottlenecks and Inadequate Base Capacity

No specific data were collected relative to the base capacity of the roadways being studied. Several major bottlenecks are represented in the data set. In most cases, bottlenecks are located at the ends of study sections. One type of bottleneck is a ramp terminal at the end of a roadway. Two examples of this occur: the eastern end of SR 520 (affecting SR 520 Redmond eastbound) and the western end of I-90 (affecting I-90 Seattle westbound). A second type of bottleneck is a freeway-to-freeway ramp interchange, where ramp volumes overwhelm the interchange capacity. One example is the interchange between northbound SR 167 and I-405 (both directions). This bottleneck affects SR 167 Renton northbound, I-405 Kennydale southbound, and I-405 South northbound. Other freeway-to-freeway ramps also contribute to congestion, usually because the mainlines to which they lead experience routine backups. Although these may not be classic bottlenecks, ramp queues can cause congestion. Freeway-to-freeway ramps that exhibit these conditions fairly frequently include SR 520 Redmond going westbound to I-405 Kirkland northbound and I-405 Bellevue central business district (CBD) southbound; SR 520 Seattle westbound to I-5 Seattle North northbound; and I-5 Seattle CBD southbound. Both the northbound Seattle CBD and southbound Seattle North sections of I-5 can be affected by queues extending from the eastbound SR 520 Seattle study section. Similarly, both directions of the Seattle CBD sections of I-5 are affected by queues on the westbound I-90 Seattle section. Finally, the I-90/I-405 ramps cause delays primarily to four movements: to westbound I-90 from the northbound (Eastgate) and southbound (Bellevue CBD) sections of I-405, and to westbound I-90 from northbound I-405. The ramp to southbound I-405 also backs up, but the queues to that ramp rarely affect I-90 performance because of the storage available on the ramps.

The I-5 Seattle CBD sections in both directions contain several bottlenecks. In addition to the freeway interchanges, this section of freeway is affected by several C-class weaving movements, a variety of lane drops and adds, and the northbound entrance and southbound exit from the I-5 express lanes. (The performances of the I-90 and I-5 express lanes were not included in this study.) The southbound entrance and exit to the express lanes also affect traffic on I-5 southbound on the North King study section and northbound on the Seattle North section. The I-90 express lane entrances and exits have less of an impact (the westbound on-ramp modestly affects the I-90 bridge section in both directions).

The other major bottlenecks of special significance are the two Lake Washington floating bridges (SR 520 and I-90). The entrances to the SR 520 bridge, in particular, are major bottlenecks, as they both involve a combination of narrow lanes, strong visual impacts, and ramp entrances. In both cases, the bridge bottlenecks are located in the middle of the study section. The affected sections are the two Seattle sections of SR 520 and the two bridge sections of I-90.

No attempt was made to quantify the specific capacity reductions caused by these bottlenecks. However, as the results presented later in this report show, these sections all experience considerably more delay than freeway sections without bottlenecks.

Computed Variables Used for Tracking the Influence of Disruptions on Travel Times and Delays

The interaction of all of the factors discussed above is very complex. All analytic methodologies have limitations when trying to determine how each factor of a given set of factors affects the delays experienced by a traveler using the roadway system. To decrease the effects of these limitations, the research team developed additional variables to help associate travel times and delays with specific disruptions. To understand the need for these variables, consider the following example incident.

A major traffic accident occurs early in the morning, before the start of the morning commute, in the outer extent of the metropolitan region. The accident blocks most of the freeway and lasts 2 hours, forming a significant queue despite the early hour. Because traffic from the outlying areas is blocked, inbound commute travel times downstream of the accident start off better than normal. The accident is cleared after the morning commute peak begins. Once the accident has been cleared, a major pulse of traffic flows downstream from the accident location because the roadway clearance releases the large queue of vehicles stored upstream of the accident scene. That pulse of traffic nearly equals roadway capacity. When normal on-ramp volumes are added to that flow, congestion forms in unusual locations. The result is significant travel time delay that continues well after the accident has been cleared from the roadway, with the congestion occurring well downstream of the accident location.

If a queuing analysis is performed for the accident location, only the delay computed upstream of the accident location is attributed to the accident, as the downstream congestion occurs both after the accident has been cleared and at locations that are geographically removed from the accident site. Thus, the delays associated with the accident are computed to be smaller than the real congestion caused by the accident, which should include the delays occurring downstream of the accident site.

At the same time, some of that congestion should rightly be attributed to routine peak period morning traffic, which always causes congestion. Therefore, not all the delays in the corridor should be attributed to the accident. The delays are influenced by the accident, but high volumes also contributed to the measured delay.

With the above scenario in mind, the project team developed a set of variables to help relate the measured performance of the roadway (travel times, volumes, and delays) to known disruptions. A value was assigned for each of these new, computed variables for every 5-minute time interval in the analysis data set (i.e., all of 2006). These additional variables included the following:

- Travel delays were computed by corridor segment so that all delay (any travel less than 60 mph, in units of vehicle seconds) was computed.
- The times when potential disruptions took place were identified for each type of disruption event, and variables identifying that a disruption was active or not present were created for each 5-minute interval for the year.
- Binary influence variables were computed for which *influence* was defined as occurring when either (*a*) the potential disruption event was active during a given 5-minute period or (*b*) travel times for the corridor were observed to be slower than any observed during the observed disruption. This definition of influence essentially means that slowdowns occurring in the corridor during the period of active disruption are at least partially caused by that disruption; that is, travel times are influenced by a given disruption. In the analysis, the binary influence tag stays on until travel times in the corridor return to values equal to or faster than the fastest travel time observed during the duration of the event itself. That is, if a crash or incident occurs at the beginning shoulder of a peak period and some congestion forms (even if the majority of that congestion is caused by the increasing peak period volumes), then the influence tag will likely stay on until after the peak period congestion eases. This is an intended outcome. It signals that the disruption (crash or incident) may have caused congestion to be worse and last longer than it otherwise would have. The influence tag is turned off once travel times return to predisruption levels, indicating that any queues present in the corridor are no larger than those that existed before the effects of the disruption. (A more complete discussion of the influence variables is found in Appendix D.)
- Influence variables were computed for (*a*) all incidents, (*b*) only those incidents that involved lane closures, (*c*) vehicle crashes, (*d*) active construction events, (*e*) bad weather,

and (*f*) rubbernecking, where *rubbernecking* was defined as a time during which a crash or incident was active on the roadway section being studied, but in the opposite direction of travel. A variety of influence variable calculations were computed and tested. Variables were developed that would allow off-segment congestion influences to be related to the segment under study. (A detailed description of the variable codes or categories used to indicate the influence of congestion from off-study segments on the study section of interest is found in Appendix C.) These variables were activated when the first detector (mainline or ramp) downstream of the study section had an occupancy value of greater than 35% for the 5-minute period of interest. When that occurred, these variables were set to a categorical value that described the influences on the congestion of that downstream segment. Variables were created for the downstream mainline roadway sections, for freeway-to-freeway ramps known to experience backups, and for major off-ramps known to spill back on the mainline roadway during peak commute periods. These variables were designed to allow transfer of the effects of a downstream disruption to an upstream roadway study segment when queues from that disruption extended off the end of the downstream segment. For example, if a crash on the roadway section just north of the CBD caused a queue on I-5 northbound that reached the detector just downstream of the northbound CBD roadway study section, the variable representing the mainline roadway section downstream of the CBD section would be set to *crash-influenced congestion* so that analyses of the CBD roadway section would include the fact that an off-segment crash was influencing the performance of the roadway segment.

- The *regime* variable was developed to describe the worst condition found in the test segment during each 5-minute interval. (A detailed description of the regime variable is found in Appendix C.) Regime is a categorical variable in which 1 = free-flow traffic, low volumes; 2 = free-flow traffic, less than one lane of capacity remains; 3 = constrained flow, very high volumes; 4 = congestion exists; and 5 = recovery. Regime, which is illustrated in Figure 5.2, was used to define the basic operating condition of the roadway study section.
- Six binary variables were defined to indicate whether a roadway section moved from a free-flowing regime to a congested regime within a given time frame. These variables allowed an estimate of the probability that a specific event resulted in congestion formation when the period was compared with similar time periods on other days when operating conditions were similar. Three binary variables described whether roadway operation moved from Regime 2 to Regime 4 within 5, 10, or 15 minutes. The other three variables described whether roadway operation moved from Regime 3 to Regime 4 within 5, 10, or 15 minutes.
- The time when congestion ended was computed for both the a.m. and p.m. peak periods. This time was defined as the first 5-minute period after the start of the peak period (7:00 a.m. or 4:00 p.m.) when travel times were no more than 5% above travel at the speed limit. For example, if travel at the speed limit required 300 seconds, congestion ended for the peak period on any given day when four consecutive travel times were observed to be below 315 seconds. (A more complete discussion of this variable is included in Appendix C.) On 11 of the 42 study sections, this definition created mean congestion ending times for

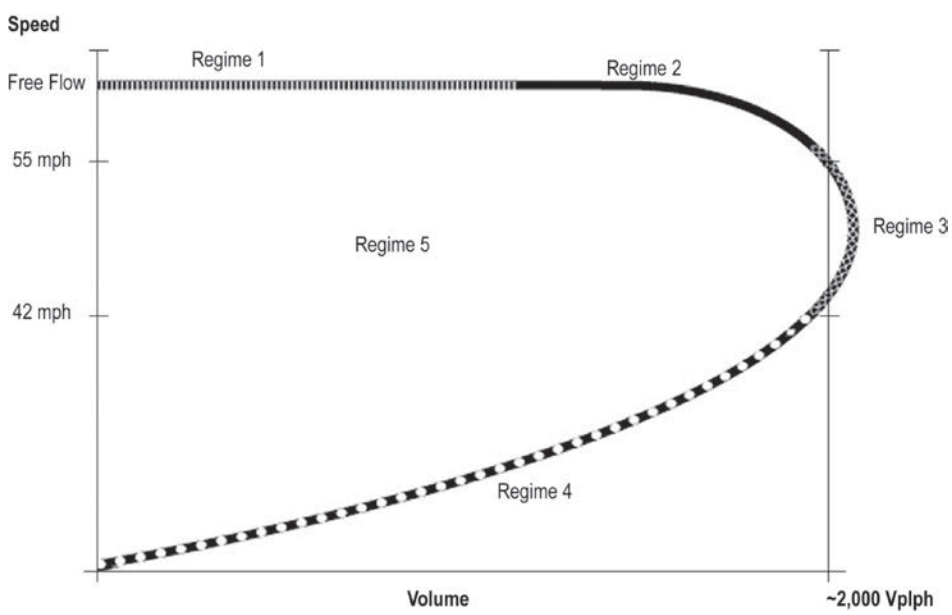

Figure 5.2. Illustrations of roadway operating regimes.

the a.m. peak period that were later than noon because of various volume and bottleneck conditions that caused midday traffic to routinely travel below the speed limit. For some specific analyses, congestion was defined *on these sections only* as being when travel time dropped to within 10% or 20% of travel at the speed limit.

Findings from Seattle

The findings are divided into four major subsections:

1. Congestion by source;
2. The effect of weather;
3. The effects of crashes and incidents on travel times; and
4. The effects of crashes and noncrash incidents on the extent of congestion.

The first subsection examines, at an aggregated annual level, how delay changes with different types of disruptions to the fixed infrastructure. Congestion sources examined include weather, crashes, other noncrash incidents, and construction activities.

The second subsection looks specifically at how weather, primarily rain, affects travel times and congestion formation.

The third subsection examines how travel times change given the occurrence of incidents and the queues that result from those incidents. As part of this analysis, the specific effects of vehicle crashes are examined, both independent of noncrash incidents and in combination with noncrash incidents.

The fourth subsection examines how the duration of peak period–related congestion changes as a result of crashes and noncrash incidents. The intent of this analysis was to put into context how crashes and incidents change the travel experiences of commuters in a congested urban area.

Congestion by Source

This analysis examined how different types of disruptions influence the formation of congestion and the degree of delay experienced by travelers. It covered only general-purpose travel lanes (no high-occupancy vehicle [HOV] or high-occupancy toll lanes) and used units of vehicle hours of delay, not person hours, as the available data did not account for changes in vehicle occupancy during different days of the week, times of day, or types of facilities (e.g., weekends having much higher vehicle occupancy rates than weekdays, commute hours having generally higher occupancy rates than the middle of the day on weekdays, and HOV lanes having much higher occupancy rates than general-purpose lanes). The analysis covered only urban freeways in the Seattle metropolitan region. The analysis did not attempt to differentiate among relative causes when two or more causative factors were present. That is, when a crash happened in the rain during the peak period in the peak direction, the analysis did not attempt to determine how much of the delay was caused by the crash, how much was caused by rain, and how much was caused by high peak period volumes.

Methodology

The congestion by source analysis computed delay per 5-minute period for all 5-minute periods in the year (2006) and assigned that delay on the basis of the influence variables associated with each of those 5-minute periods. (See Appendix C for a description of the influence variables.) Delay was computed with the following equation:

$$\begin{aligned}\text{delay} = &(\text{actual travel time} - \text{travel time at the speed limit})\\ &* (\text{roadway segment volume})\end{aligned}$$

where roadway segment volume was the maximum volume observed in the study section for that 5-minute period. Actual volume counts tend to underestimate the number of vehicles queued within a section during times of heavy congestion; consequently, this equation slightly overstated delay in lower-volume periods but better estimated the number of vehicles actually in the roadway section during times of peak congestion. When study section travel times were faster than the speed limit, conditions were assumed to be operating at the speed limit.

A categorical variable was developed that allowed any combination of influences to be maintained simultaneously. The following influences were tracked:

- No cause indicated;
- Only incident-influenced queues are present;
- Only crash-influenced queues are present;
- Only rain is present;
- Both a crash and an incident have influenced queues that are present;
- Both rain and an incident have influenced queues that are present;
- Both rain and a crash have influenced queues that are present;
- Rain, a crash, and an incident have influenced queues that are present;
- Queues from a ramp have influenced mainline queues, but the ramp delays have no identified influence factor;
- Construction activity has influenced queues;
- Construction and queues from a ramp (cause unknown) have influenced mainline queues;
- Construction and an incident have influenced queues that are present;
- Construction and a crash have influenced queues that are present;

- Construction and rain have influenced queues that are present;
- Construction, a crash, and an incident have influenced queues that are present;
- Construction, rain, and an incident have influenced queues that are present;
- Construction, rain, and a crash have influenced queues that are present; and
- Construction, rain, a crash, and an incident have influenced queues that are present.

Delay statistics were then aggregated by type of influence present. Traffic volume, whether it was routine volume or an unusual surge in volume associated with something like a special event, was not explicitly tracked in this analysis. Unexplained congestion was assumed to be caused exclusively by the presence of too much traffic volume.

Results

Table 5.3 summarizes the amount of delay influenced by each type of disruption tracked in this study. Percentage of delay was computed by totaling all vehicle hours of delay in the region associated with each type of disruptions, and then dividing by the sum of all measured delays. This computation automatically weighted the delays experienced by each roadway on the basis of the relative number of vehicle hours traveled on that roadway section.

Of interest is the fact that rain had almost as much influence on congestion as vehicle crashes. Not surprisingly, construction (defined as lane closures during active construction or maintenance activity) had the least influence on congestion formation. The percentage of delay associated with construction is small mainly because construction closures are only allowed on urban area freeways during the late-night hours, when volumes are low. Thus, even when congestion (measured in terms of either the queue length or the amount of time an individual spends in that queue) is significant as a result of construction lane closures, total vehicle delay (vehicle hours) is small relative to the amount of delay experienced in the peak periods, when volumes are high.

Table 5.3. Percentage of Delay by Type of Disruption Influencing Congestion

Type of Disruption	Delay[a] (%)
Incidents	38.5
Crashes	19.5
Bad weather (rain)	17.7
Construction[b]	1.2
No cause indicated (mostly volume)	42.2

[a] Delays that occurred when more than one type of disruption influenced the size and scope of that delay were counted in each of the categories of disruption and, therefore, the percentages total to more than 100%.
[b] Construction delays do not include any delays caused because general roadway capacity was reduced as a result of temporarily narrowed or reconfigured lanes. Construction delay was computed only when construction activity actively took place along the roadway.

One type of construction delay not included in Table 5.3 is delay caused by the temporary geometric changes (narrowed lane widths, lane shifts) that are commonly required by many urban freeway construction activities. These geometric restrictions are likely to cause congestion to form earlier and last longer than it would with the roadway's normal geometry. The project team did not attempt to establish when these semipermanent geometric conditions were implemented, nor did the team attempt to associate delays with these changes during nonclosure hours (e.g., a.m. and p.m. peak periods).

"No cause indicated" in Table 5.3 means that no cause of congestion was reported other than high traffic volume levels. The team examined a number of these conditions as case studies. It was clear from that review that a variety of disruptions occur that affect traffic flow but that are not recorded within conventional traffic operations databases. Many of these disruptions are visual distractions (e.g., boats on the lake, slowdowns due to sunglare) that cause measurable delays only when traffic volumes are relatively high. In some of the case study investigations, traffic volumes on the study corridor were abnormally high because of disruptions on parallel roadways. This analysis did not attempt to track route diversion onto parallel roadways and, therefore, was not able to associate congestion on one roadway with disruptions occurring on a second roadway. This subject is discussed in more detail later in this section.

Table 5.4 shows a more disaggregated version of Table 5.3 in that it tracks multiple disruptions occurring at the same time. Table 5.4 also illustrates the wide variation among the 42 study sections in the percentage of delay influenced by any given cause (e.g., incident-influenced queues may have been much more prevalent at one study site than at another) by presenting the maximum and minimum values observed for each combination of delay causes.

Table 5.5 shows the total number of vehicle hours of delay measured. Note that the northbound I-405 data sets are missing about 1.5 months of data (mostly from November and December); other corridors periodically missed days or weeks of data as a result of various data quality and availability issues. These missing data mean that the total measured delay was not the true annual delay for the region's freeways. However, the missing data should have only a marginal effect on the percentages of delay associated with different types of disruptions. In general, the roadway corridors with the highest

Table 5.4. Percentage of Delay by Type of Disruption Influencing That Congestion

Type of Disruption	Delay (%)	Maximum Percentage Within a Corridor (%)	Minimum Percentage Within a Corridor (%)
No cause indicated	37.1	74.2	14.3
Incident-influenced queues are present	23.9	48.2	1.0
Crash-influenced queues are present	6.0	25.3	1.7
Rain is present	8.4	25.8	2.0
Both a crash and an incident have influenced queues that are present	9.2	23.9	0.5
Both rain and an incident have influenced queues that are present	5.0	8.9	0.0
Both rain and a crash have influenced queues that are present	1.6	8.7	0.2
Rain, a crash, and an incident have influenced queues that are present	2.4	13.6	0.0
Queues from a ramp (cause unknown) have influenced mainline queues	5.1	37.3	0.0
Construction activity has influenced queues	0.6	16.2	0.0
Construction and queues from a ramp (cause unknown) have influenced mainline queues	0.0	0.2	0.0
Construction and an incident have influenced queues that are present	0.2	2.6	0.0
Construction and a crash have influenced queues that are present	0.1	1.4	0.0
Construction and rain have influenced queues that are present	0.1	4.6	0.0
A crash, an incident, and construction have influenced queues that are present	0.1	1.2	0.0
Construction, rain, and an incident have influenced queues that are present	0.0	0.5	0.0
Construction, rain, and a crash have influenced queues that are present	0.0	0.7	0.0

percentage of delay attributed to unknown causes tended to be those roadway sections with the least absolute vehicle delay. That is, nine of the 10 sections with the highest percentage of delay not caused, at least in part, by a known traffic disruption were among the 13 sections with the lowest total vehicle delay for the year.

The converse of this statement was not true. Although the two test sections with the most vehicle hours of delay did have fairly low percentages of delay not associated with known disruptions, only half of the 10 test sections with the highest vehicle delay were among the 10 sections with the lowest percentage of congestion influenced by an unspecified disruption. The sections with very large amounts of total vehicle delay and large amounts of delay caused by unknown disruptions were all segments where frequent, significant peak period delays occurred. The westbound segment of the SR 520 Seattle bridge has a large bottleneck at the eastern end of the 2-mile-long floating bridge. Both SR 520 and I-405 Kennydale (both directions for both corridors) operate near or above capacity for 10 to 14 hours per day. The two I-5 sections (the South section northbound and North King section southbound) experience routine a.m. peak congestion. Consequently, it is reasonable to assume that large amounts of the delay in these corridors are simply caused by too much peak period volume.

The percentage of delay occurring with no reported disruption also was compared with the a.m. and p.m. peak period travel rates (defined as the mean travel time for the peak period converted to units of minutes per mile) for each corridor. No correlation between these values was apparent.

This lack of correlation between different measures of congestion and the amount of delay without a known disruption

Table 5.5. Hours of Delay Versus Percentage of Delay Without a Known Type of Disruption

Corridor	Vehicle Delay (h)	Delay Not Associated with a Disruption (%)
I-5 Seattle CBD northbound	28,689,099	14.3
I-5 Seattle North southbound	19,828,935	23.1
I-5 South southbound	14,063,546	27.7
I-5 Seattle CBD southbound	12,997,924	21.5
SR 520 Seattle bridge westbound	12,901,102	43.3
I-405 Kennydale northbound	11,531,897	55.3
I-405 Bellevue southbound	11,345,712	20.8
I-405 Kennydale southbound	11,077,760	56.9
I-5 North King southbound	10,782,330	45.2
I-5 South northbound	10,441,430	41.6
I-405 Kirkland southbound	9,655,929	34.0
I-405 Kirkland northbound	9,651,791	24.4
I-405 North southbound	9,116,178	44.2
I-5 Lynnwood southbound	8,517,553	39.8
I-5 Lynnwood northbound	7,733,702	53.5
SR 520 Seattle bridge eastbound	6,445,475	29.6
I-5 North King northbound	6,020,659	22.6
I-5 Tukwila northbound	5,997,528	42.5
I-90 Bridge westbound	5,310,825	57.3
SR 167 Renton northbound	4,980,431	28.0
SR 167 Renton southbound	4,582,608	58.3
I-5 Seattle North northbound	4,399,711	35.9
I-405 North northbound	4,327,382	56.4
I-405 South northbound	4,091,618	61.8
I-5 Tukwila southbound	3,863,679	45.1
I-5 Everett northbound	3,838,909	33.0
I-405 Bellevue northbound	3,773,393	52.0
I-90 Bridge eastbound	3,744,002	17.2
SR 520 Redmond eastbound	3,307,029	36.2
SR 167 Auburn southbound	3,305,901	59.9
I-90 Issaquah westbound	3,229,088	73.4
I-405 Eastgate southbound	2,861,851	64.8
I-405 South southbound	2,740,581	74.2
SR 167 Auburn northbound	2,167,614	73.0
I-90 Seattle eastbound	1,738,429	65.6
I-405 Eastgate northbound	1,715,306	64.4
I-90 Bellevue westbound	1,705,939	30.6
SR 520 Redmond westbound	1,399,767	19.7
I-5 Everett southbound	915,200	41.2
I-90 Bellevue eastbound	519,902	66.1
I-90 Seattle westbound	454,026	40.8
I-90 Issaquah eastbound	256,341	63.5

was not expected at the outset of this analysis. It had been assumed that most of the delay without an observable cause was primarily due to too much traffic volume. The expectation was that highly congested locations, especially those with well-known geographic bottlenecks, would have the most delay with unspecified causes because the congestion would be caused by a combination of volume and roadway geometry–based capacity limitations. Test sections with lower levels of routine delay were expected to have higher percentages of delays with identified disruptions, as delay would exist on those road segments primarily when unusual events occurred.

Instead of simple volume and capacity issues being the primary cause of high levels of delay unrelated to observable disruptions, further analysis of the study corridors identified at least three major reasons for delay occurring without known disruptions being present:

1. Operating agencies simply do not record many of the disruptions that occur, especially on less congested corridors and during less congested periods (weekends, at night);
2. In several cases, the research team's analytic approaches did not adequately track all of the disruptions that occurred, given the data available to indicate when and where those disruptions actually happened; and
3. Even on Seattle's less congested urban freeway segments that do not have major geometric bottlenecks, volume is frequently sufficient to cause at least modest amounts of delay.

When total delay values are small, these types of no-cause delays can represent a fairly high percentage of total annual delay.

These conclusions were supported by several case study examinations of the various study corridors. One case study was performed on the I-90 Issaquah eastbound section, which had the lowest measured annual delay of all 42 segments studied for this project. Only 256,000 vehicle hours of delay were measured in 2006, and 63.5% of that delay was not associated with an identified disruption. This roadway segment experienced two major delay-causing events in November 2006 that were not identified by the analysis methods described above. One of those events was a snow storm; the second was a major truck accident. A special analysis of the snow event determined that roughly 5.9% of all delay measured for the year for this section of roadway occurred during that event. Yet because the snow stopped falling (at least at the weather station from which data were obtained) several hours before congestion started on this freeway segment, the congestion delays recorded were not associated with that weather phenomenon. A review of newspaper stories published the next morning confirmed that massive snow-related problems occurred that night on that roadway section. Additional discussion of the difficulty in analyzing snow-related delays is presented later in this report.

On a second day in November 2006, an accident involving a truck killed the driver of a passenger car on I-90. That accident was not listed in either the state accident database or the WSDOT WITS database. Newspaper accounts indicated that the crash occurred in the westbound lanes of I-90 at 10:38 a.m. west of Front Street, which is on the eastern end (but within the boundaries) of the I-90 Issaquah test section. Although the crash occurred in the direction opposite the I-90 Issaquah eastbound section examined in the case study, the eastbound section reported far longer delays than the westbound section after 10:30 a.m. The longer delay may have been due to the location of the crash, which likely caused much of the westbound queue to form east of the monitored portion of the roadway. In addition, the eastbound delays were likely primarily rubbernecking delays, although some response equipment may have been parked on the eastbound section of the roadway. The exact reasons are not clear, but it was clear from the database that travel times were significantly affected, as would be expected with an accident involving a truck and with the time and lane closures required to investigate a fatal accident. Although some delays on that day were associated with rain, the majority of delay was not associated with any disruption. Thus, another 5.1% of all annual delay (8.1% of delay not associated with a disruption) was erroneously attributed to no cause other than volume.

Consequently, for this roadway section, of the 63.5% of delay "not associated with a disruption," 11% was actually associated with just two events, leaving at most 53% caused only by too much traffic volume.

Similar case study analyses of significant but unexplained delays were undertaken on road segments with greater congestion. One of the most congested segments in the region is the westbound section of SR 520 as it crosses Lake Washington from Bellevue to Seattle. This segment experiences over 50 times the annual delay experienced on the I-90 Issaquah section discussed above. The SR 520 bridge operates near or over capacity for 13 to 14 hours every weekday. It is parallel to another cross-lake bridge (the I-90 bridge, located to the south of SR 520), which is close enough so that motorists can easily divert between the two when one of them experiences heavy congestion.

Each August, a major hydroplane race takes place on Lake Washington south of the I-90 bridge. During the weekend of the race, the Navy's Blue Angels flying team also performs an air show in between hydroplane race heats. The Blue Angels practice their routine during the day on the Thursday and Friday preceding the air show. During the times when the Blue Angels are practicing or performing their show, the I-90 bridge is closed to traffic.

Not surprisingly, considerable delay occurs that week crossing the two bridges. Much of that delay is caused by the visual distraction of pleasure boats on the lake going to and from the race course and by airplanes flying low overhead. In addition, because the I-90 bridge is closed to traffic during the Blue Angel flights, considerable traffic diverts to the SR 520 bridge. All this activity results in the perfect storm for creating congestion on SR 520, much of which is not related to a specific disruption on SR 520. The disruption (as noted in VMS records) is on I-90.

In 2006, on the Thursday before the hydroplane races, westbound SR 520 did not experience any major disruptions (i.e., recorded construction, lane closures, crashes, or rain). However, it did experience 117,000 vehicle hours of delay (roughly half the total annual delay of the I-90 Issaquah eastbound test section). About half of that delay was not associated with a disruption in the analysis database, and that value was over 2.5 times the usual noninfluenced Thursday delay. It is obvious from a manual review of the data that these delays were caused by excessive demand resulting from the 2-hour closure of the I-90 bridge combined with a high level of visual distraction for motorists crossing the lake. However, because the delays routinely experienced on this section of roadway are so high, this very bad day for travel on this section only contributed 0.9% of the total annual delay for this test section, and thus the large not-influenced delay for that day was less than 0.5% of the annual total.

Taken together, these case studies illustrate that a large percentage of the congestion in the analysis data set without a cause can be traced back to some type of unusual occurrence. However, because of limitations in both the analysis data set and the methodology used to associate delays with specific events, this analysis was unable to reliably identify all these congestion sources. Consequently, three conclusions were drawn from the above examples:

1. The statistics presented in this report should be assumed to be a very conservative estimate of the amount of delay caused by the various types of disruptions;
2. The percentage of delay caused by any given factor can be a misleading statistic about the importance of that factor, since it is highly correlated to the total amount of delay on a given roadway; and
3. In the presence of moderately heavy volumes, a large number of factors that are not tracked by operating agencies may be the cause of congestion.

Effects of Weather

The case study of delays on I-90 when snow fell illustrates the difficulties in determining the effects of weather on roadway performance. The largest roadway performance effects caused by the snowfall did not occur while the snow was falling at the weather station. Instead, they occurred as a result of snow accumulation on the roadway and the conversion of that snow into sheet ice on some roadway sections. The latter of these events took place well after the snow had stopped falling at the weather station.

In addition, the analysis of that case study reveals that delays did not happen similarly on all roadway sections that evening (although the newspaper reported long delays on several corridors). In fact, the eastbound and westbound sections of I-90 (presumed to experience the same level of snowfall) experienced very different roadway performance (delay) conditions during and after the snow storm. While the westbound direction showed modest delays in the evening, with moderate delays occurring between 6:00 and 9:00 p.m., the eastbound section experienced an unusually heavy day of congestion before the snowfall, and then a major additional pulse of congestion starting at 8:00 p.m. and lasting well into the morning hours. Exacerbating the eastbound congestion was the traffic volume added because of a professional football game that occurred that night in downtown Seattle. The Seahawks played the Packers on Monday Night football, adding 65,000 fans, divided across multiple freeways, to the outbound traffic beginning at about 8:30 p.m.

Methodology

The snowfall case study revealed a number of the analytic problems associated with an analysis of the effects of bad weather. The first major problem is defining, in analytic terms, *bad weather.* As discussed previously, the key regionwide weather variable used to indicate bad weather was whether measurable rain had fallen in the past hour. This variable was then used as an independent variable to predict the probability that any given roadway section was operating in a given regime (essentially, level of service).

The analysis computed the probability that a given test section of roadway was operating in each regime for each time slice of a day. These probabilities were computed for days when rain occurred within the past hour and were then compared with probabilities on days when the same roadway was dry at that same time of day. The mean, median, 80th percentile, and 95th percentile travel times for each corridor and time period also could be computed for wet and dry conditions.

One limitation with the travel time analysis is best explained with an example. Rain falls between 3:00 and 4:00 p.m. The time periods between 3:00 and 5:00 p.m. are assumed to be rain affected (within 1 hour of when measurable rain has fallen). Travel times occurring at 4:55 p.m. that day are rain affected, but travel times at 5:05 p.m. are considered dry trips. The limitation with this analysis is that the rain may have created a queue that affects the 5:05 p.m. dry trip. For the analysis results in the discussion below, such a possibility was ignored, thus slightly underestimating the potential impacts of rain on travel time.

Sensitivity tests were performed with various definitions of rain (e.g., requiring different fractions of an inch of rain falling within the previous hour for the pavement to be considered wet) and with different time periods within which rain had to have fallen (e.g., within the past hour or 2, 4, or 8 hours for the pavement to be considered wet) to test how sensitive the results were, given different definitions of *wet.* In general, any measurable rain falling within the past hour had the greatest effect on congestion formation and the resulting travel time. Other values showed slightly lower effects.

The effects of wind on roadway performance were analyzed differently from the effects of rain. This is partly because, other than the lasting effects of any queues being formed, wind does not have a lasting effect similar to that of rain. Once wind stops, its direct effects stop. That is, wind does not have a lasting effect equivalent to spray from wet roadways caused by rain. The lack of this effect also limited the team's confidence in the use of the available NOAA wind data for specific roadway sections.

As a consequence, the wind gust variable produced by NOAA was not used. The project team had little confidence that this variable was effectively applicable to geographically removed locations. Similarly, the wind speed variable that was used was assumed to be only a reasonable surrogate for windy conditions, and not a definitive statistic indicating the precise wind speed at which travel might be affected.

To test the effects of wind on travel times, the data set was divided into wind-affected and not-wind-affected groups on the basis of the wind speed variable present in each 5-minute time slice. The travel times for these two groups were then compared within specific time intervals with both traditional *t*-tests, which assumed normally distributed travel times within those time periods, and nonparametric tests of the sample means. Tests were performed only for nonholiday Tuesdays, Wednesdays, and Thursdays (combined).

Sensitivity tests were performed with different values of the wind speed variable to determine the sensitivity of the analysis results to the breakpoint selected for identifying windy versus not-windy conditions. The performance of different roadway corridors was found to be sensitive to different wind speeds. The authors believe that this is due in part to differences between actual wind speeds within the study corridor and those measured at the airport, and in part to the way that site-specific roadway geometry affects how drivers respond to wind. For example, travel times over the SR 520 floating bridge, which has narrow lanes, no shoulders, and physically moves when struck by wind-blown waves, are affected at much lower wind speeds than travel times on I-5 in the northern reaches of the metropolitan region, where lanes are wider, full-width shoulders exist, and wind does not cause the roadway to move. In the end, sustained wind speeds of 16 mph were used as the primary split between windy and not-windy conditions. Adopting a different definition would marginally change the travel times associated with windy and not-windy conditions for some corridors but would not change the ultimate conclusions of the study.

Results

Not surprisingly, the results uniformly showed that the occurrence of rain led to a statistically significant increase in the amount of congestion, but only during periods of moderately high traffic volume. That is, rain does not cause congestion uniformly throughout the day. The probability of congestion forming as a result of rain is a function of the underlying level of vehicular demand. And given the time series nature of traffic flow, time of day and day of week can be used as surrogates for vehicular demand when estimating the probability of congestion forming.

Rain causes the roadway to operate just a little less efficiently than it would otherwise (*2,* pp. 1–14; *3,* pp. 8–18). The result, as observed in the data set, is that given a normal commute period, the roadway is likely to break down a little earlier than it would otherwise under conditions of similar demand on dry roadways. The amount of rainfall likely determines the degree to which roadway efficiency declines, but an analysis confirming this was not completed for this study. Because the roadway breaks down earlier than it would if rain had not occurred, the queues grow larger than they otherwise would, and consequently last longer. The moderate rate at which rain falls in Seattle (or more accurately, the region's frequently wet roadways) does not *cause* congestion; it simply lowers the amount of traffic volume that a given roadway can handle before it becomes congested. Therefore, the roadway breaks down earlier in the commute period than it would otherwise.

Figure 5.3 illustrates this trend for SR 520 Seattle westbound crossing the Lake Washington floating bridge. The gray line shows the probability of a traveler experiencing congestion on this corridor on a dry day. The black line illustrates the probability of being in congestion if rain has fallen within the past hour. SR 520 westbound into Seattle is one of the more congested roadway segments in the region. It experiences congestion during both the a.m. and p.m. peaks, as well as periodically in the middle of the day.

Figure 5.4 shows one of the less congested roadway sections in the region. In this case, only the a.m. peak period routinely experiences congestion. Therefore, in the morning when volumes are high, if rain falls, the probability of congestion forming in the next hour increases. However, after the peak period ends, the fact that rain has fallen has no discernible impact on the formation of congestion. Yes, falling rain may increase accident rates during off-peak times (see the discussion below on accident rates and the presence of rain),

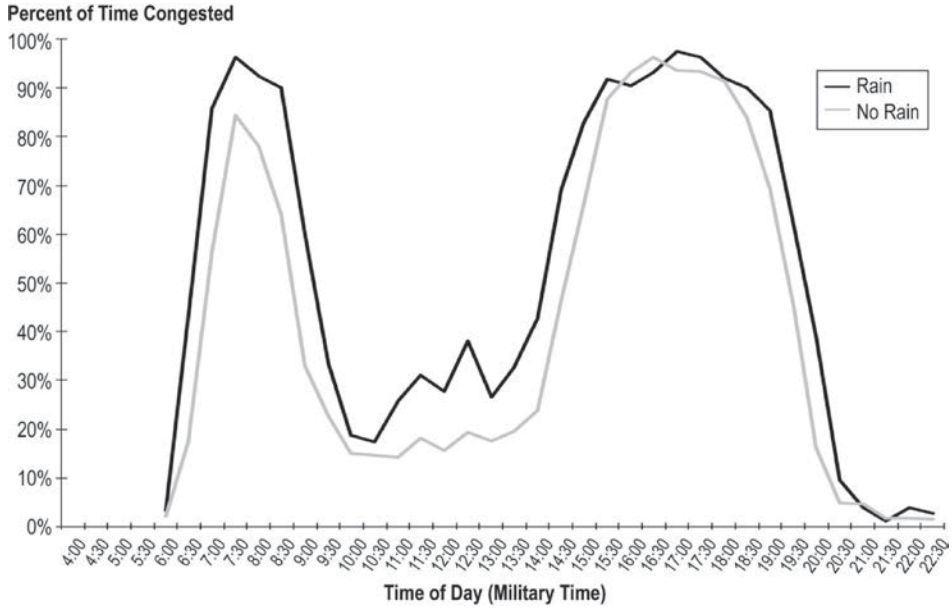

Figure 5.3. Probability of being in congestion: rain versus no rain on SR 520 westbound from Bellevue to Seattle.

but congestion caused by that increase in accident rates is no more likely to occur than congestion from other sources.

The greater probability of congestion early in the peak period and the longer queues that result from that early start to congestion also mean longer travel times on rainy days.

Figure 5.5 illustrates how mean travel times increase along with the increased probability of being in congestion. This graphic shows the probability of congestion having formed by time of day when the roadway is dry (gray line) or has been rained on in the past hour (black line). It also shows the change in mean travel time when rain has fallen (dashed line), where the travel time increase is shown on the right-hand axis. As Figure 5.5 shows, at no time does the mean travel time decrease with statistical significance when rain is present. Interestingly, this figure also shows that the declining volumes at the end of the commute period quickly moderate the travel time effects of the congestion developed as a result of early queue formation in the rain. That is, even though the queues are longer and the travel times worse in the peak period, the mean travel time for a trip starting at the end of

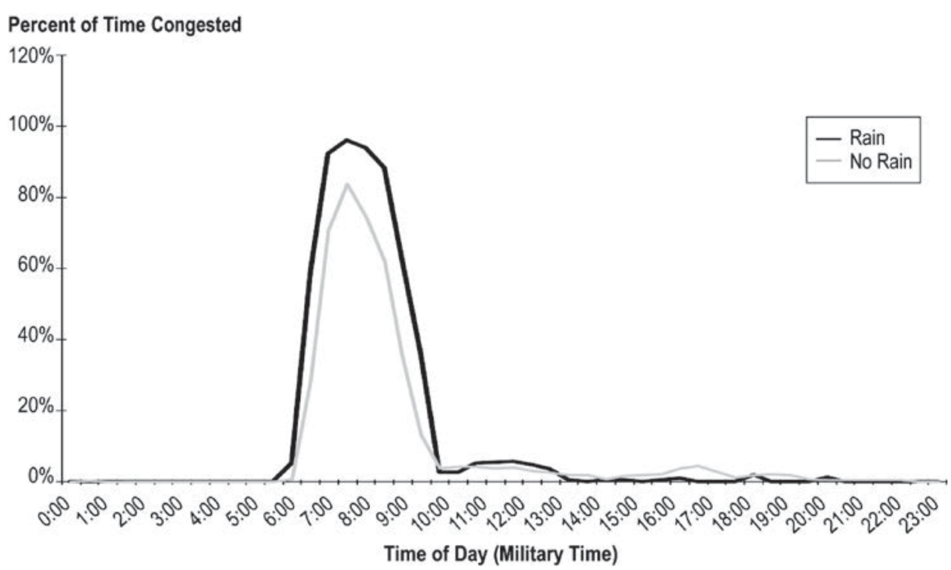

Figure 5.4. Probability of being in congestion: rain versus no rain on I-90 westbound from Issaquah to Bellevue.

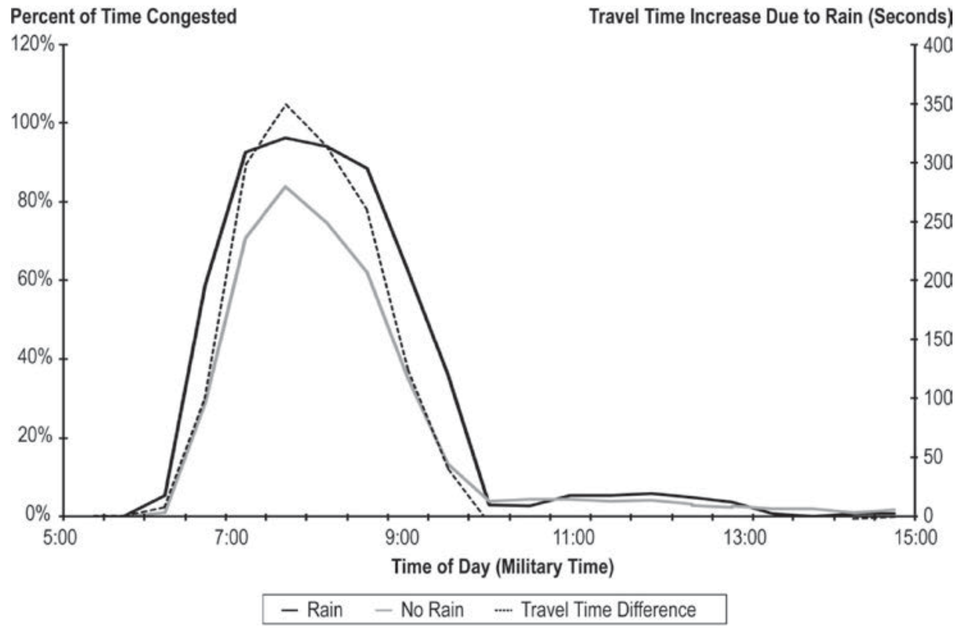

Figure 5.5. Correspondence of increase in mean travel times with increase in probability of congestion due to rain on I-90 westbound from Issaquah.

the commute period is only marginally worse than normal, and by the end of the peak period, travel times are nearly the same as normal, regardless of whether rain has fallen.

While the effects shown in Figure 5.5 were observed fairly universally for all roadway segments studied, further analysis of the 42 study segments revealed two significant differences in the effects of rain between less congested and more congested roadway segments. First, on the more congested segments, enough volume exists during the middle of the day that rain causes an increased likelihood of congestion forming during midday periods. On less congested roadway segments this is not the case. The project team believes that on road segments that operate near capacity during midday, the decreasing roadway efficiency caused by wet pavement is sufficient to create congestion, regardless of increases in crash rates caused by the wet pavement. Additional analysis is required to determine the effects of the increased accident rates versus the simple effect of wet pavements. On less heavily traveled (and thus less congested) roadway segments, the modest loss of efficiency caused by wet pavement does not create conditions that result in congestion, except on rare occasions when major crashes occur.

The second significant difference between heavily congested and less heavily congested roadway segments is that on the most congested segments, the probability of congestion during the heart of the peak period approaches 100%. As a result, rain does not increase the probability of congestion forming during those periods. On less congested roadways, there are lower-volume commute periods (e.g., the workdays near major holidays) when congestion may not form. Rainfall on those lower-volume work days may decrease roadway performance to a degree sufficient for congestion to form.

Figure 5.5 illustrates the effects of rain on a moderately congested roadway segment (there are no uncongested freeway segments in the Seattle region). Figure 5.6 illustrates how rain affects a heavily congested segment. In this figure, it is easy to see that the probability that congestion will form does not change significantly during the core of the p.m. peak period. However, during the early portion of the p.m. peak, travel times do increase when rain falls. This is because queues form earlier than normal and are, therefore, longer than normal at later points in the day. Interestingly, in Figure 5.6 the travel time increases in the rain are briefly moderated just after the midpoint of the p.m. peak period. The increases in travel time caused by rain approach zero shortly before 6:00 p.m. (18 on the *x*-axis of the graph), only to rebound by 6:30 p.m. This outcome does not represent a lack of effect from the rain on commute times. Instead, it is an artifact of the roadway segmentation used for this specific analysis. On this particular roadway segment, the normal queue extends roughly to the end of the roadway analysis segment at the peak of the p.m. peak period. This maximum queue length occurs at roughly 6:00 p.m. Because the section already is fully congested, estimated travel times for the segment do not increase on the study section when it rains, and thus travel times do not increase. Instead, travel times increase on the upstream section of the roadway (in this case the SR 520 Redmond westbound study section) because the queue from the

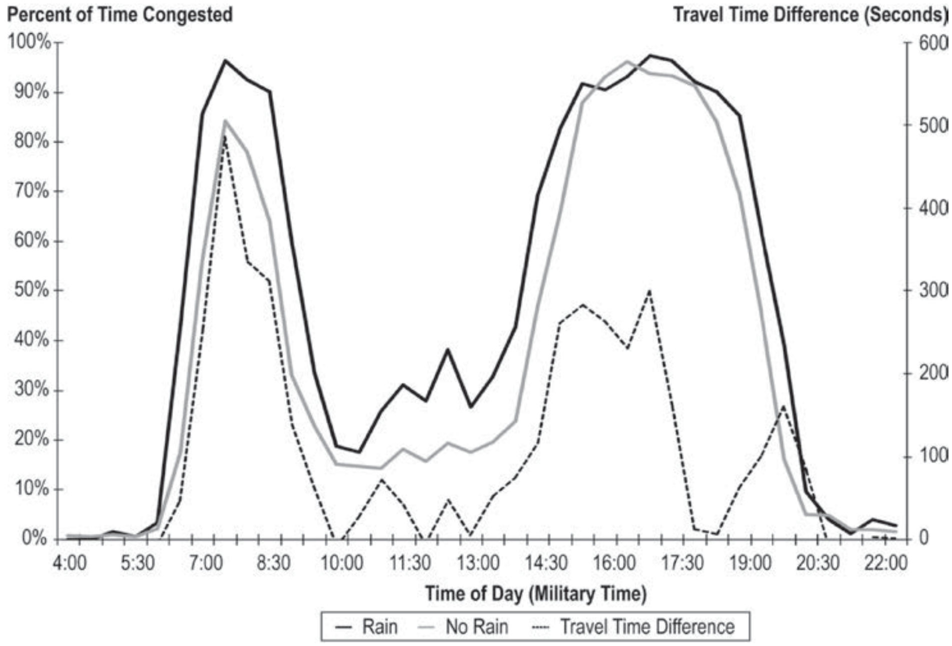

Figure 5.6. Correspondence of increase in mean travel times with increase in probability of congestion due to rain on SR 520 westbound, Bellevue toward Seattle.

first section has extended back onto the second section. Thus, travelers do experience slower trip times, but the reported travel time on this section is not worse. As the extra-long queue moderates toward the end of the peak period, travel times on the Seattle test section again increase, simply because the normal queue is once again shorter than the length of the entire roadway section.

Research (and most drivers' personal experience) has shown that high winds frequently cause motorists to drive more slowly and carefully, as wind can affect vehicle handling. Under high winds, many drivers slow slightly (*4; 5,* pp. 24–30). As with rain, this more cautious approach to driving under heavy wind conditions can negatively affect the relationship of vehicle volume and speed, causing the roadway to operate less efficiently. Given high enough traffic volumes, this loss of efficiency results in congestion, although under normal circumstances it would not form. Under these conditions, wind will result in statistically significant increases in travel time.

An analysis of roadway performance and wind data in the Seattle region supported these basic findings. However, the analytic tests performed on the Seattle test corridors showed that travel times in all test corridors were not equally affected by wind. In fact, in many corridors, wind did not have any statistically significant effect on travel times. In other corridors, wind had a very high impact on roadway performance. Table 5.6 gives examples of how wind affected various corridors differently, even though the corridors are directly connected. Table 5.6 also gives examples of the results of the sensitivity tests performed with different wind speeds to separate windy from not-windy conditions.

As can be seen in Table 5.6, the SR 520 bridge is affected by relatively moderate winds (10 mph sustained wind speeds). The bridge is a 2-mile-long floating span with a roadway two lanes in each direction with no shoulders. In even moderate wind, a driver can feel the bridge sway. The wind also can create some spray when wind-driven waves break against the bridge, causing drivers to slow down. Because the bridge operates near capacity 12 to 14 hours each weekday, these wind effects are sufficient to cause congestion.

The I-90 bridge, located nearby to the south, also is affected by wind, but to a lesser extent than the SR 520 bridge. This is most likely due to a combination of factors: the I-90 bridge is more modern, has full shoulders, and sits higher off the water (and, therefore, experiences less wind-driven spray). Interestingly, the evening commute across the I-90 bridge is affected by wind but the morning commute is not, even though traffic volumes are similar in both periods. This difference is partly because the test section that included the I-90 bridge also included a large segment of nonbridge travel across Mercer Island. Backups on the bridge affecting eastbound traffic actually create some free-flow conditions on the island itself, decreasing the travel time impact of the wind. However, wind-caused backups significantly affect the upstream section of eastbound I-90 (the Seattle section is also shown in Table 5.6). This explains why the I-90 Seattle section is statistically affected by wind in the morning, even though it does

Table 5.6. Example Effects of Wind on Travel Times by Corridor

Route	Mean Travel Time							
	A.M. Peak				P.M. Peak			
	With Wind[a] (s)	Without Wind (s)	Difference (s)	Statistically Significant?	With Wind (s)	Without Wind (s)	Difference (s)	Statistically Significant?
I-5 Everett southbound	190	207	–17	No	191	209	–18	No
I-5 North King southbound	759	690	68	Yes	400	422	–22	No
I-5 North Seattle southbound	751	606	145	Yes	926	686	239	Yes
I-5 South northbound	1,671	1,073	598	Yes	649	649	0	No
SR 520 Seattle westbound	1,020	638	382	Yes	1,548	1,052	495	Yes
I-90 Bridge Eastbound	425	410	15	No	543	437	106	Yes
I-90 Seattle eastbound	198	169	29	Yes	151	115	36	Yes
SR 520 Seattle westbound, 10 mph wind speed	781	626	154	Yes	1,093	1,049	44	Yes
I-90 Bridge eastbound, 10 mph wind speed	434	407	27	No	431	441	–10	No
I-90 Seattle eastbound, 10 mph wind speed	174	169	5	No	107	118	–12	No

[a] Sustained wind speed is greater than 16 mph.

[b] Sustained wind speed is less than or equal to 16 mph.

not include the bridge itself. At more moderate wind speeds (e.g., 10 mph sustained winds), none of the I-90 segments show a statistically significant change in expected travel time.

Looking at the I-5 segments included in Table 5.6, it can be seen that wind affects some corridors in some peak periods, but not all corridors or all peak periods within all corridors. In general, high peak period volumes relative to capacity make roadway segments more likely to be affected by high winds. Other reasons that a roadway may be susceptible to winds are that the road segment is exposed to high levels of wind (e.g., the I-5 North Seattle segment crosses the Ship Canal Bridge, an exposed portion of road where wind is often felt) or that the segment is immediately upstream of another segment that is wind affected. The I-5 North King segment is upstream of the I-5 North Seattle segment. The I-5 Everett segment is considerably farther north and does not experience spillback from North King or North Seattle segments, except in very extreme cases.

Figure 5.7 illustrates how wind affects the SR 520 bridge westbound, and Figure 5.8 illustrates the I-90 eastbound bridge section. In both figures, it can be seen that the primary effects of wind are in the peak periods when traffic volumes are highest. If the same graphic were presented with a higher wind speed, more impacts would be seen in the middle of the day, especially on SR 520.

In Figure 5.8, wind appears to have a significant effect on expected travel times during the later portion of the a.m. peak period, but not on the earlier portion of the peak. This helps explain why the difference in mean travel times shown in Table 5.6 is not statistically significant.

Given Seattle's relatively benign climate, it can be said that most weather impacts in the Seattle region are small, at least in terms of the changes in vehicle speed and throughput that they directly cause. During most parts of the day, on most roadway segments, the travel time changes that these small differences in speed create are not statistically significant. However, when those small changes occur in combination with large traffic volumes, especially during the beginning shoulder of a peak period, those small changes can result in congestion that will, in turn, generate much more significant increases in expected travel times.

The use of rain variables that account for the continuing presence of spray from wet roadways suggests that spray has as much of an impact on roadway performance as moderate rainfall itself. Similarly, except in the case of heavy snowfall (when low visibility affects drivers' behavior), the major impacts of snow are the result of snow accumulation, not the snowfall itself. Anecdotal evidence of this same effect also was apparent for ice formation in Seattle. The project team attempted to compute times when black ice formation might be present by using humidity and temperature data from the Sea-Tac weather station. However, these factors did not result in successful identification of ice formation in the informal tests conducted during the winter of 2008. Therefore, the team concluded that using regional weather station data is not an effective way to accurately determine the presence of snow and ice on roadways.

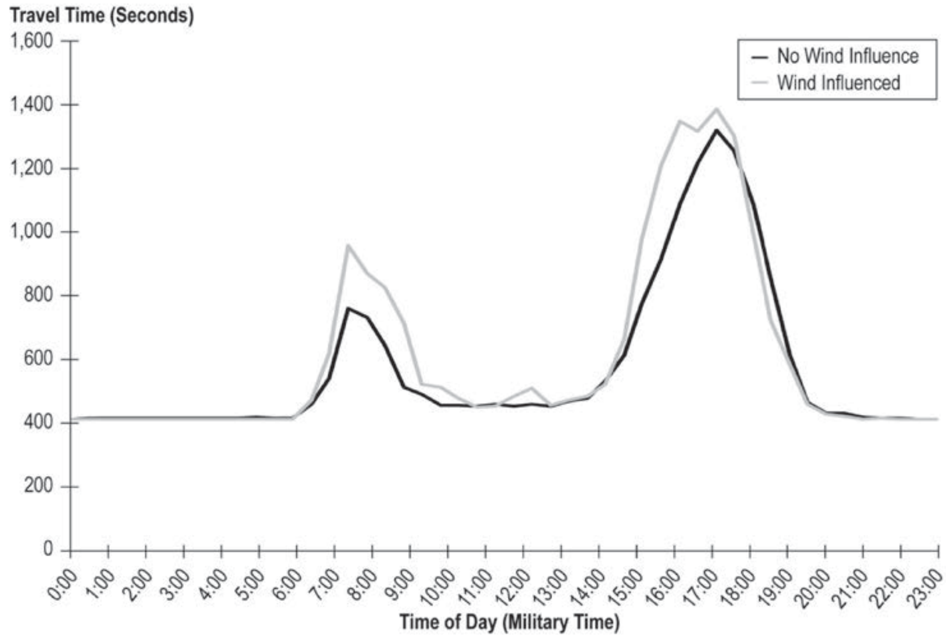

Figure 5.7. Mean travel times by time of day in wind and no-wind conditions on SR 520 westbound, Bellevue toward Seattle.

The effects of wind are similar to those of rain. High winds cause motorists to drive more cautiously. The degree to which they adjust their behavior for a given wind condition is a function of the roadway section: How wide are the lanes? Are there shoulders? How exposed is the roadway section to wind? This in turn reduces the functional capacity of the roadway during high-wind conditions. These effects do not appear to be as uniform as the effects of rain, since geographic differences in terrain and geometric differences in roadway right-of-way appear to play bigger roles in determining the effects of wind on roadway performance than they do in the case of rain.

When wind is significant and traffic volumes are light, travel times increase only marginally, in direct proportion to

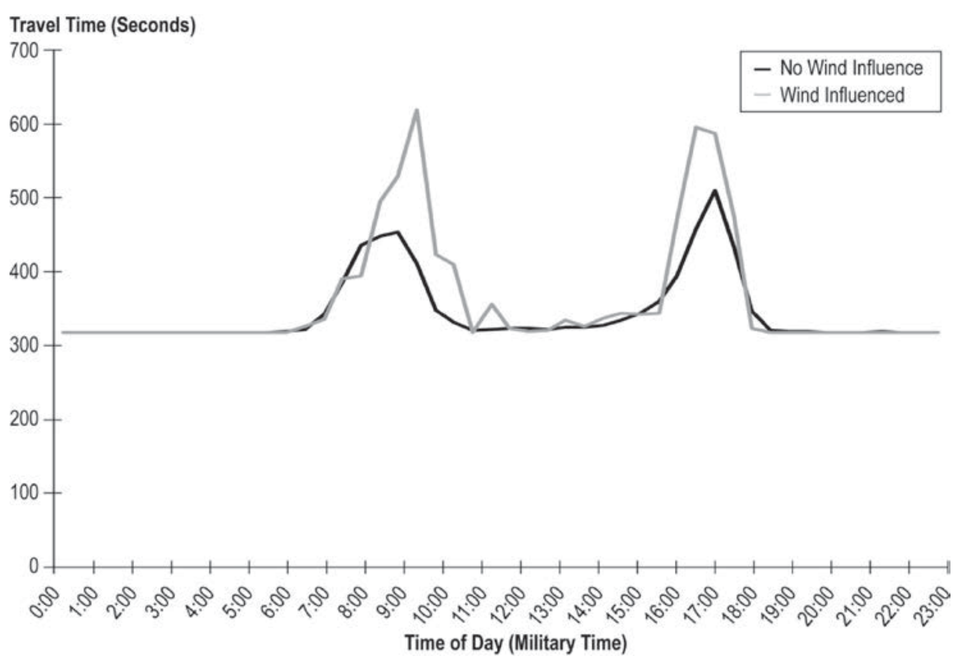

Figure 5.8. Mean travel times by time of day in wind and no-wind conditions on I-90 bridge section eastbound, Seattle toward Bellevue.

the slowing that individual vehicles exhibit under windy conditions. However, when volumes are high, the reduced functional roadway capacity resulting from motorists' voluntary slowing can create congestion that would not occur under average weather conditions. That congestion frequently becomes self-sustaining during peak periods; that is, the queue itself creates a further decrease in functional roadway capacity, which further increases the length of the queue and increases travel times on the roadway section.

In summary, the analysis of the impacts of bad weather on congestion formation on Seattle freeways identified the following major conclusions:

- Small disruptions, such as those caused by moderate amounts of rain or even spray from wet pavements, only cause congestion when they occur in combination with sufficient volume relative to the available capacity;
- Precipitation can affect roadway performance as long as the roadway remains wet;
- The probability that bad weather will significantly affect roadway performance on any given roadway section is a function of the expected demand and capacity condition of that road section and the significance of the weather event (e.g., light rain versus a heavy thundershower); and
- Bad weather also increases the probability of crashes occurring, which further increases the probability of significantly increased travel times.

Effects of Incidents and Crashes

The effects of crashes and other kinds of traffic disruptions are of significant interest both because they are common causes of travel delay and because they are disruptions over which operating agencies have some level of control. That is, highway agencies cannot prevent rain, but they can design roadways to minimize the number and severity of crashes, and they can respond effectively and efficiently to crashes to limit their duration. Consequently, the project team looked at the effects of both crashes and noncrash incidents.

Incidents and crashes differ from weather in three significant ways. First, incidents and crashes are highly correlated with traffic volume, while weather is not. More crashes occur when volumes increase, but increasing volumes do not affect rainfall. Therefore, crashes and incidents are not evenly distributed over time, but bad weather (at least in Seattle) is much more evenly distributed throughout the day.

Second, incidents and crashes have small footprints in comparison to weather. A crash or incident occurs at a specific location, which has a relatively small geographic scope (this does not include any queues that may form), but the same weather generally occurs over a larger geographic area. This small footprint can have considerable impact on segment-based analysis procedures. This impact is discussed below in the subsection on methodology.

Finally, crashes and incidents are, in many ways, even more variable than weather. Incidents can be anything from minor debris in the roadway (e.g., pieces of a blown truck tire), to a distraction on the side of the road (e.g., a stalled car), to a fatal crash.

Methodology

Considerable research has been conducted to explore the impacts of incidents on roadway performance, especially in terms of vehicle throughput, queue formation, and roadway recovery at the incident scene. Much of this work has involved the use of queuing theory to explore the size and speed of queue formation, given incoming and exiting traffic volumes, along with descriptors of specific incidents (duration, number of lanes closed). The intended result of most of these efforts has been to determine the benefits that can be gained from improvements in incident response efforts.

One limitation in these studies has been the fact that once queues form during peak periods, the queue itself can become its own self-sustaining bottleneck. Thus, even after the incident has been cleared, the back of the queue may become the point at which congestion forms, effectively replacing the incident scene that started the congestion. A second limitation is that a bottleneck at one point of a roadway segment has implications on the performance of the rest of that roadway segment, as well as the segments upstream and downstream from that segment.

Consequently, this project used two approaches to examine the larger, corridor-long effects of incidents and crashes. The first approach examined the travel times that occur under incident or crash conditions. This analysis took advantage of influence variables (these are discussed above and in Appendix A). As described, the influence of every crash and incident was noted in the 5-minute travel time records for each roadway test segment. It was possible, for any definition of disruption, to segregate the travel time records for a given test section into two groups: those influenced by a specific type of disruption and those not influenced by that type of disruption.

Statistical tests could then be performed on those two groups. Because of the time series nature of travel times, combined with the time-lagged nature of the effects of incidents, these statistical comparisons were somewhat complex. That is, traffic conditions at 7:00 a.m. on a Monday are different than those at 8:00 a.m. for that same stretch of road, so travel times at these two times should not be directly compared. Similarly, a crash that happens at 7:00 a.m. has a different effect on travel time at 7:05 a.m. than it has at 7:15 a.m. Because disruptions happen at different times during the day, the aggregated effects of these disruptions are complex.

The primary statistical test used to compare influenced and noninfluenced travel times was an independent sample *t*-test. The majority of tests involved only data for Tuesdays, Wednesdays, and Thursdays to limit the effects that variations in day-of-week traffic volumes would have on the statistical results. This test was originally applied independently for each 5-minute period. That is, influenced travel time data for the 7:00 to 7:05 a.m. period for all Tuesdays through Thursdays were compared with noninfluenced travel times for that one period. Because each 5-minute time period occurred on a different day, each sample was truly independent of all other samples; that is, the 7:00 a.m. travel time today has no influence on the 7:00 a.m. travel time tomorrow. Because travel times were taken from only one 5-minute period, the time-dependent effects of travel also were removed.

The difficulty with this approach is that it required performing 288 statistical tests to examine the daily differences in incident-influenced and noninfluenced travel times. To reduce the analytic load, the project team grouped the 5-minute average travel times by 30-minute increments, with the statistical tests performed for each 30-minute interval.

In this approach, the six 5-minute travel times were treated as independent travel time estimates within that 30-minute period. For example, assume that no incident happens on a study corridor on March 7 until the 7:15 a.m. period. That incident influences the rest of the morning commute. The average 5-minute travel times stored in the 7:00, 7:05, and 7:10 a.m. analysis time periods are reported as not incident influenced. All three 5-minute average travel times are included in the computation of the travel time distribution for the not incident–influenced 30-minute period covering 7:00 to 7:29 a.m., and the three 5-minute periods from 7:15 to 7:25 a.m. are included in the influenced travel time distribution for that same 7:00 to 7:29 a.m. period.

There were two advantages to the 30-minute approach. One was the reduction in the number of statistical tests that had to be performed and summarized. The second was the increase in the sample size for each test. The downside of the 30-minute test was that the six travel times were no longer truly independent samples, as the 7:05 a.m. travel time would be highly correlated to the 7:00 a.m. travel time.

When the results of tests conducted with both levels of aggregation were analyzed, little difference was found between the statistical outcomes of the 5- and 30-minute comparisons, so most analysis results in this report are presented in the 30-minute format to make the results more readable. When the results of the 5- and 30-minute analyses were compared, the most significant differences were found in the shoulders of the peak period. These differences did not change any of the basic conclusions of this report.

Statistical comparisons between influenced and noninfluenced travel times were made in a number of ways. Various comparisons were possible because of the multiple ways that influence was calculated in the project database. Influence was examined for crashes (only crashes reported in the state accident records), for incidents (any incident reported by WSDOT's service patrol), for any incident reported by WITS that involved lane closures, or for any one of these types of disruptions. Travel times associated with these disruptions could then be compared with either all other travel times or only travel times when no disruption influenced travel.

This flexibility allowed a very thorough comparison of incident-influenced conditions. In most cases, the best comparison was with no known disruption currently influencing conditions, but in some cases it was important to make a comparison with all other travel times (e.g., comparing travel times when crashes had influenced travel versus noncrash-influenced travel).

In most cases, nonholiday Tuesday through Thursday travel times were used as the population for which travel times were compared. Some analyses also were performed for weekends and for all weekdays combined. Although these analyses were useful for describing total delay in a year caused by a specific type of disruption, they were not as useful in describing the effects of disruptions on travel times compared with normal conditions. Therefore, most results presented in this report involve Tuesday through Thursday (nonholiday) comparisons.

One difficulty with these comparisons is that they were not measures of what would have happened if the disruption had not taken place. They were simply comparisons of the expected conditions when a specific type of disruption occurred versus expected conditions when those types of events had not taken place. The research team hoped that by combining an entire year's worth of data, the number of events included in the database would limit the biases in travel time impacts that could be associated with specific incidents occurring at specific times and locations. To make a direct comparison of actual conditions versus what would have happened would require a carefully calibrated microscale simulation model. Such an effort was well beyond the scope of this project.

Because they are not direct measures of what would have happened, the resulting graphs and computed statistics must be used carefully. They describe the differences in expected conditions if a specific type of event has occurred and its influences are still being felt. That second clause is important. One problem with not using a simulation to make this comparison is answering the question, when does the influence of an event end? The travel time comparisons assumed that the effects of any disruption ended once conditions returned to what they were at the time the disruption took place, not the condition that would normally be present at that time. This definition was selected because a review of the project data set found

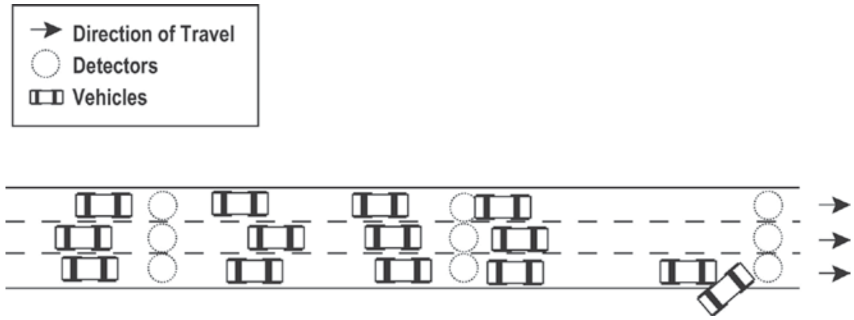

Figure 5.9. Illustration of a crash at the downstream end of a test corridor.

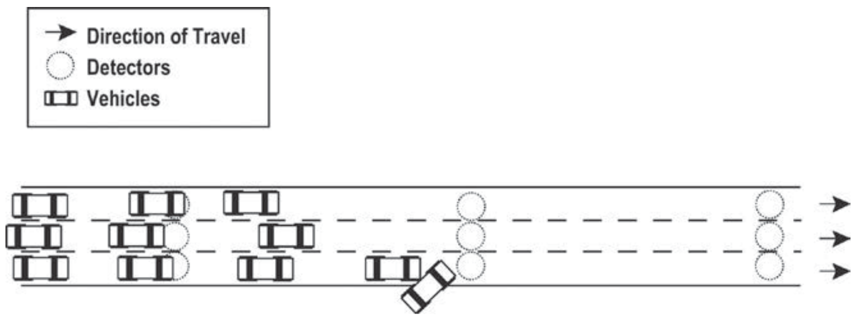

Figure 5.10. Illustration of a crash in the middle of a test corridor.

many cases in which predisruption travel times were much faster than normal; when the disruption occurred, travel times slowed, but they never degraded to the point of normal conditions. Moreover, travel times returned to the faster-than-normal conditions that existed before the disruption. If normal travel times had been used as the measure of influence, these events would have had no influence. But they obviously caused delay. As a result, the definition of influence was based on travel times returning to preexisting conditions.

A second limitation with the corridor-based analysis process described above was caused by the site-specific nature of crash and incident impacts relative to the roadway segmentation used for the analysis. The disadvantage of using travel times is that travel time is a function of selected segment end points, and those defined segments may or may not include all the effects (e.g., slow-moving vehicles) caused by a given incident. Figures 5.9 through 5.11 illustrate this problem. Taken together, they show how the location of a crash or incident within a corridor can influence how effectively the measured travel times in a test section reflect the delays caused by that crash or incident.

In Figure 5.9, the crash occurs near the downstream end of the roadway segment. In this case, travel times measured in the corridor capture all the delays occurring in the test section,

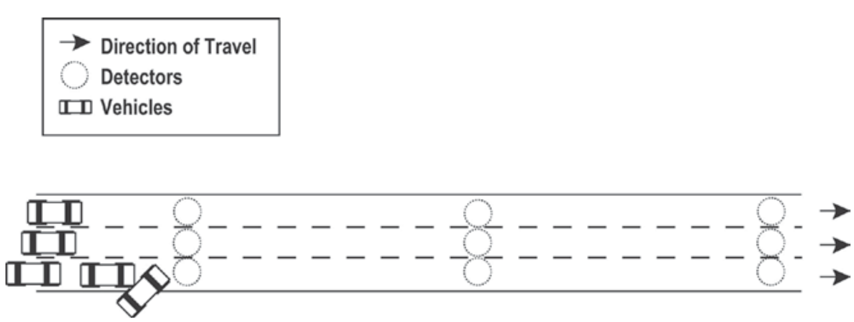

Figure 5.11. Illustration of a crash at the upstream end of a test corridor.

unless the queue is longer than the test section. This situation did happen on the test sections, but given the 2-mile minimum length of those test sections, it was unusual.

In Figure 5.10, the crash occurs in the middle of the test section. In this case, if the queue is minor, the entire queue and the travel time influences of that queue are contained in the test corridor. However, if the queue is long, it will extend back into the upstream roadway segment, creating delays on that segment that are not explained by an incident or crash within that segment. Thus, the study segment that contains the crash will see some, but not all, of the delays associated with the crash, while the upstream segment will see unexplained congestion.

In Figure 5.11, the crash occurs near the upstream end of the study segment. In this case, the study segment will not experience the majority of the delays caused by the crash. Those delays will occur on the test section upstream of the study section. The study section is likely to show good travel times because in this study, travel times are based on multiple-point speed measurements, and the queues at the upstream end will allow the majority of the study segment to operate in a free-flow condition.

The moderately long roadway segments and the careful selection of the breakpoints between those segments in this study limited the frequency with which congestion crossed segment boundaries, but there were still many occasions when this happened. The travel time analyses presented in the following section do not effectively account for these cross-segment boundary occurrences. When they occurred, the slower travel times these extended queues caused were associated with normal (or nonincident) conditions. As a result, the comparisons between incident-influenced and nonincident-influenced conditions described below should be considered conservative measures of the effects of incidents on travel times and travel time reliability, as many off-segment effects of crashes and incidents were not accounted for.

Although they are useful in describing the effects that different types of disruptions have on travel time, the definition of influence described above and the statistical travel time comparison based on that definition have significant explanatory limitations. In particular, analysis using this definition of influence does not do a good job of answering questions such as, "What impact does a crash have on my commute?" The different times and locations of such a disruption will result in different outcomes, and it cannot be known when the individual asking that question makes his trip. Consequently, a second type of analysis was performed that examined changes in congestion from a different perspective.

In this second set of analyses, the study team defined when congestion ends at the end of both the a.m. and p.m. peak periods. The idea came from two observations noted in the development of the influence variables: (*a*) once congestion starts (often as a result of a disruption) during the peak period, that congestion tends to last until the end of the peak; and (*b*) although the previously described analysis can predict how much longer a given trip will last once a disruption has occurred, it does not estimate how long the congestion effect will last. Determining how much longer congestion lasts would provide insight into that missing piece of information.

To perform the required analysis, *end of congestion* was defined as the time when 20 consecutive minutes (four 5-minute periods) of travel time were less than travel time at the speed limit plus 5%. The 20-minute interval was selected to account for modest fluctuations in travel times (vehicle speeds) caused by unstable traffic flow occurring as congestion eases. The 5% value was selected as a result of sensitivity tests; while it represents a fairly small increase in travel time, it does appear to identify the effects of modest congestion that occur at a single location within a longer corridor.

Once the end of congestion was identified for each peak period for each day, three sets of travel time statistics were computed for all nonholiday Tuesdays, Wednesdays, and Thursdays describing the time that congestion ended for days when (*a*) any crash occurred (the crash must have occurred after 4:00 a.m. for the morning peak period test or after 3:00 p.m. for the evening peak period test), (*b*) any noncrash incident occurred, or (*c*) no incident occurred. Only one end of congestion time was assigned for each peak period for each day; that is, the first time period that met the selected criteria was the end of congestion for that peak period. Occasionally disruptions of one type occurred after congestion ended, creating a second congestion period within the traditional hours associated with the peak period. These cases were treated as occurring after the peak period had ended. These statistics were compared by using both normal and nonparametric statistical tests to determine the extent to which crashes and other types of traffic disruptions can be expected to extend peak period congestion.

A problem arose in that the definition for end of congestion proved too strict for some segments. The mean time when the a.m. peak period congestion ended was well after noon on 11 test sections, and frequently it did not end until after 6:00 p.m. on these corridors. A review of the travel times routinely experienced on these routes showed that a variety of traffic flow conditions (e.g., excessive merging at bottlenecks near the end of the corridor, large volumes of heavy trucks) frequently kept these road segments operating slightly below the speed limit even during late morning and midday periods. These routes all operated at or above the speed limit during late-night hours and during many midday hours. But they routinely operated at speeds lower than the speed limit during the middle of the day for reasons other than traffic disruptions.

This normal condition limited the benefit of the intended analysis. As a result, for the a.m. peak period on these 11 routes, *end of congestion* was redefined as being sustained speeds within either 10% or 20% of the speed limit, depending on the corridor. The intent of this new, corridor-specific definition was simply to allow better examination of how crashes and other disruptions affect when slow travel associated with peak period volumes ends.

These lowered expectations were tested on other corridors and for other periods. The results were generally not good. Using lowered average travel speeds to define end of peak period congestion frequently caused the end of congestion flag to be set during obviously congested conditions on these other routes. This was particularly true in the afternoon peak period, when all routes reached travel times within 5% of that achieved at the speed limit by a reasonable time of day. Consequently, the slower speed that was required to allow this approach was used only for those 11 roadway segments and only for the a.m. peak period.

Results: Travel Time Effects of Incidents and Crashes

In general, the effects of crashes and incidents on travel times were similar to each other and to the expected travel times that resulted from rainfall. That is, the shape of the expected (mean) travel time patterns by time of day when incidents and crashes occurred was similar in shape to the expected travel times when rain fell. These similarities are illustrated in Figures 5.12 through 5.14.

Figures 5.12 through 5.14 illustrate the mean travel time for nonholiday Tuesdays, Wednesdays, and Thursdays for all of 2006 (*a*) under nonrain conditions (regardless of incident conditions), (*b*) when rain had fallen within the past hour (regardless of incident conditions), (*c*) when a crash on the study section was influencing traffic conditions, and (*d*) when any traffic incident was reported as occurring on the study section by WSDOT's service patrols. Thus, the four expected travel time conditions are not fully independent of each other. But each gives an excellent understanding of expected conditions. For example, the rain travel time line answers the traveler's question, "How long should I expect my commute trip to last on this corridor if it is raining?" The response includes days when crashes occur and others when they do not occur. Note that during any given period the crash and incident travel time curves drop to zero when there were no reported crashes or incidents.

As the curves show, when free-flow conditions are the routine condition, incidents and rain have little effect on mean travel times. In some cases, crashes create sufficient disruption that travel times increase in lower-volume periods.

In the figures, the relative size of the travel time changes measured during incident and crash conditions (e.g., compared with the no-rain condition) is not consistent from corridor to corridor. These differences are caused by a variety of factors, including differences in (*a*) the sizes of the incidents and crashes occurring on each study segment during 2006, (*b*) the locations of the incidents and crashes relative to the end points of each study segment, and (*c*) the volume-to-capacity ratio occurring on the study section at the time of the traffic disruption. Perhaps even more importantly, the travel time statistics do not account for off-segment traffic

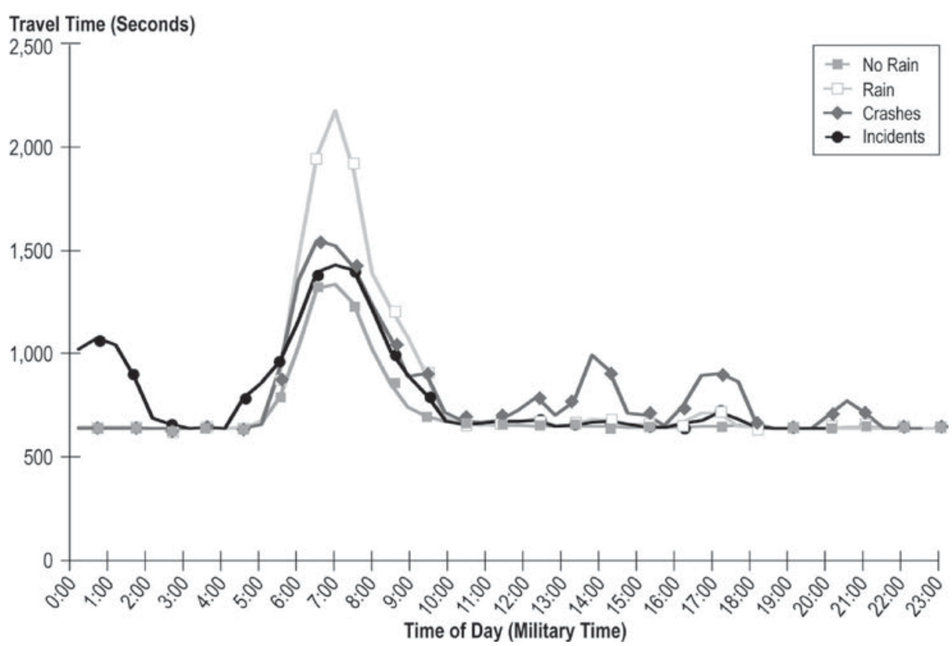

Figure 5.12. Mean travel times under rain, crash, or noncrash traffic incident conditions on I-5 northbound, South corridor.

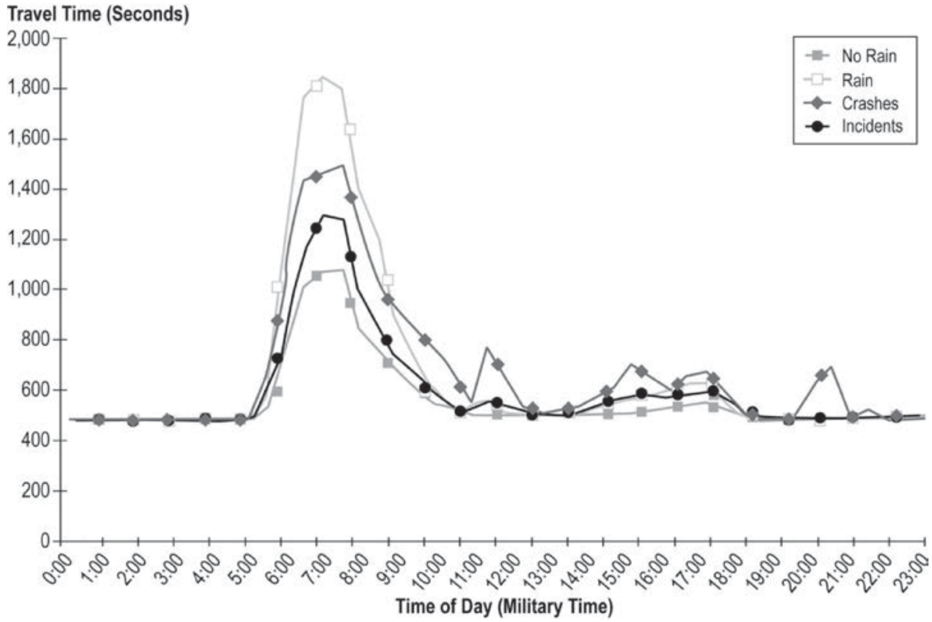

Figure 5.13. Mean travel times under rain, crash, or noncrash traffic incident conditions on I-5 southbound, Lynnwood corridor.

disruptions. That is, case studies of a number of specific days in 2006 showed that congestion on one roadway segment can frequently grow to the point that it affects the upstream road segment. While roadway segment boundaries can be chosen to minimize the effects of known geometric bottlenecks, major traffic disruptions often create temporary bottlenecks that are not located at known bottleneck locations. The congestion on study segments caused by these off-segment events increased the noninfluenced travel times against which study outcomes were compared.

The combined result of these various factors is that the relative importance of any specific type of traffic disruption varies from study segment to study segment.

In the northbound I-5 South segment (Figure 5.12), rain had a more substantial effect on the a.m. peak period travel times than did crashes. Late at night (midnight to 2:00 a.m.),

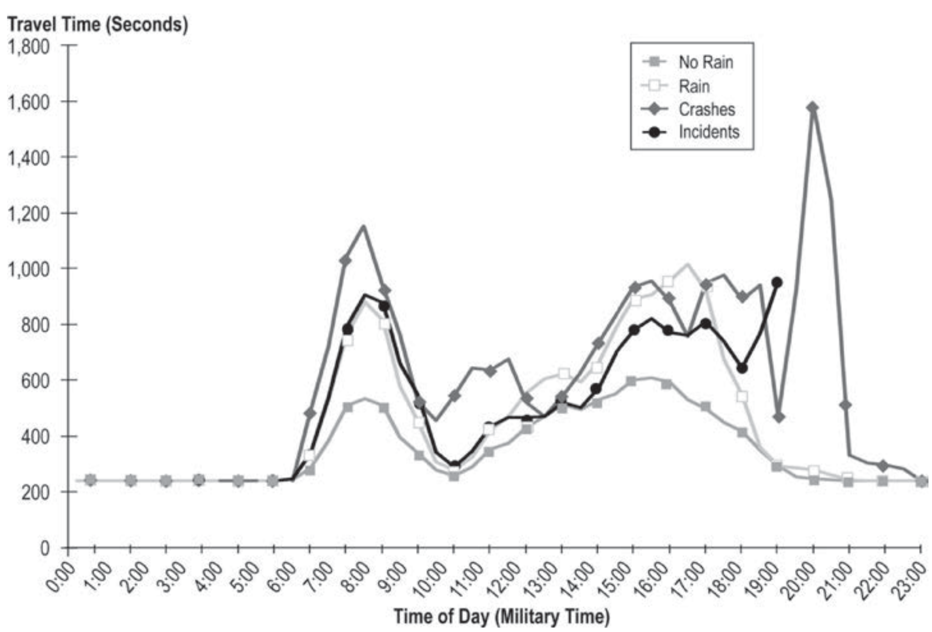

Figure 5.14. Mean travel times under rain, crash, or noncrash traffic incident conditions on I-5 southbound, North Seattle corridor.

incidents were seen to have a significant impact. A review of these data indicated that the incidents in question occurred during a planned construction lane closure, resulting in a large roadway capacity reduction during that maintenance activity, with substantial congestion being the result. In the middle of the afternoon and during the p.m. peak period (when the northbound I-5 South corridor operates in the reverse of the peak direction and is, therefore, not usually congested), crashes were the primary causes of travel time delays.

The Lynnwood corridor (Figure 5.13) presented the most normal effects of both weather and traffic disruptions. No late-night congestion is apparent in the figure, although some late-evening delays (~9:00 p.m.) are evident as a result of vehicle crashes. In the a.m. peak period, rain had the greatest effect in terms of increasing expected travel times. Both rain and vehicle crashes tended to cause travel delays slightly earlier in the a.m. peak period than did incidents, which tracked more closely to the normal peak period travel times until almost the peak of the a.m. travel time curve, when the effects of incidents caused substantial additional travel time. In the p.m. peak period (again, on this corridor the p.m. peak is a reverse-direction commute), only modest increases in travel times due to rain, incidents, or crashes occurred, with crashes having the most significant impact.

On the North Seattle southbound corridor (Figure 5.14), travel times routinely degrade in both peak periods. This corridor differed from the other two examples in that crashes had a more significant impact on mean travel time in the a.m. peak than did rain. This is partly due to the fact that this corridor ends in two back-to-back C-class weaving sections that constitute both a major routine bottleneck and a high-accident location. The result is that most of the causes of congestion in this section occurred within this section. Congestion spillback from downstream roadway segments on rainy days was not as significant a factor on this section as it was on the Lynnwood section. Consequently, crashes were more often a factor, especially in the morning.

A comparison of the three figures indicates that Figure 5.14 shows more off-peak congestion than Figures 5.12 and 5.13. The southbound I-5 North Seattle roadway corridor carries considerable traffic volume relative to the roadway's capacity even in off-peak periods. This large traffic volume frequently results in moderate southbound congestion, even in the middle of the day. As a result, relatively minor traffic incidents or bad weather can start with a moderate situation in the middle of the day and make it considerably worse. In contrast, Figures 5.12 and 5.13 show that traffic disruptions have relatively little impact on midday and evening roadway performance on the other example roadway segments.

Thus, the impacts of any disruption are a function of the underlying traffic volume condition during which that disruption occurs. The next most important factor is the size of the disruption imposed on the traffic stream. Therefore, crashes frequently have more significant effects during times of lower volume. But during peak conditions, the simple creation of congestion, which can occur given a much smaller disruption, may be as significant as the size of the disruption itself. That is, once the roadway congests, a large disruption adds only a marginal increase to the delay, whereas a smaller disruption occurring before congestion forms can create an even larger change in expected travel times during the course of the peak period because of the growth of the queue associated with the initial congestion point.

Results: Effects of Crashes or Noncrash Incidents on Peak Period Travel Time and Travel Reliability

The previous section illustrates that traffic volumes during Seattle's peak periods are sufficient on many corridors to create congestion, and that congestion may result in a variety of travel times. When the effects of disruptions were added to those traffic volumes, travel times generally increased, as illustrated in Figures 5.12 through 5.14. When computing incident-influenced travel times, only incidents that had a still-active effect on roadway performance were considered (*still active* means that travel times in the test section were slower than measured when the disruption was actually in place). One difficulty with this approach is that it is hard to explain. It also does not generalize well.

For a different approach to looking at the effects of traffic disruptions on travel times, this study computed the expected mean, 80th percentile, and 95th percentile peak period travel times for each study corridor, accounting for whether a disruption (crash or noncrash reported incident) had taken place. This approach basically answers the traveler's question, "If a crash (or other noncrash disruption) occurs today, how much worse will my commute be?"

To analytically answer this question, each nonholiday Tuesday through Thursday, 5-minute travel time was placed in one of three categories: (*a*) not influenced, (*b*) influenced by a crash, or (*c*) influenced by a reported noncrash incident. Once a disruption had occurred during a peak period, all remaining 5-minute travel times for the rest of that peak period were assumed to be influenced by that event. The a.m. peak was assumed to occur between 6:30 and 9:30 a.m. Any disruption that occurred after 4:00 a.m. was included in the analysis. The p.m. peak was assumed to occur between 3:00 and 7:00 p.m. Only traffic disruptions that occurred after 2:00 p.m. were included in the analysis. If a crash occurred at 5:00 p.m., the 5-minute travel times before 5:00 p.m. were classified as noninfluenced, and those after 5:00 p.m. were crash influenced. If both a crash and a noncrash incident occurred, all time periods after the crash were considered crash influenced. Because the mean, 80th percentile, and 95th percentile travel times were computed from the entire pool of travel times within each classification of trips, this approach did create a minor bias toward lower travel times in the noninfluenced category, as a disproportionate number of travel times for that category were taken from the early (least congested) portion of the peak periods. This bias was somewhat balanced by the inability of this analysis to account for the effects of congestion spillback from one roadway segment to another.

The results of this analysis are shown in Table 5.7, which describes the impacts of crashes and noncrash incidents on the mean travel times computed for the a.m. peak period. For each study corridor, the mean travel time increase (in seconds)

Table 5.7. Effects of Incidents and Crashes on A.M. Peak Period Travel Times

Study Corridor	A.M. Peak Travel Rate		Mean Travel Time Increase from All Traffic Incidents (s)	Increase over Nonincident Conditions (%)	
	Mean	Median		Noncrash Incident	Crash
I-405 Kennydale northbound	3.66	3.4	179	11	17
I-405 North southbound	2.82	2.4	347	35	45
I-5 North King southbound	2.07	1.8	139	22	43
I-5 Seattle CBD northbound	1.91	1.8	361	51	57
I-405 Kirkland southbound	1.76	1.8	80	9	14
SR 520 Seattle eastbound	1.70	1.8	98	13	32
I-5 Lynnwood southbound	1.89	1.6	251	31	60
I-5 South northbound	1.75	1.6	364	43	58
SR 167 Auburn northbound	1.68	1.6	21	8	15
I-405 Eastgate northbound	1.66	1.6	17	8	24
I-5 Seattle North southbound	2.15	1.4	232	47	84
I-405 Kennydale southbound	1.54	1.4	96	15	34
I-405 South southbound	1.45	1.4	50	28	14
SR 167 Renton northbound	1.62	1.2	390	75	76
SR 520 Seattle westbound	1.51	1.2	183	30	19
I-5 Tukwila northbound	1.50	1.2	254	57	76
I-90 Issaquah westbound	1.46	1.2	169	29	60
I-90 Bellevue westbound	1.30	1.2	73	24	22
I-405 Bellevue northbound	1.27	1.2	39	12	27
I-405 South northbound	1.24	1.2	30	19	15
I-90 Seattle eastbound	1.96	1	50	27	36
I-90 Seattle westbound	1.20	1	20	21	27
I-90 Bridge Eastbound	1.18	1	40	9	38
I-405 Bellevue southbound	1.16	1	25	11	62
I-5 Everett southbound	1.15	1	39	20	90
I-90 Bridge westbound	1.15	1	40	11	22
I-5 Seattle CBD southbound	1.10	1	48	9	24
SR 167 Auburn southbound	1.06	1	–2	–1	–6
I-405 Eastgate southbound	1.05	1	9	7	76

(continued on next page)

Table 5.7. Effects of Incidents and Crashes on A.M. Peak Period Travel Times (continued)

Study Corridor	A.M. Peak Travel Rate		Mean Travel Time Increase from All Traffic Incidents (s)	Increase over Nonincident Conditions (%)	
	Mean	Median		Noncrash Incident	Crash
SR 167 Renton southbound	1.04	1	–1	0	–6
I-5 Tukwila southbound	1.02	1	14	3	–2
SR 520 Redmond westbound	1.02	1	29	8	7
I-405 North northbound	1.02	1	8	2	4
I-5 Everett northbound	1.01	1	5	3	51
I-5 Lynnwood northbound	1.01	1	16	3	52
I-5 Seattle North northbound	1.01	1	3	1	0
I-90 Bellevue eastbound	1.01	1	–1	–1	0
I-5 South southbound	1.00	1	23	4	3
I-405 Kirkland northbound	1.00	1	7	1	1
SR 520 Redmond eastbound	1.00	1	1	0	0
I-90 Issaquah eastbound	1.00	1	–1	0	0
I-5 North King northbound	1.00	1	1	0	0

caused by noncrash traffic incidents is presented. This increase is then shown as a percentage change in study section travel time in comparison with the mean travel time with no disruption. The percentage increase in travel time associated with a crash is shown to illustrate the relative significance of crashes and noncrash traffic disruptions. The 42 study segments are sorted from most congested to least congested on the basis of their median and mean travel rates for all weekdays.

As Table 5.7 shows, the mean travel time increased when traffic disruptions occurred for all corridor study segments that had a mean travel rate greater than 1.0. (A travel rate equal to 1.0 indicates that vehicles can operate at the speed limit [60 mph].) For all but four of those corridors, the occurrence of a crash had a greater impact on expected travel times than a reported noncrash incident. A more mixed effect of both crashes and noncrash incidents is evident for corridors that did not routinely exhibit at least a modest level of congestion. No direct correlation is observable between the delays that occurred in response to traffic incidents and either the mean or median travel rates.

The p.m. peak period version of Table 5.7 is shown in Table 5.8. As with the a.m. peak results, all the p.m. corridors with a median travel rate greater than 1.0 showed increases in mean travel time when any kind of traffic disruption occurred. Crashes resulted in a greater increase in the mean travel time than noncrash incidents on all but four of the study corridors. Because p.m. peak travel is different from a.m. peak travel, the corridors in Table 5.8 do not match those in Table 5.7.

Other than the basic, if obvious, conclusion that traffic disruptions can be expected to increase travel times for moderately to heavily congested travel corridors, there are relatively few patterns in the data contained in Tables 5.7 and 5.8. There appears to be no consistent relationship between the percentage change in travel time and the base statistics that describe mean peak period travel conditions (either mean travel rate or median travel rate). On some heavily congested corridors (e.g., I-405 Bellevue southbound p.m. peak, I-5 North Seattle southbound p.m. peak, I-5 South northbound a.m. peak), crashes and other incidents caused dramatic increases in expected travel times, even doubling the expected time to traverse the study section. On other heavily congested corridors (e.g., I-405 Eastgate southbound p.m. peak, I-405 Kennydale northbound a.m. peak), the travel time effects were considerably smaller, in the range of a 10% to 25% increase in expected travel times.

When looked at more comprehensively, noncrash incidents increased travel times an average of 17% in the morning and 21% in the evening on corridors that had mean peak period travel rates above 1.10. However, mean travel time changes ranged from 9% to 75% in the morning. In the evening, travel times changes ranged from 6% to 119%. If only crashes are considered, the a.m. peak changes ranged from 14% to 90%, with an average of 40%. The p.m. changes ranged from 9% to 176%, with an average of 41%.

Table 5.8. Effects of Incidents and Crashes on P.M. Peak Period Travel Times

Study Corridor	P.M. Peak Travel Rate		Mean Travel Time Increase from All Traffic Incidents (s)	Increase over Nonincident Conditions (%)	
	Mean	Median		Noncrash Incident	Crash
I-405 Bellevue southbound	3.73	3.6	400	88	102
I-405 Eastgate southbound	2.73	2.6	29	10	25
SR 520 Seattle westbound	2.72	2.6	230	23	18
I-405 South northbound	2.58	2.6	47	17	14
I-5 Seattle North southbound	2.56	2	410	119	138
I-405 Kirkland northbound	1.99	2	127	14	26
I-5 Seattle CBD northbound	1.96	1.8	350	52	60
I-405 Kennydale southbound	1.90	1.8	109	15	23
I-5 North King northbound	1.79	1.8	92	17	24
I-5 Seattle CBD southbound	1.72	1.8	153	22	30
SR 167 Auburn southbound	1.96	1.6	90	29	33
SR 520 Redmond eastbound	1.87	1.6	83	14	34
I-5 South southbound	1.76	1.6	265	30	46
I-405 North northbound	1.61	1.6	37	6	29
I-5 Everett northbound	1.87	1.4	128	50	55
I-5 Seattle North northbound	1.74	1.4	73	18	29
SR 167 Renton southbound	1.63	1.4	180	31	57
I-405 South southbound	1.52	1.4	79	43	26
I-90 Bridge westbound	1.73	1.2	122	25	12
SR 520 Seattle eastbound	1.49	1.2	115	20	34
I-5 Lynnwood northbound	1.38	1.2	101	17	45
I-405 Bellevue northbound	1.34	1.2	89	35	68
I-90 Seattle westbound	1.13	1.2	7	8	9
SR 520 Redmond westbound	1.49	1	168	38	40
I-90 Seattle eastbound	1.43	1	84	72	54
I-90 Bridge eastbound	1.40	1	111	27	35
I-5 North King southbound	1.33	1	232	67	176
I-90 Bellevue westbound	1.30	1	154	63	96
I-5 Tukwila southbound	1.19	1	102	22	66
SR 167 Renton northbound	1.17	1	151	37	40
I-405 Kennydale northbound	1.17	1	84	17	56
I-90 Bellevue eastbound	1.11	1	48	19	50
I-5 Everett southbound	1.10	1	16	8	63
I-5 Lynnwood southbound	1.10	1	59	11	44
I-405 North southbound	1.09	1	64	16	37
I-405 Kirkland southbound	1.09	1	101	19	27
I-5 Tukwila northbound	1.07	1	96	24	81
SR 167 Auburn northbound	1.05	1	13	6	16
I-405 Eastgate northbound	1.04	1	19	16	18
I-90 Issaquah eastbound	1.01	1	0	0	–1
I-5 South northbound	1.01	1	14	2	6
I-90 Issaquah westbound	1.00	1	17	4	5

A review of base data for a sample of these corridors suggested that two factors contributed to this variation. In some cases, the noninfluenced annual mean travel time was significantly affected by downstream congestion when that downstream congestion was caused both by routine conditions and by traffic disruptions on the downstream roadway segments. The result of this downstream congestion backing up on the study section was that an abnormally high mean travel time for nondisruption-influenced travel times occurred on the study section. This result, in turn, decreased both the absolute and percentage differences in crash-influenced travel times.

The second factor was simply the number and variety of incidents or crashes occurring in the different test sections. Some traffic disruptions were more significant in terms of the number of lanes they blocked and the time at which they occurred. A modest number of very bad traffic disruptions can cause a fairly high increase in the mean travel time because of the modest number of data points in each sample.

To further explore the effects of incidents and crashes on travel time reliability, Tables 5.9 and 5.10 describe the measured changes in the 80th and 95th percentile travel times when crashes and noncrash incidents occur. Similar to Tables

Table 5.9. Effects of Crashes and Noncrash Incidents on A.M. Peak Period 80th and 95th Percentile Travel Times

Study Corridor	Mean A.M. Peak Travel Rate	Increase in Travel Time (%)			
		Noncrash Incident		Crash	
		80th Percentile	95th Percentile	80th Percentile	95th Percentile
I-405 Kennydale northbound	3.66	6.3	10.9	9.4	8.2
I-405 North southbound	2.82	–6.4	9.6	2.1	13.5
I-5 North King southbound	2.07	0.0	–5.3	16.8	25.8
I-5 Seattle CBD northbound	1.91	15.4	17.1	40.5	35.4
I-405 Kirkland southbound	1.76	–2.2	–4.6	1.1	2.3
SR 520 Seattle eastbound	1.70	5.6	12.0	20.5	52.5
I-5 Lynnwood southbound	1.89	–16.0	–15.4	9.5	15.0
I-5 South northbound	1.75	–18.6	–16.8	–6.1	–0.1
SR 167 Auburn northbound	1.68	2.3	7.5	18.3	37.9
I-405 Eastgate northbound	1.66	5.5	6.7	6.8	30.9
I-5 Seattle North southbound	2.15	2.5	–0.1	31.3	24.7
I-405 Kennydale southbound	1.54	–1.7	10.1	21.7	27.8
I-405 South southbound	1.45	2.7	20.3	–0.5	17.0
SR 167 Renton northbound	1.62	–4.2	–14.7	84.8	61.8
SR 520 Seattle westbound	1.51	–0.2	–4.1	17.9	12.7
I-5 Tukwila northbound	1.50	–5.4	–13.4	16.8	12.3
I-90 Issaquah westbound	1.46	21.0	0.5	28.3	36.2
I-90 Bellevue westbound	1.30	–0.5	30.2	12.6	10.8
I-405 Bellevue northbound	1.27	18.5	23.9	33.4	35.2
I-405 South northbound	1.24	0.6	–0.5	2.7	9.7
I-90 Seattle eastbound	1.96	–2.1	–9.7	23.3	45.8
I-90 Seattle westbound	1.20	9.2	–5.9	35.0	11.8
I-90 Bridge eastbound	1.18	34.1	12.7	51.2	41.5
I-405 Bellevue southbound	1.16	0.3	–5.1	93.2	114.6
I-5 Everett southbound	1.15	–2.6	–29.2	4.1	17.6

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Table 5.9. Effects of Crashes and Noncrash Incidents on A.M. Peak Period 80th and 95th Percentile Travel Times (continued)

Study Corridor	Mean A.M. Peak Travel Rate	Increase in Travel Time (%)			
		Noncrash Incident		Crash	
		80th Percentile	95th Percentile	80th Percentile	95th Percentile
I-90 Bridge westbound	1.15	0.0	–1.0	56.2	162.0
I-5 Seattle CBD southbound	1.10	1.8	–1.3	13.0	28.6
SR 167 Auburn southbound	1.06	2.7	8.8	No crashes	a.m. peak
I-405 Eastgate southbound	1.05	0.3	–0.1	6.5	76.5
SR 167 Renton southbound	1.04	2.5	1.3	0.8	0.1
I-5 Tukwila southbound	1.02	0.0	–0.4	0.4	0.4
SR 520 Redmond westbound	1.02	0.6	12.7	29.3	76.6
I-405 North northbound	1.02	–0.2	1.1	1.2	6.2
I-5 Everett northbound	1.01	–0.1	–0.1	1.2	38.4
I-5 Lynnwood northbound	1.01	0.1	0.1	0.6	195.6
I-5 Seattle North northbound	1.01	2.3	2.9	5.9	5.3
I-90 Bellevue eastbound	1.01	0.0	0.9	0.0	0.7
I-5 South southbound	1.00	0.0	0.0	0.0	19.6
I-405 Kirkland northbound	1.00	0.2	2.4	0.2	0.2
SR 520 Redmond eastbound	1.00	–10.5	–14.9	–9.3	–16.5
I-90 Issaquah eastbound	1.00	0.0	0.0	0.0	0.0
I-5 North King northbound	1.00	0.0	0.0	0.0	0.0

Table 5.10. Effects of Crashes and Noncrash Incidents on P.M. Peak Period 80th and 95th Percentile Travel Times

Study Corridor	Mean P.M. Peak Travel Rate	Increase in Travel Time (%)			
		Noncrash Incident		Crash	
		80th Percentile	95th Percentile	80th Percentile	95th Percentile
I-405 Bellevue southbound	3.73	9.8	–3.4	10.4	0.3
I-405 Eastgate southbound	2.73	3.0	–5.8	6.4	27.3
SR 520 Seattle westbound	2.72	21.4	4.1	25.7	1.7
I-405 South northbound	2.58	12.4	7.8	7.0	8.4
I-5 Seattle North southbound	2.56	5.2	1.3	21.8	14.9
I-405 Kirkland northbound	1.99	4.6	3.6	18.7	27.6
I-5 Seattle CBD northbound	1.96	29.5	26.0	52.4	30.8
I-405 Kennydale southbound	1.90	–11.6	9.0	–6.4	–0.1
I-5 North King northbound	1.79	12.6	10.9	11.3	17.1

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Table 5.10. Effects of Crashes and Noncrash Incidents on P.M. Peak Period 80th and 95th Percentile Travel Times (continued)

Study Corridor	Mean P.M. Peak Travel Rate	Increase in Travel Time (%)			
		Noncrash Incident		Crash	
		80th Percentile	95th Percentile	80th Percentile	95th Percentile
I-5 Seattle CBD southbound	1.72	2.4	–3.1	5.2	12.7
SR 167 Auburn southbound	1.96	0.6	22.5	29.4	11.2
SR 520 Redmond eastbound	1.87	–10.5	–14.9	–9.3	–16.5
I-5 South southbound	1.76	10.3	9.8	16.8	34.9
I-405 North northbound	1.61	8.4	30.5	27.4	59.5
I-5 Everett northbound	1.87	–6.8	–0.2	–3.4	2.5
I-5 Seattle North northbound	1.74	9.4	11.4	18.3	0.1
SR 167 Renton southbound	1.63	15.9	16.3	48.2	67.7
I-405 South southbound	1.52	5.1	6.9	7.8	22.6
I-90 Bridge westbound	1.73	48.8	29.6	47.5	13.4
SR 520 Seattle eastbound	1.49	24.4	21.3	32.1	42.9
I-5 Lynnwood northbound	1.38	12.8	2.4	43.1	60.9
I-405 Bellevue northbound	1.34	7.3	–8.0	54.5	68.1
I-90 Seattle westbound	1.13	0.6	7.7	1.7	9.5
SR 520 Redmond westbound	1.49	169.2	23.4	171.8	50.9
I-90 Seattle eastbound	1.43	25.9	–31.4	33.4	13.2
I-90 Bridge eastbound	1.40	51.3	15.4	83.5	21.5
I-5 North King southbound	1.33	9.9	86.8	151.5	114.6
I-90 Bellevue westbound	1.30	494.3	244.6	213.0	107.2
I-5 Tukwila southbound	1.19	8.4	7.9	48.6	18.0
SR 167 Renton northbound	1.17	6.3	23.1	26.3	44.4
I-405 Kennydale northbound	1.17	7.1	–3.9	40.4	98.1
I-90 Bellevue eastbound	1.11	3.2	–0.2	19.0	419.0
I-5 Everett southbound	1.10	5.9	8.6	57.5	149.3
I-5 Lynnwood southbound	1.10	–0.4	–7.2	20.6	41.3
I-405 North southbound	1.09	0.3	45.0	58.1	41.6
I-405 Kirkland southbound	1.09	6.6	19.3	20.9	29.1
I-5 Tukwila northbound	1.07	2.1	–6.7	113.7	146.3
SR 167 Auburn northbound	1.05	5.4	139.6	61.0	58.6
I-405 Eastgate northbound	1.04	–2.0	–6.8	26.7	142.6
I-90 Issaquah eastbound	1.01	1.2	1.0	0.1	–6.0
I-5 South northbound	1.01	–0.2	–0.1	4.7	77.8
I-90 Issaquah westbound	1.00	0.1	3.5	–0.4	–0.5

5.7 and 5.8, these two tables are sorted from most congested to least congested study corridor. Table 5.9 presents the changes to a.m. peak period travel times, and Table 5.10 presents the p.m. peak period results.

As the tables show, in most cases, crashes had a greater impact than noncrash traffic incidents in both the a.m. and p.m. peak periods. In addition, the least congested corridors in both peak periods generally showed the least change in the measured 80th and 95th percentile travel times when crashes and other traffic incidents occurred.

The most significant difference was that all corridors with median peak period travel rates for all weekdays above 1.0 or mean weekday travel rates above 1.10 showed an increase in mean travel times on days when either a crash or noncrash incident occurred. However, many corridors did not show increased 80th or 95th percentile travel times under those same incident conditions, especially for noncrash incidents. The effects of noncrash incidents were particularly mixed. Eleven of 27 corridors in the a.m. peak period and four of 34 corridors in the p.m. peak period did not have increased 80th percentile travel times due to noncrash incidents. Only two corridors in the morning and three corridors in the afternoon among these moderately to heavily congested corridors had peak periods in which the 80th percentile travel times did not increase under crash conditions. Similarly, 15 of these corridors in the morning and 10 of them in the afternoon did not show an increased 95th percentile travel time. Only one corridor in the a.m. peak and two in the p.m. peak had 95th percentile travel times that did not increase when crashes occurred. In all cases, several additional corridors showed only marginal changes in these statistics.

If the results for the corridors with average weekday mean travel rates above 1.10 are simply averaged, then

- Noncrash incidents increase the 80th percentile travel times only 2% in the a.m. peak and 29% in the p.m. peak;
- Noncrash incidents increase the 95th percentile travel times only 1% in the a.m. peak and 16% in the p.m. peak;
- Crashes increase the 80th percentile travel times 24% in the a.m. peak and 39% in the p.m. peak; and
- Crashes increase the 95th percentile travel times 33% in the a.m. peak and 47% in the p.m. peak.

Taken together, these results indicate that noncrash incidents were mostly responsible for modest changes in travel times. Those changes were more pronounced during periods of higher traffic volume and were thus generally more significant in the p.m. peak than in the a.m. peak. Noncrash incidents generally had very modest impacts on the worst travel days.

In contrast, crashes had more substantial impacts on both the a.m. and p.m. peak periods. The fact that an accident occurred could be expected to add 20% to 40% to the travel times in much of the travel time distribution curve, whether that was the mean, 80th percentile, or 95th percentile travel time, with some crashes being responsible for much larger increases.

Results: Incident-Related Changes in When Peak Period Congestion Ends

In Figures 5.12 through 5.14, only those travel times influenced by an incident or crash were included in the computation of the mean travel time associated with incidents and crashes. The problem with this (or any) approach to defining the influence of disruptions on travel times is understanding when those influences end. That is, the definition of incident influence used in the previous section means that only incidents that had a still-active effect on roadway performance were considered when computing incident-influenced travel time (where *still active* means that travel times in the test section were slower than those measured when the disruption was occurring). If an incident is quickly cleared and the disruption is minimized, how does that event affect the travel time experienced?

To better understand the effects of incidents and crashes, an entirely different examination of the impacts of those disruptions is discussed below that examines when congestion, as part of the normal peak period increase in travel demand, can be expected to end. An examination of Figures 5.12 through 5.14 shows that mean travel times slow earlier in the day and last longer into the day whenever traffic disruptions occur. From the motorists' perspective, this means not only that their trip during the heart of the commute is longer, but that even if they have delayed their trip until after the normal peak period, they may still be stuck in congestion.

To examine this phenomenon, the project team computed when the a.m. and p.m. peak periods normally ended for each study corridor. The team then examined whether the ending time of the peak period changed as a result of the occurrence of crashes or noncrash incidents. The resulting summary statistics for these analyses are shown in Tables 5.11 and 5.12. (All the statistics generated from this analysis are shown in Appendix D.) The tables are sorted so that the study sections with the slowest, most congested corridors (as defined by their peak period median travel rate in minutes per mile) are at the top of the table, and the fastest, least congested corridors are at the bottom. Within a given travel rate, routes are sorted by their mean travel rate. Both tables show the mean time of day when congestion ended on days that did not experience reported incidents or crashes, and the mean difference (in minutes) in the time of day for the end of congestion for each corridor when at least one crash or incident was reported within the study section in the indicated direction of travel. If both a crash and a noncrash incident occurred,

Table 5.11. Effects of Incidents and Crashes on Ending Time of P.M. Peak Period Congestion

Study Corridor	P.M. Peak Travel Rate		Normal Time When Congestion Ended	Additional Congestion Time (min)	
	Mean	Median		Noncrash Incident	Crash
I-405 Bellevue southbound	3.73	3.6	19:44	0:00	0:20
I-405 Eastgate southbound	2.73	2.6	19:12	0:00	0:15
SR 520 Seattle westbound	2.72	2.6	20:00	0:00	0:12
I-405 South northbound	2.58	2.6	20:41	0:00	0:00
I-5 Seattle North southbound	2.56	2	18:49	0:00	0:31
I-405 Kirkland northbound	1.99	2	19:03	0:00	0:11
I-5 Seattle CBD northbound	1.96	1.8	18:53	0:00	0:00
I-405 Kennydale southbound	1.90	1.8	19:27	0:00	0:00
I-5 North King northbound	1.79	1.8	18:55	0:00	0:12
I-5 Seattle CBD southbound	1.72	1.8	18:20	0:00	0:00
SR 167 Auburn southbound	1.96	1.6	18:47	0:00	0:08
SR 520 Redmond eastbound	1.87	1.6	19:09	0:00	0:00
I-5 South southbound	1.76	1.6	18:08	0:00	0:00
I-405 North northbound	1.61	1.6	19:18	0:00	0:14
I-5 Everett northbound	1.87	1.4	17:08	0:28	0:58
I-5 Seattle North northbound	1.74	1.4	18:34	0:00	0:00
SR 167 Renton southbound	1.63	1.4	18:47	0:00	0:00
I-405 South southbound	1.52	1.4	19:36	0:00	0:00
I-90 Bridge westbound	1.73	1.2	18:25	0:34	0:48
SR 520 Seattle eastbound	1.49	1.2	18:52	0:00	0:22
I-5 Lynnwood northbound	1.38	1.2	19:00	0:00	0:00
I-405 Bellevue northbound	1.34	1.2	18:09	0:00	0:27
I-90 Seattle westbound	1.13	1.2	17:29	0:00	0:00
SR 520 Redmond westbound	1.49	1	16:51	1:24	1:53
I-90 Seattle eastbound	1.43	1	17:07	0:00	1:05
I-90 Bridge eastbound	1.40	1	18:18	0:22	0:35
I-5 North King southbound	1.33	1	16:47	0:29	1:57
I-90 Bellevue westbound	1.30	1	16:13	1:21	2:10
I-5 Tukwila southbound	1.19	1	17:18	0:21	0:51
SR 167 Renton northbound	1.17	1	17:22	0:27	0:57
I-405 Kennydale northbound	1.17	1	18:05	0:00	0:23
I-90 Bellevue eastbound	1.11	1	16:35	0:00	1:02
I-5 Everett southbound	1.10	1	16:35	0:24	0:57
I-5 Lynnwood southbound	1.10	1	17:21	0:00	1:09
I-405 North southbound	1.09	1	17:40	0:00	0:46
I-405 Kirkland southbound	1.09	1	16:55	1:00	1:21
I-5 Tukwila northbound	1.07	1	16:23	0:23	1:56
SR 167 Auburn northbound	1.05	1	17:31	0:00	0:00
I-405 Eastgate northbound	1.04	1	16:24	0:00	0:47
I-90 Issaquah eastbound	1.01	1	16:10	0:00	0:00
I-5 South northbound	1.01	1	16:05	0:00	0:45
I-90 Issaquah westbound	1.00	1	16:05	0:00	0:00

Table 5.12. Effects of Incidents and Crashes on Ending Time of A.M. Peak Period Congestion

Study Corridor	A.M. Peak Travel Rate		Normal Time When Congestion Ended	Additional Congestion Time (min)		Adjusted End of Congestion
	Mean	Median		Noncrash Incident	Crash	Travel Time Value[a]
I-405 Kennydale northbound	3.66	3.4	11:47	0:00	1:33	10%
I-405 North southbound	2.82	2.4	9:56	1:27	2:09	NA
I-5 North King southbound	2.07	1.8	11:06	0:48	1:29	10%
I-5 Seattle CBD northbound	1.91	1.8	12:15	0:00	0:00	No disruption-free days
I-405 Kirkland southbound	1.76	1.8	10:16	0:56	1:14	NA
SR 520 Seattle eastbound	1.70	1.8	11:54	6:02	6:53	NA
I-5 Lynnwood southbound	1.89	1.6	10:06	1:57	1:39	NA
I-5 South northbound	1.75	1.6	9:16	0:00	0:22	NA
SR 167 Auburn northbound	1.68	1.6	11:40	0:00	0:00	20%
I-405 Eastgate northbound	1.66	1.6	11:38	0:00	1:04	10%
I-5 Seattle North southbound	2.15	1.4	9:38	0:00	4:58	NA
I-405 Kennydale southbound	1.54	1.4	9:08	1:19	1:23	20%
I-405 South southbound	1.45	1.4	12:46	3:12	2:17	20%
SR 167 Renton northbound	1.62	1.2	9:13	1:47	1:22	20%
SR 520 Seattle westbound	1.51	1.2	9:51	0:00	2:54	10%
I-5 Tukwila northbound	1.50	1.2	10:06	0:00	0:32	NA
I-90 Issaquah westbound	1.46	1.2	9:10	0:00	0:33	NA
I-90 Bellevue westbound	1.30	1.2	9:26	0:13	0:00	NA
I-405 Bellevue northbound	1.27	1.2	11:01	3:34	5:00	10%
I-405 South northbound	1.24	1.2	8:21	4:49	7:47	20%
I-90 Seattle eastbound	1.96	1	8:45	0:00	1:05	NA
I-90 Seattle westbound	1.20	1	7:35	0:42	1:52	NA
I-90 Bridge eastbound	1.18	1	9:23	0:45	1:04	NA
I-405 Bellevue southbound	1.16	1	8:27	7:56	11:07	10%
I-5 Everett southbound	1.15	1	7:08	0:00	1:06	NA
I-90 Bridge westbound	1.15	1	8:04	0:26	1:30	NA
I-5 Seattle CBD southbound	1.10	1	9:28	0:00	4:57	NA
SR 167 Auburn southbound	1.06	1	8:58	7:29	9:59	NA
I-405 Eastgate southbound	1.05	1	7:22	0:00	0:32	NA
SR 167 Renton southbound	1.04	1	9:42	7:33	7:30	NA
I-5 Tukwila southbound	1.02	1	7:08	0:00	7:51	NA
SR 520 Redmond westbound	1.02	1	7:09	0:56	2:10	NA
I-405 North northbound	1.02	1	7:56	0:12	1:47	NA
I-5 Everett northbound	1.01	1	7:05	0:00	0:14	NA
I-5 Lynnwood northbound	1.01	1	7:13	0:00	0:00	NA
I-5 Seattle North northbound	1.01	1	7:07	0:00	0:00	NA

(continued on next page)

Table 5.12. Effects of Incidents and Crashes on Ending Time of A.M. Peak Period Congestion (continued)

Study Corridor	A.M. Peak Travel Rate		Normal Time When Congestion Ended	Additional Congestion Time (min)		Adjusted End of Congestion
	Mean	Median		Noncrash Incident	Crash	Travel Time Value[a]
I-90 Bellevue eastbound	1.01	1	7:05	0:00	0:00	NA
I-5 South southbound	1.00	1	7:07	0:08	0:00	NA
I-405 Kirkland northbound	1.00	1	7:05	0:05	0:00	NA
SR 520 Redmond eastbound	1.00	1	7:05	0:00	0:00	NA
I-90 Issaquah eastbound	1.00	1	7:05	0:00	0:00	NA
I-5 North King northbound	1.00	1	7:05	0:00	0:00	NA

[a] On some study corridors, for the end of congestion to occur before noon after the a.m. peak period on days without incidents or crashes, it was necessary to change the definition of *congestion* from 20 consecutive minutes of average travel times being faster than 1.05 times the travel time at the speed limit to either 1.10 times the travel times at the speed limit (indicated by the value of 10%) or 1.20 times for travel time at the speed limit (indicated by 20%).

the day was classified as being affected by a crash. For the a.m. peak, the crash or incident must have taken place after 4:00 a.m. and before the end of congestion was reached. For the p.m. peak, the crash or incident must have taken place after 3:00 p.m. and before the end of congestion was reached. Statistical comparisons were performed by using the nonparametric Anderson–Darling k-sample test, with p-values of less than .01 being used to determine statistically significant end of congestion times. Statistically insignificant differences are set to zero in Tables 5.11 and 5.12.

While the nature (size, duration, and specific location) of incidents affects exactly how much disruption each incident causes, and these differences in incident size and duration are not directly accounted for, some generalizations can be made from these tables. Among these are the following:

- Incidents that occur in the evening peak period have little measurable effect on the time that peak period congestion abates for (*a*) very heavily congested roadway sections or (*b*) very lightly congested sections;
- Crashes extend the evening commute period's congestion more significantly than noncrash incidents, and they are more likely to affect roadway performance than other kinds of incidents; and
- The duration of congestion on a surprising number of corridors is not significantly affected by a crash occurring on that section.

Of the 18 corridors with a median p.m. peak period travel rate of 1.4 or greater, the end of congestion was extended by noncrash incidents in a statistically significant manner for only one. For nine of 19 corridors with a median travel rate equal to the speed limit, the end of congestion time was extended when incidents occurred.

Several significant differences were observed between the effects of incidents and crashes in the morning peak period described in Table 5.12 and those shown for the evening peak period in Table 5.11. The most significant difference is that the heavily congested a.m. corridors are much more sensitive to incidents than their p.m. peak period counterparts. None of the 14 corridors with p.m. peak median travel rates above 1.4 had congestion durations that showed sensitivity to noncrash incidents, but five of the 10 morning peak corridors operating at this level of congestion were sensitive to noncrash incidents. One corridor, I-5 Seattle CBD northbound, had so many disruptions that no comparison could be made. This study segment had only one day among all nonholiday Tuesdays, Wednesdays, and Thursdays in 2006 that did not contain either a crash or a WITS-reported incident. Clearly, one day is not sufficient to make a statistically significant comparison.

A second difference between the morning and evening periods was the size of the change when incidents and crashes affected the end of congestion. When incidents and crashes had an effect in the evening, the mean change in the duration of the peak period tended to be between 15 minutes and 1 hour, at most (35 of 45 statistically significant differences were less than 1 hour). In contrast, morning peak period corridors affected by crashes and other incidents routinely saw congestion extend for more than an hour, and in many cases, multiple hours.

However, at the less congested end of the congestion distribution, the morning peak period was similar to the evening peak period. More than half of the study corridors with a median travel rate equal to the speed limit (1.0) had congestion ending times that were not statistically affected by incidents. The majority of these corridors also had a mean travel rate of less than 1.02 and were reasonably insensitive to congestion caused by crashes. These results indicate that if traffic volume relative to capacity is low enough to not produce even light routine congestion, then only very large incidents and crashes will create congestion. These observed differences further strengthen the primary finding of this study: the overriding factor affecting travel time reliability is the background traffic volume.

Although there were many differences in the a.m. and p.m. peak periods, one of the key differences was that the morning leading (early) shoulder had very low traffic volumes. Therefore, as noted earlier, incidents tended to have little impact early in the a.m. peak period. In the evening, traffic volume dropped off rapidly at the end of the peak period, and congestion frequently abated rapidly simply because traffic volumes were low enough for queues to clear. At the end of the morning peak, however, traffic volumes remained modest because of the addition of noncommute trips to the traffic stream. Thus, incident congestion formed during the a.m. peak tended to last much longer than incident congestion formed in the p.m. peak.

Conversely, significant incidents that occurred well before the start of the p.m. peak period had the potential to cause the entire p.m. peak period to be congested if they were not cleared quickly, but incidents occurring an hour before the start of the a.m. peak, if they were cleared with even modest speed, were far less likely to affect the morning commute.

Summary: Causes of Congestion

Congestion occurs when there is too much volume and too little roadway capacity. This can occur because

- Traffic demand is too great for the designed roadway capacity; or
- Some disruption reduces functional roadway capacity (supply) to levels below demand.

Demand varies because of repeating travel patterns (e.g., time of day, day of week, seasonal patterns) and as a result of unusual activity that causes more travelers than typical to use a roadway at a given time. These unusual activities can be planned events, such as a major sporting event, or unplanned events, such as vehicles diverting to one roadway to avoid congestion on another.

Functional roadway capacity (supply) can vary as a result of numerous factors, including weather, traffic management strategies (work zones, the application of different traffic control plans), and a variety of traffic incidents that disrupt the normal operations of a roadway. This combination of supply and demand effects are generally categorized into the seven sources of congestion. These factors interact in the formation of congestion, and the relative importance of any one of these factors varies from location to location.

In many rural areas, demand is routinely low relative to roadway capacity. Consequently, delay only happens when major disruptions occur, usually as a result of bad weather (e.g., snow), a major traffic incident, or reductions in roadway capacity due to road construction and maintenance activities.

In other rural areas, especially those that experience recreational traffic flows, large and somewhat predictable surges of traffic demand create traffic congestion during times of peak demand. Similarly, in suburban and urban areas, traffic flows associated with work and other common activities often reach levels that typically push traffic demand beyond available roadway capacity, creating routine congestion. In both of these cases, a large percentage increase in congestion can occur on top of the existing base congestion as a result of a disruption in roadway operations, especially when that disruption occurs during times of high traffic volumes.

Lastly, in larger urban areas, traffic can routinely exceed roadway capacity for many hours each work day. In these areas, numerous roads operate near capacity for many additional hours of the day. Disruptions on these roads can add large amounts of delay, but that added delay may be only a modest percentage increase in total annual delay. In simple terms, routine congestion already may have slowed traffic, so that a fender-bender in the existing queue slows vehicles only a little more because they already are moving slowly.

The 42 directional roadway sections studied in this analysis all experienced at least some routine congestion in either the a.m. or p.m. peak periods. Many sections experienced routine congestion during only one of the peak periods, but a number of the sections experienced significant congestion in both peaks, as well as periodic congestion in the middle of the day.

Table 5.13 summarizes the amount of delay influenced by each type of disruption tracked in this study. Delay was calculated for each 5-minute time interval of 2006 for each roadway segment in units of vehicle seconds as follows:

$$\text{delay} = (\text{actual travel time} - \text{travel time at the speed limit}) \\ * (\text{roadway segment volume})$$

The percentage of delay was computed by totaling all vehicle hours of delay in the region associated with each type of disruption, and then dividing by the sum of all measured delays. When more than one disruption occurred simultaneously, the resulting delay was credited to all of the associated causes. Thus the sum of the percentages in Table 5.13 exceeds 100%.

Taken at face value, this simple summary table supports the commonly heard statement that "incidents and crashes cause between 40% and 60% of all delay." In reality, the

Table 5.13. Percentage of Delay by Type of Disruption Influencing Congestion Duration and Severity

Type of Disruption	Delay (%)
Incidents	38.5
Crashes	19.5
Bad weather (rain)	17.7
Construction[a]	1.2
No cause indicated (mostly volume)	42.2

[a] Construction delay was computed only when construction work actively took place along the roadway and did not include any delays caused because general roadway capacity was reduced as a result of temporarily narrowed or reconfigured lanes.

amount of delay caused by incidents was actually less than that indicated in Table 5.13 because a considerable portion of the incident- and crash-associated delay was caused by large traffic volumes. There were numerous examples in the analysis data set of significant crashes and other incidents that caused little or no congestion because of when they occurred. These examples showed that without sufficient volume, an incident causes no measurable change in delay.

Travel Time Impacts Caused by Disruptions

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse. Figure 5.15 illustrates the interwoven effects of incidents, bad weather, and traffic volumes on travel times on I-5 northbound heading toward downtown Seattle. This graphic shows that congestion formed only as traffic volumes peaked. It also shows that the resulting congestion reduced observed throughput while increasing travel times. In addition, it illustrates how all types of disruptions to normal roadway performance (rain, crashes, noncrash incidents) caused congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times.

Incidents and other disruptions also can cause congestion to form during times of the day that are normally free from congestion, but only when the disruption lowers functional capacity below traffic demand. Thus, as seen in Figure 5.15, minor disruptions such as rain or noncrash incidents on this section of I-5 did not cause congestion in the midday or the evening peak period (in the off-peak direction). For this four-lane freeway section, enough unused capacity exists during those periods that modest disruptions to roadway capacity did not cause congestion, although some crashes caused sufficient disruption to create congestion during these off-peak periods. Late at night, because construction activity was taking place along this roadway segment, even smaller incidents (combined with those construction lane closures) caused congestion to form.

Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion. Disruptions then significantly increase the delay that the basic volume condition creates.

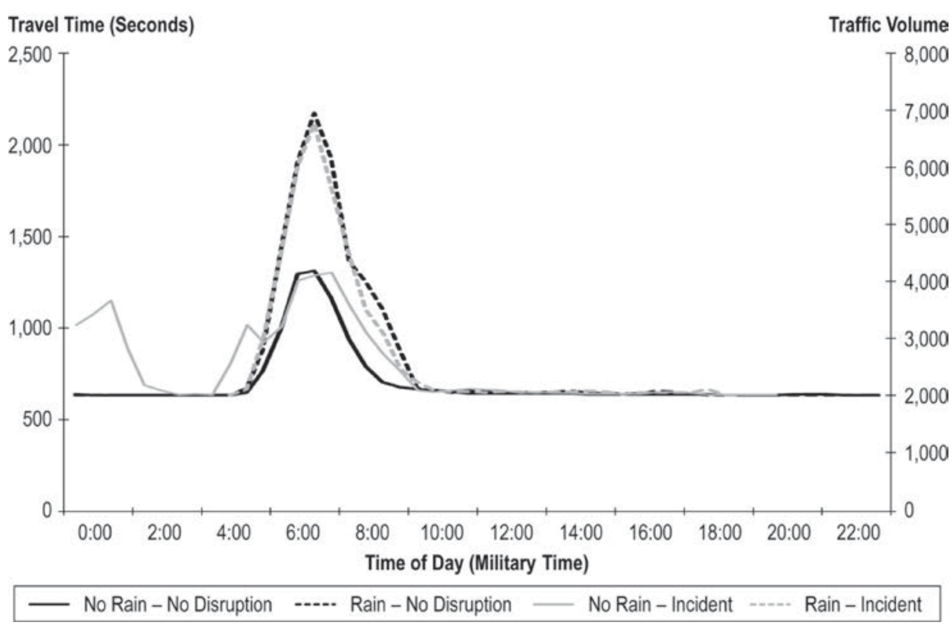

Figure 5.15. Effect of disruptions and traffic volume on travel time on I-5, northbound South section.

Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions had a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite was true. In the afternoon, as Figure 5.16 shows, disruptions began to cause greater travel time changes well before the start of the traditional peak period. However, most congestion ended very close to when congestion under no rain-no disruption conditions would have occurred. The effects of late-night crashes can be seen in the graph.

The volume lines in Figures 5.15 and 5.16 explain the discrepancies in the end times of the a.m. and p.m. peak congestion. Very early in the a.m. peak period, insufficient volume exists to cause congestion to form. Once volumes grow and congestion occurs, disruptions (incidents or rain) make that congestion worse. Because midday volumes are still fairly high, residual queues can take a long time to clear.

In the p.m., those same fairly high midday volumes (especially for corridors experiencing peak direction movements) mean that even small disruptions are likely to cause congestion before the normal start of the p.m. peak period. However, even though queues grow larger than usual during those peak periods, the sharp decline in traffic volumes at the end of the p.m. peak means that as long as the disruption has been cleared, those queues tend to dissipate quickly at the end of the peak period.

Although results varied dramatically between study sections, if the results of all 42 study sections are simply averaged, a crash occurring during the a.m. peak period adds an average of 2 hours and 17 minutes to the duration of the morning's peak period congestion. In the p.m. peak, a crash adds only adds 33 minutes to the time when congestion normally can be expected to clear. Similarly, a noncrash incident adds 1 hour and 14 minutes to the morning peak, but in the p.m. only 10 minutes are added to the time that congestion can be expected to last.

As seen in Figure 5.15, travel times also generally increased within the peak period when disruptions occurred to normal freeway flow. If the peak period is held constant (6:30 to 9:30 a.m. for the morning peak and 3:00 to 7:00 p.m. for the evening peak), average travel times during those periods increased when a crash or noncrash incident occurred on a roadway segment. Morning travel times increased by 17% in corridors that experienced even modest a.m. peak period congestion when noncrash incidents occurred. Noncrash incidents increased p.m. travel times an average of 21% on corridors that experienced any routine increase in p.m. peak travel. In both the a.m. and p.m. peaks, crashes added roughly 40% to the expected travel times.

These effects varied significantly from corridor to corridor, depending on the nature of the traffic volumes and routine congestion patterns. They also changed dramatically within any given corridor on the basis of the size, duration, and timing of the disruption. Interestingly, 80th and 95th percentile travel times were less affected by noncrash incidents, but crashes generally had significant impacts on both of these performance measures. This is not surprising because

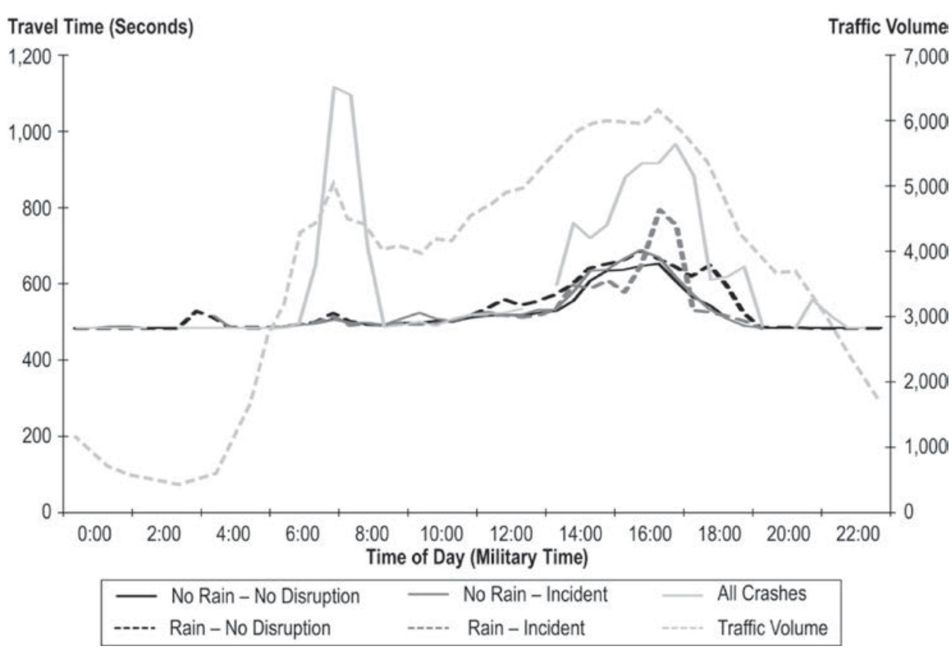

Figure 5.16. Effect of disruptions and traffic volume on travel time on I-5, northbound Lynnwood section.

noncrash incidents tend to be smaller disruptions, and consequently have less of an impact on those very bad days when congestion is at its worst. Crashes, however, are often one of the contributing factors to very bad commute days.

Summary

Analysis of 42 roadway segments in the Seattle area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions plays a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption can vary considerably from corridor to corridor.

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CHAPTER 6

Before-and-After Studies of Reliability Improvements

Introduction

The research team pursued an empirical approach to studying the determinants of reliability, and specifically, how reliability changes with improvements. Continuous travel time data are required for empirical studies of reliability, and the team was experienced with using these data on past projects. A great deal of continuous travel time data is collected by public agencies (i.e., traffic management centers [TMCs]). Technically, TMC data are almost exclusively speed, volume, and lane occupancy measurements from roadway-based detectors, but if the detectors are closely spaced (half a mile or less), travel times can be reasonably estimated from them. Even if the resulting travel time estimates are off the true value, the variability (used to define reliability) would still be internally consistent. Further, relative (percentage) changes are likely to be in line with perfectly and continuously measured distance-based travel times, a standard that has not yet been achieved in practice. Continuous travel time data are an absolute requirement for empirical studies of reliability because reliability is defined by how travel times vary over a considerable time span. Exploratory research revealed that a minimum of 6 months of data is necessary for urban freeways where winter weather is not a problem; more data are needed where winter weather causes problems on a significant number of days. The team strove for a complete year's worth of data in developing reliability patterns, and achieved this in all but a few cases.

Because of the need to obtain traffic data of the highest quality that considered moderately to severely congested locations, the research team did not initially seek locations that were candidates for before-and-after studies. Rather, the team first sought data from locations known from previous experience to satisfy the project requirements and then looked for before-and-after improvements in these areas. Fortunately, 17 before-and-after instances were identified at the study locations. These instances covered only a few types of reliability improvements, which the team knew from the beginning would be difficult to cover completely. This known difficulty resulted in the reliance on statistical model development specified in the original work plan. The types of improvements studied were

- Ramp metering (four locations);
- Incident management large-truck rapid clearance policies (two locations);
- Freeway service patrol implementation (two locations);
- High-occupancy toll lane conversion (one location); and
- Capacity additions and bottleneck improvements (eight locations).

Previous work by members of the research team provided preliminary insight into what could be expected from the before-and-after tests (*1*). In a hypothetical experiment, travel time data for a complete year on a heavily congested section of I-75 in Atlanta were used. From the travel time distribution, all of the abnormally high travel times (those greater than 7 minutes for the 4.05-mile corridor) were artificially reduced by an across-the-board 25%. This reduction was made to simulate the results of a wide variety of possible improvements on travel times, including capital improvements and operations strategies targeting the events that cause higher-than-normal travel times. As shown in Figure 6.1 and Table 6.1, the effect of this hypothetical before-and-after condition is to reduce delay and improve reliability.

Because the analysis reduced all higher-than-normal travel times (not just the travel times on days when disruptions occurred), the experiment is especially relevant for gauging the effects of capital improvements, which will improve travel times on all days, not just the ones with disruptions. The results show that such strategies will improve both the average travel time and reliability.

Another previous study by members of the team developed predictive models for recurring and incident delay using a stochastic modeling approach (*2*). In this approach, a simple test link was used in conjunction with a queuing model to estimate the total delay caused by congestion on the link. Both demand volumes and incident characteristics were

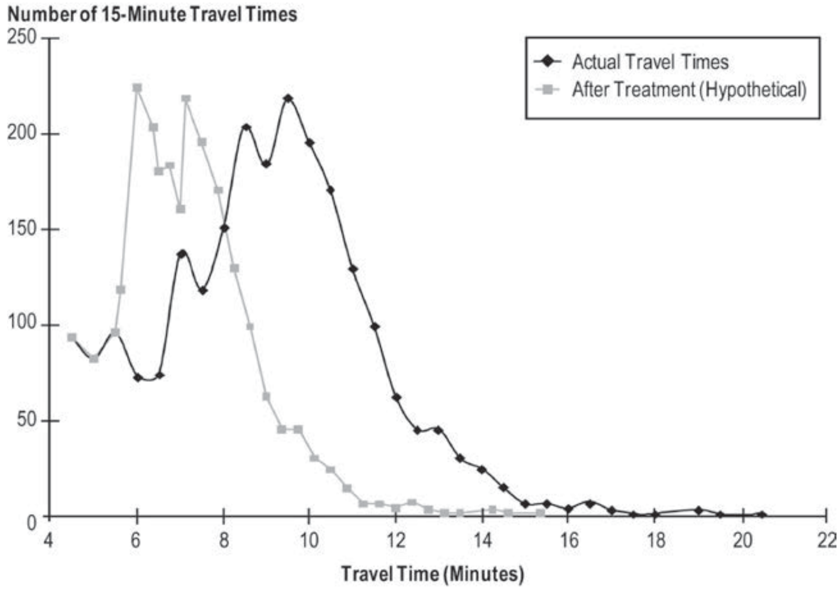

Figure 6.1. Actual and (hypothetical) improved peak period travel times on I-75 southbound in central Atlanta, 2002 (1).

allowed to vary stochastically; basically, this was a Monte Carlo simulation that for any given run determined whether an incident occurred and if it did, what its lane blocking and duration characteristics were. A series of equations were fit to the results of the Monte Carlo simulation. The results showed that both recurring and incident delay are positively correlated with the annual average daily traffic (AADT)-to-capacity (AADT/C) ratio (Table 6.2). Note that the units used to define delay in Table 6.2 differ because recurring delay is a function of the number of vehicles trying to get through a bottleneck, and incident delay is a function of both number of vehicles and section length; longer sections will have more incidents.

Results

A full description of the before-and-after analyses is given in Appendix B. A review of the results in Appendix B shows that the Buffer Index is an unstable indicator of changes in reliability, sometimes showing an increase, sometimes a decrease, even when average congestion has decreased. The instability of the Buffer Index is consistent with the results presented in Chapter 4. As a result, the team chose the Planning Time Index (95th percentile travel time divided by free-flow travel time) to be the primary reliability metric. A summary of the findings appears in Table 6.3, and complete findings are shown in Appendix B. In nearly all cases, the improvements studied proved to be beneficial for both average congestion and reliability. The increases in two cases in Minneapolis–St. Paul may be the result of data problems or major shifts in travel patterns in the after condition. The evaluation of adaptive ramp metering on I-210 is ongoing as the system continues to be refined, but the first results showed that algorithms were not operating as expected. Given the results from all of the sections showing positive effects on both average congestion and reliability, the team does not recommend use of the

Table 6.1. Hypothetical Case of Treating Unreliable Travel Times on Southbound I-75 in Central Atlanta, 4:00 to 7:00 P.M. (1)

Travel Time Measure	Observed Travel Times	Abnormally High Travel Times Reduced by 25%
Average travel time (min)	9.0	7.1
95th Percentile (min)	13.1	9.8
Buffer Time Index	46%	39%

Table 6.2. Model-Developed Relationship Between AADT/C and Delay (2)

AADT/C	Recurring Delay Due to Queues (h/vehicle)	Incident Delay (h/vehicle mile)
8	0.0000	0.0011
9	0.0086	0.0019
10	0.0271	0.0029
11	0.0551	0.0042
12	0.0924	0.0056
13	0.1389	0.0072
14	0.1942	0.0088

Table 6.3. Summary of Urban Freeway Before and After Studies

No.	Urban Area	Highways Covered	Improvement	Reliability Impacts (Peak Period)
1	Los Angeles	I-210	Ramp metering: design, field implementation, and evaluation of new advanced on-ramp control algorithms on westbound direction of I-210.	Slight increases in average travel time and Planning Time Index (PTI) were observed. However, subsequent to this evaluation, the algorithms have been adjusted.
2	San Francisco Bay Area	I-580	Ramp metering.	22% reduction in average travel time. 20% reduction in PTI.
3	Seattle	SR 520	Ramp metering.	11% reduction in average travel time. 12% reduction in PTI.
4	Atlanta	I-285, Northern Arc	Ramp metering.	9% reduction in average travel time. 7% reduction in PTI. 3% increase in sustainable service rate.
5	Atlanta	All freeways inside beltway perimeter	Incident management: incentive program for reducing large-truck crash incident duration (90 minutes).	13% reduction in large-truck crash incident duration. 9% reduction in lane hours lost per large-truck crash.
6	Los Angeles	I-710	Incident management: evaluation of pilot project to deploy towing service for big-rig tractor trailers.	10% reduction in average travel time. 20% reduction in PTI.
7	San Diego	I-8	Incident management: expansion of the existing Freeway Service Patrol Beat-7 on I-8.	3% reduction in average travel time. 4% reduction in PTI.
8	San Diego	SR 52	Incident management: expansion of the existing Freeway Service Patrol.	20% reduction in average travel time. 10% reduction in PTI.
9	Minneapolis–St. Paul	I-94	Capacity expansion: add third lane in each direction.	43% reduction in average travel time. 46% reduction in PTI.
10	Minneapolis–St. Paul	I-494	Capacity expansion: add third lane in each direction.	31% reduction in average travel time. 16% reduction in PTI.
11	Minneapolis–St. Paul	I-394	Capacity expansion: add auxiliary lanes westbound.	35% reduction in average travel time. 38% reduction in PTI.
12	Minneapolis–St. Paul	Highway 169	Capacity expansion: convert signalized intersections to diamond interchanges.	16% increase in average travel time. 11% reduction in PTI.
13	Minneapolis–St. Paul[a]	Highway 100	Capacity expansion: add third lane northbound. Add auxiliary lane southbound. Convert Highway 7 interchange from a clover leaf to a folded diamond.	20% reduction in average travel time. 30% increase in PTI.
14	Seattle	I-405 Southbound	Capacity expansion: addition of one general-purpose lane.	11% reduction in average travel time. 11% reduction in PTI.
15	Seattle	I-405 Northbound	Capacity expansion: addition of one general-purpose lane.	42% reduction in average travel time. 35% reduction in PTI.
16	Seattle	I-405–SR 167 Interchange	Capacity expansion: grade separation ramp connecting southbound I-405 off-ramp with southbound SR 167 on-ramp.	20% reduction in average travel time. 23% reduction in PTI.
17	Minneapolis–St. Paul	I-394	High-occupancy toll lane conversion.	8% reduction in average travel time. 30% reduction in PTI.

[a] This long (16-mile) study segment was influenced by a downstream bottleneck.

two Minneapolis studies and the I-210 study in user applications.

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CHAPTER 7

Cross-Sectional Statistical Analysis of Reliability

Potential Model Forms

Background

The primary goal of the statistical analysis was to produce a highly practical set of relationships that could be used to predict reliability, especially within the contexts of existing technical applications such as travel demand forecasting models and simulation models. The Phase 1 report proposed two model forms to be investigated: (*a*) a detailed deterministic model that uses all the data being collected to the maximum degree (data-rich model) and (*b*) a simpler model reflecting the fact that many of the applications (e.g., *Highway Capacity Manual* [HCM] and travel demand forecasting models) work in an environment with limited data (data-poor model). The first model will reveal a deep understanding of reliability and its causal factors; the second makes the relationships operational for many applications.

It should be pointed out that the model forms are aimed at predicting reliability, which is based on summarizing travel times that occur over the course of a year. So, every observation in the analysis data set represents summarized conditions for a study section for a year. The statistical models are not designed to predict what a specific travel time will be given a set of conditions (e.g., volume, weather, and incident characteristics). Such prediction can be done with a variety of other analytic methods, such as microsimulation. Prediction or the probability of a specific travel time occurring is related to reliability, but predicting reliability metrics is not the purpose of this research. However, the microscale analysis done for the congestion by source analysis (Chapter 5) does get down to this level.

Data-Rich Model

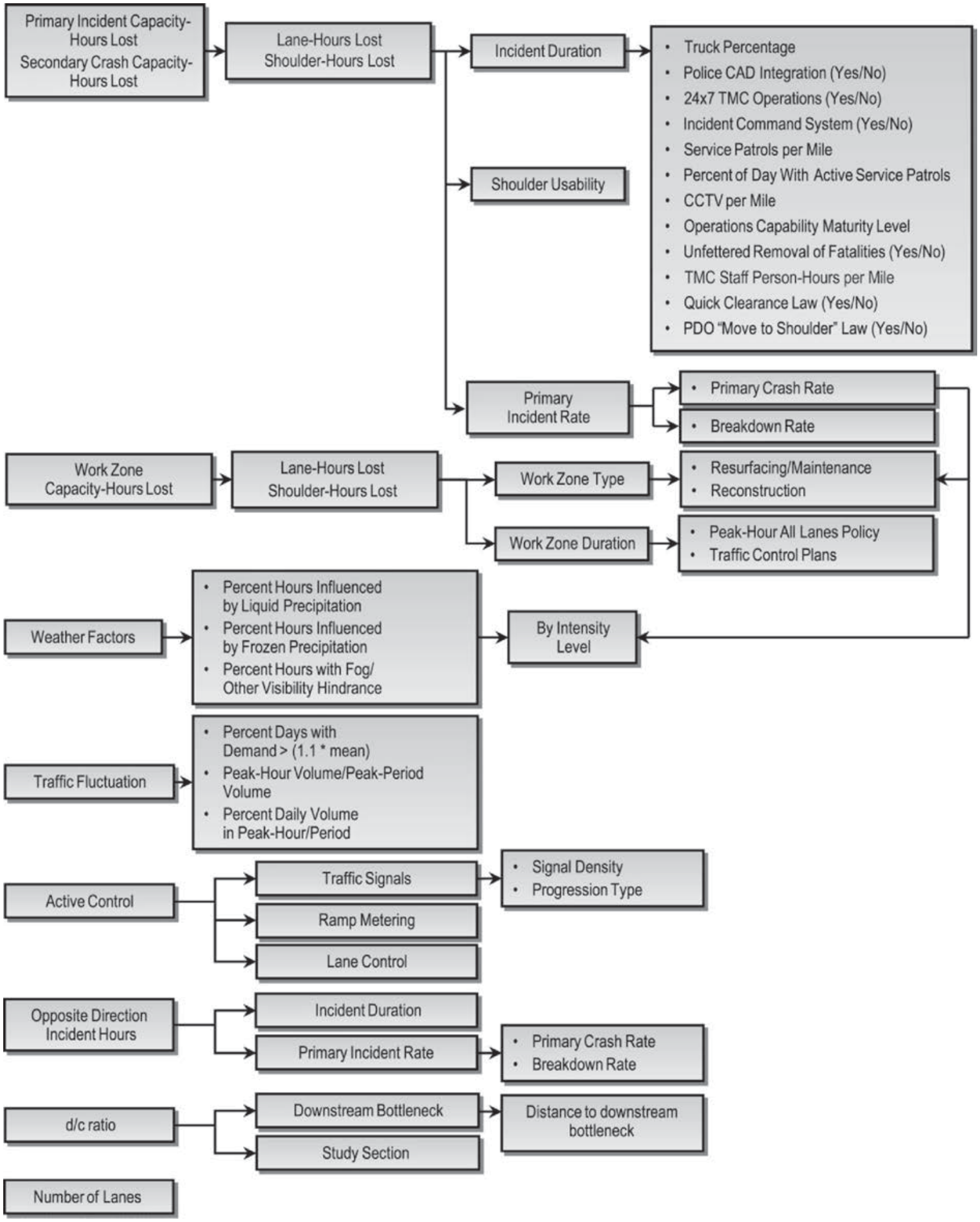
The data-rich model structure is mechanistic in nature; the factors (the mechanisms) that cause unreliable travel times were postulated based on the research team's past experience. It also is a tiered model in which the independent variables at lower levels (left side of the model chain) become dependent variables at higher levels. The key feature of this model structure is that improvements can be traced to a relatively small number of factors, which reduces the need to observe reliability changes in before-and-after experiments. As discussed earlier, to conduct before-and-after tests of all improvements would be cost prohibitive.

The structure of the data-rich deterministic (tiered) model is outlined in Figure 7.1 and explained below.

The data-rich model structure can be explained as a series of causal mechanisms that influence each other. Each tier is constructed so that the most immediate and direct influences (independent variables) are used to explain the effect of the dependent variable. For example, for the effects of incidents, it is postulated that incident-related reliability is most directly affected by the capacity hours lost (a combination of lane hours and shoulder hours lost because of blockages) due to incidents. The capacity hours lost attributable to incidents are directly affected (i.e., caused) by incident duration, the usability of shoulders, the incident rate, and so on.

In Figure 7.1, Reliability is equal to *f*{demand-to-capacity (d/c) ratio, distance to downstream bottleneck, number of lanes, primary incident capacity hours lost, secondary crash capacity hours lost, opposite direction incident hours (rubbernecking of incidents in the opposite direction by motorists in the study direction), work zone capacity hours lost, weather factors, traffic fluctuation, active control type}. Note that *capacity hours lost* is a way to combine lane hours lost and shoulder hours lost for incidents, as well as an approximation for the additional hours lost because of work-zone visual effects. This is not the measured capacity loss, but the straight translation of lanes and shoulders lost to HCM-based (theoretical) capacity. Measured capacity loss due to incidents will be greater.

Reliability is measured by one of the metrics in Chapter 2; for d/c ratio, demand is measured as the average for the time



Notes: 1) "⟶" means "...is a function of..."
2) Primary Incident and Secondary Crash hours lost are modeled similarly.

Figure 7.1. Variables and tiered structure for the mechanistic (data-rich) model.

slice under study, and capacity is physical (HCM) capacity. The d/c ratio should be estimated as the average for the study section or, alternatively, the critical (highest) d/c ratio for the links on the study section.

An explanation of the some of the other factors in Figure 7.1 follows:

- Incident capacity hours lost = *f*{incident duration, primary incident rate, shoulder usability}. Lane hours lost may be used instead of capacity hours lost because it can be measured directly; capacity is a transformed measure as it requires using analytic methods to calculate.
  - Duration = *f*{equipment, incident management policies, truck percentage}. Truck percentage is used as a surrogate to capture the different types of incidents that can occur (lateral locations, blockages).
  - Primary incident rate = *f*{primary crash rate breakdowns}. It was not the research team's intent to conduct a detailed safety analysis yielding a predictive relationship for accident (crash) rate. Crash reduction factors recently compiled by FHWA can be used to trace the impacts of safety-related geometric improvements through to changes in reliability (*1*).
  - Shoulder usability is the presence of a shoulder wide enough to store vehicles involved in a minor crash or breakdown.
- Opposite direction incident hours = *f*{incident duration, incident rate} (for the opposite direction of travel).
  - Duration = *f*{equipment, incident management policies, truck percentage}.
  - Primary incident rate = *f*{primary crash rate, breakdowns}.
- Work zone capacity hours lost = *f*{work zone type, work zone duration}.
  - Work zone duration = *f*{work zone management policies}.
- Weather factors = *f*{precipitation type, precipitation intensity, temperature, fog}.

Data-Poor Model

Originally, a model form using a combination of easily obtained data items was envisioned (Table 7.1). This simpler form would be compatible with many user applications for which detailed data are not available. However, during the course of the research, the team decided on a different strategy for the data-poor model. As discussed in the following section, it became apparent that all of the reliability metrics could be predicted as a function of mean travel time. This feature greatly simplifies the construction of the data-poor model and makes it compatible with most existing analytic methods.

Table 7.1. Original Independent Variables for the Data-Poor Model

Weather Variables
Same as for data-rich model form
Incident Variables
Annual collisions per million vehicle miles traveled
Proportion of fatal or injury collisions
Incident duration
Design and Control Variables
Design capacity
Speed limit
Average signal delay (if applicable)
Traffic management activities (e.g., ramp metering, freeway service patrol)
Demand Variables
Hourly, weekly, seasonal demand profile over course of year

Relationship Between Mean Travel Time and Reliability Metrics

Link Level: Urban Freeways

Exploratory Research

All travel demand models and traffic operations models can predict mean speeds of traffic and, therefore, mean travel time rates. With the mean travel time rate (minutes per mile) and the predicted 95% travel time rate, one then can compute the Buffer Index. An analysis was undertaken with a small data set to develop equations for predicting the 95% travel time rate as a function of the mean travel time rate.

The equations were developed for the weekday peak periods for two freeway corridors:

1. San Mateo SR 101 freeway between I-280 in San Francisco and SR 114 in Palo Alto, California, a distance of 27 miles; and
2. Alameda I-238 and I-580 freeways between I-238 in San Leandro and I-205 in Tracy, California, a distance of 33 miles.

Nineteen days of toll tag vehicle travel time data were collected for San Mateo SR 101 during the hours of 6:00 to 10:00 a.m. and 2:30 to 7:30 p.m. each weekday (excluding holidays) between January 5 and January 31, 2009, for four directional segments ranging from 10.8 to 15.9 miles in length. Sample sizes ranged between 8,500 and 19,200 toll tag–equipped vehicles for each direction for each peak period.

Table 7.2. San Mateo SR 101 Reliability Data

Segment	Stretch	Length (mi)	Peak Period	Mean (min)	Standard Deviation (min)	95th Percentile	Buffer Index (%)	Sample Size
SR 101 northbound	Palo Alto (SR 114) to SR 92	10.75	6:00 to 10:00 a.m.	38.4	31.2	132.2	244	8,598
SR 101 northbound	Palo Alto (SR 114) to SR 92	10.75	2:30 to 7:30 p.m.	27.8	15.2	73.5	164	19,145
SR 101 southbound	SR 92 to Palo Alto (SR 114)	10.75	6:00 to 10:00 a.m.	36.3	29.4	124.6	243	17,321
SR 101 southbound	SR 92 to Palo Alto (SR 114)	10.75	2:30 to 7:30 p.m.	26.0	18.9	82.8	219	9,864
SR 101 northbound	SR 92 to I-280	15.85	6:00 to 10:00 a.m.	46.5	29.8	136.0	193	9,395
SR 101 northbound	SR 92 to I-280	15.85	2:30 to 7:30 p.m.	33.5	24.6	107.2	220	10,696
SR 101 southbound	I-280 to SR 92	15.85	6:00 to 10:00 a.m.	48.9	34.5	152.5	212	17,679
SR 101 southbound	I-280 to SR 92	15.85	2:30 to 7:30 p.m.	44.6	22.8	113.1	154	13,108

Eight data points on reliability were obtained. A data point consisted of mean, standard deviation, and 95th percentile travel time measurements for each direction of travel on each segment for each peak period. The data for San Mateo SR 101 are given in Table 7.2. Figure 7.2 shows the regression curves fitted to the data.

Sixteen days of toll tag vehicle travel time data were collected for Alameda I-238 and I-580 during the hours of 5:00 to 9:00 a.m. and 2:30 to 7:30 p.m. each weekday (excluding holidays) between May 2 and May 23, 2008, for six directional segments ranging from 2 to 21 miles in length. Twelve data points on reliability were obtained. The data for Alameda I-238 and I-580 are given in Table 7.3. Figure 7.3 shows the regression curves fitted to the data. Figure 7.4 shows the combined Alameda and San Mateo freeway reliability relationships.

The results for this exploratory research were very encouraging. They implied that prediction of the reliability metrics could be based on the mean travel time. This led the team to

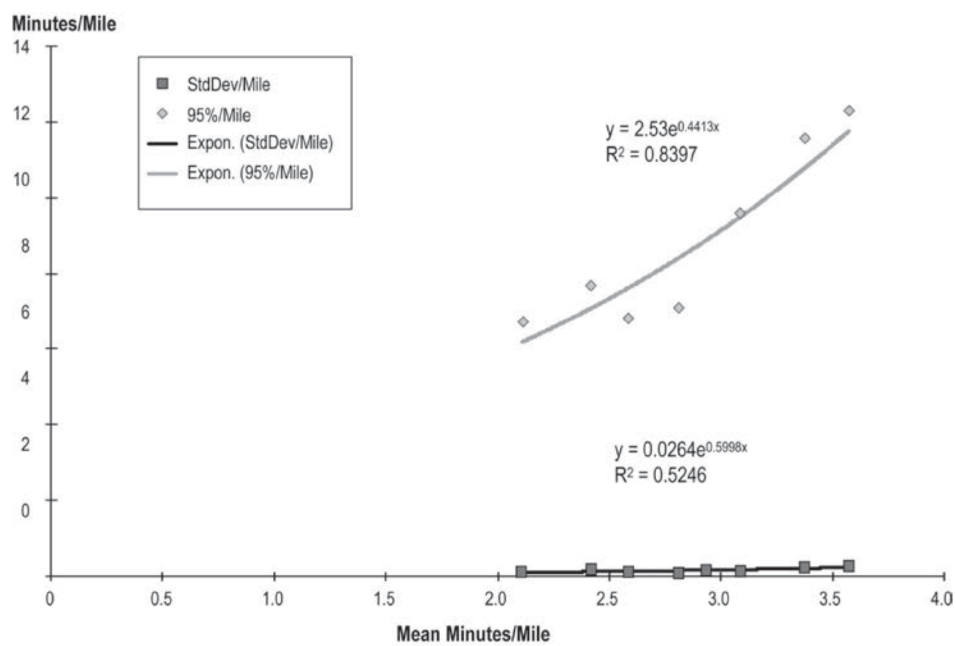


Figure 7.2. Reliability relationships for San Mateo SR 101 for weekday a.m. and p.m. peak periods, January 5 to January 31, 2010.

Table 7.3. Reliability Data for Alameda I-238 and I-580

Segment	Stretch	Length (mi)	Peak Period	Mean (min)	Standard Deviation (min)	95% Percentile	Buffer Index (%)
I-238 westbound	I-580 to I-880	2	5:00 to 9:00 a.m.	4.3	0.8	6.6	55
I-238 westbound	I-580 to I-880	2	2:30 to 7:30 p.m.	4.4	2.4	11.7	164
I-238 eastbound	I-880 to I-580	2	5:00 to 9:00 a.m.	2.2	0.1	2.7	19
I-238 eastbound	I-880 to I-580	2	2:30 to 7:30 p.m.	3.2	10.0	33.0	947
I-580 eastbound	I-238 to I-680	10	5:00 to 9:00 a.m.	9.7	0.4	10.9	12
I-580 eastbound	I-238 to I-680	10	2:30 to 7:30 p.m.	11.2	2.9	19.8	77
I-580 westbound	I-680 to I-238	10	5:00 to 9:00 a.m.	10.1	1.3	14.1	40
I-580 westbound	I-680 to I-238	10	2:30 to 7:30 p.m.	9.3	0.5	10.7	15
I-580 eastbound	I-680 to I-205	21	5:00 to 9:00 a.m.	20.5	0.5	21.9	7
I-580 eastbound	I-680 to I-205	21	2:30 to 7:30 p.m.	27.3	4.4	40.5	48
I-580 westbound	I-205 to I-680	21	5:00 to 9:00 a.m.	29.4	6.2	48.0	63
I-580 westbound	I-205 to I-680	21	2:30 to 7:30 p.m.	21.4	0.6	23.3	9

examine both link-level and section-level predictive models using more complete data sets.

Final Link-Level Reliability Predictive Models

Data from 164 detector locations on the Atlanta study sections were analyzed. A detector is considered to represent conditions on a link, and a link on a freeway is between interchanges. The Travel Time Index (TTI) was computed separately for the peak and midday time periods and combined into a single data set to get data over a wide range of congestion conditions (see Appendix G for an explanation of how the TTI was calculated and interpreted). Figures 7.5 and 7.6 show the relationships between the mean and 95th percentile TTI and 80th percentile TTI, respectively, for the Atlanta study links. Linear, exponential, and logarithmic regression models were fit to these data; the exponential form was found to provide the best fit. The models were fit without an intercept

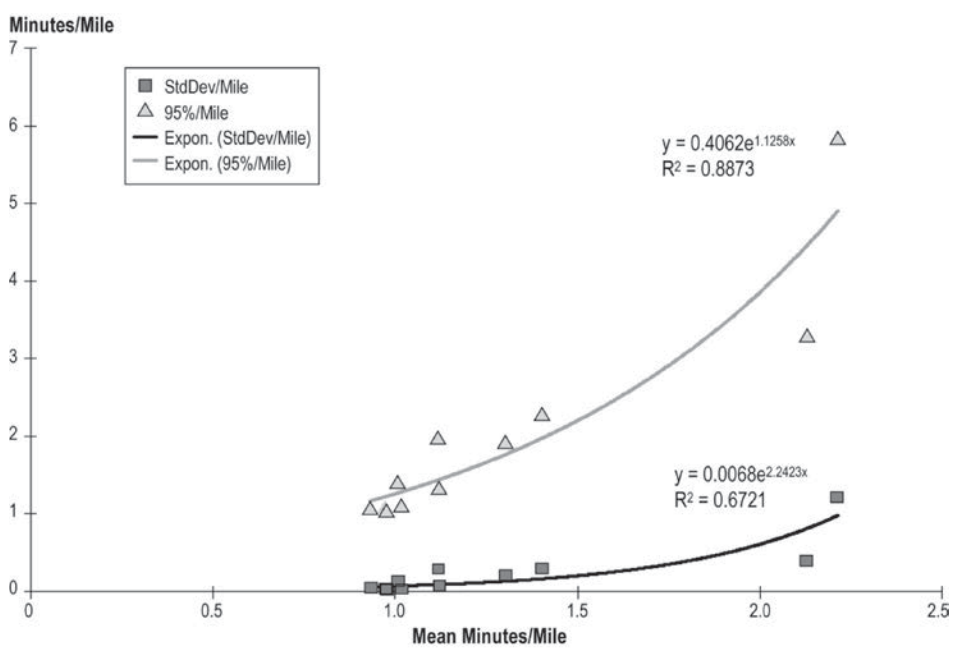


Figure 7.3. Reliability relationships for Alameda I-238 and I-580 for weekday a.m. and p.m. peak periods, May 2 to May 23, 2008.

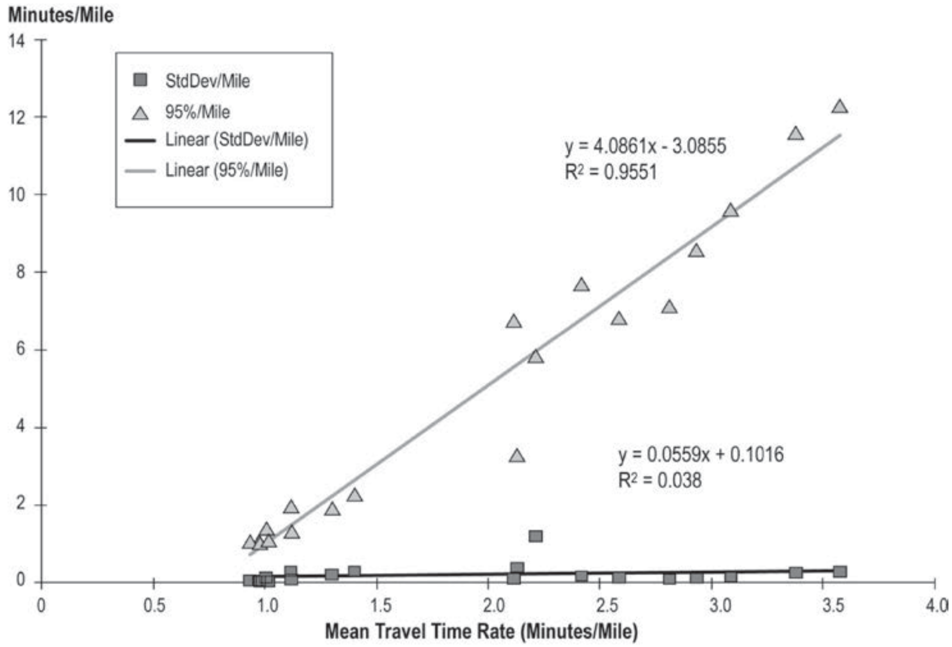


Figure 7.4. Combined travel time reliability data relationships (exploratory) for SR 101, I-238, and I-580.

term so that when the mean TTI is 1.0, the percentile values also will be 1.0. The lack of an intercept term means that the calculated R^2 values were not meaningful. Instead, root mean square error (RMSE) was used as the goodness-of-fit measure. RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data (i.e., how close the observed data points are to the model's predicted values). Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately a model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction, which is the aim here. The predictive equations are

$$\text{95th percentile TTI} = \text{mean TTI}^{1.6954}$$
$$(\text{RMSE} = 16.3\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.1)$$

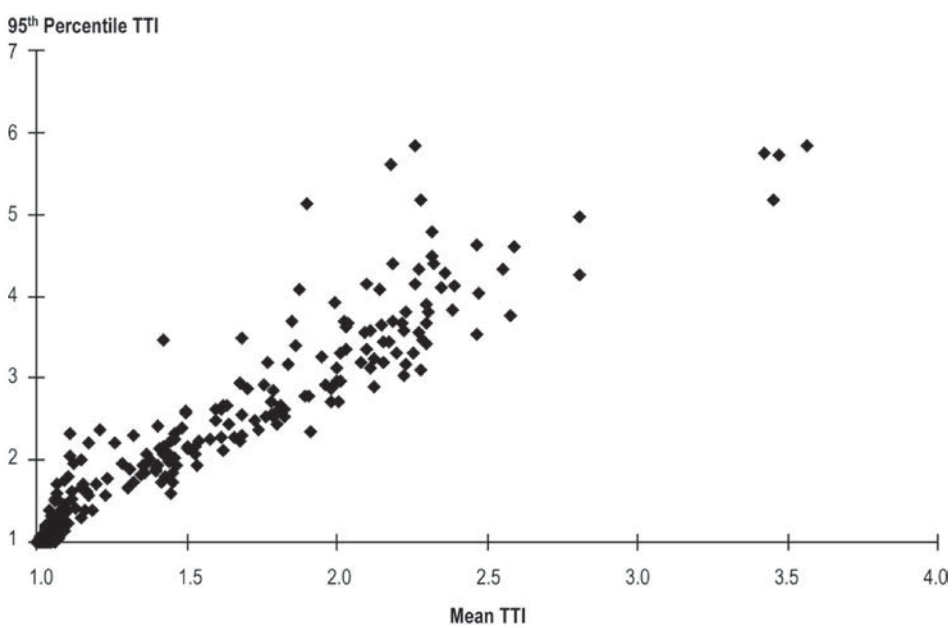


Figure 7.5. 95th percentile TTI versus mean TTI for Atlanta study links.

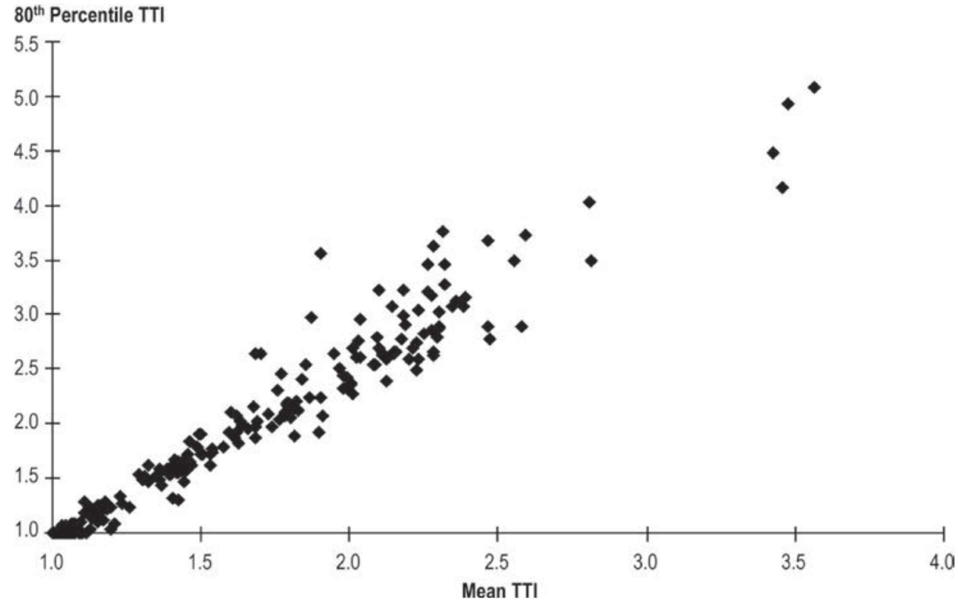


Figure 7.6. 80th percentile TTI versus mean TTI for Atlanta study links.

$$\text{80th percentile TTI} = \text{mean TTI}^{1.3162}$$

$$(\text{RMSE} = 7.4\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.2)$$

$$\text{standard deviation} = (\text{mean TTI} - 1)^{0.5231}$$

$$(\text{RMSE} = 60\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.3)$$

It is extremely important to note that in the data used to develop these equations, *mean TTI* is the grand (overall) mean; because it was developed from continuous detector data, it includes all of the possible influences on congestion (e.g., incidents and inclement weather). Almost all applications and models that predict mean travel time and speeds only consider recurring congestion. Therefore, an adjustment must be made to the recurring-only travel time so that it corresponds to the grand mean shown in Equations 6 through 8.

Data from the Atlanta and Seattle study sections were used to develop the recurring-only adjustment factor. For the peak period time slice, a simple assignment was made for each section: if either an incident or weather occurred on a particular day, the resulting TTI was considered to be nonrecurring. Otherwise it was assigned as recurring. The analysis showed that the nonrecurring TTI was 26.4% higher than the recurring TTI in Atlanta and 28.7% higher in Seattle. Table 7.4 presents the section-by-section data for Seattle and also demonstrates that, even though travel time variability (as measured by the standard deviation) is lower for disruption-free conditions, there still is a substantial amount of variability associated with recurring-only congestion.

The ratio of the overall mean to the recurring mean was also computed for the peak period; in Atlanta the overall mean TTI was 12.1% higher than the recurring-only TTI, and in Seattle it was 13.0% higher. Seattle data were also used to develop recurring-to-nonrecurring ratios for the midday and weekend time periods (Table 7.5). However, as noted in Chapter 5, the amount of nonrecurring delay depends very much on the base level or recurring delay, so applying percentages can be misleading. Therefore, the peak period, midday, and weekend and holiday results were pooled and a regression equation was developed:

$$\text{overall mean TTI} = 1.0274 * \text{recurring mean TTI}^{1.2204}$$

$$(R^2 = 0.910;\ \text{alpha level of coefficients} = 0.001 \text{ and } 0.0001,\ \text{respectively};\ n = 167) \quad (7.4)$$

where overall mean TTI is the mean TTI in the predictive equations, and recurring mean TTI is the mean TTI that considers recurring sources only.

Section Level: Urban Freeways

Data from urban freeway study sections in Atlanta, Minneapolis, Jacksonville, Los Angeles, Houston, and San Diego were used to develop relationships between a wider set of reliability metrics and mean TTI. The peak period and midday measurements were again combined to obtain a data set that had both congested and uncongested observations. The relationships for selected travel time metrics appear in Figures 7.7 through 7.14. Equations 10 through 20 below are the predictive equations. Note that the parameters necessary to compute the Buffer Index and skew statistic are estimated.

Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods

Section	Time of Peak	Congestion Type	TTI	
			Mean	**Standard Deviation**
I-405 Bellevue northbound	a.m.	Nonrecurring	1.418	0.422
		Recurring	1.215	0.252
		Total	**1.281**	**0.252**
I-405 Bellevue northbound	p.m.	Nonrecurring	1.672	0.800
		Recurring	1.206	0.274
		Total	1.346	0.274
I-405 Kennydale northbound	a.m.	Nonrecurring	4.405	1.699
		Recurring	3.198	1.480
		Total	**3.657**	**1.480**
I-405 Kennydale northbound	p.m.	Nonrecurring	1.347	0.517
		Recurring	1.130	0.212
		Total	**1.186**	**0.212**
I-405 Kennydale southbound	a.m.	Nonrecurring	1.915	0.686
		Recurring	1.427	0.395
		Total	**1.539**	**0.395**
I-405 Kennydale southbound	p.m.	Nonrecurring	2.200	0.975
		Recurring	1.730	0.579
		Total	**1.898**	**0.579**
I-405 Kirkland northbound	a.m.	Nonrecurring	1.017	0.055
		Recurring	1.009	0.016
		Total	**1.011**	**0.016**
I-405 Kirkland northbound	p.m.	Nonrecurring	2.120	0.788
		Recurring	1.712	0.677
		Total	**1.995**	**0.677**
I-405 Kirkland southbound	a.m.	Nonrecurring	1.917	0.535
		Recurring	1.574	0.450
		Total	**1.766**	**0.450**
I-405 Kirkland southbound	p.m.	Nonrecurring	1.161	0.303
		Recurring	1.032	0.097
		Total	**1.104**	**0.097**
I-405 North northbound	a.m.	Nonrecurring	1.065	0.095
		Recurring	1.039	0.082
		Total	**1.045**	**0.082**
I-405 North northbound	p.m.	Nonrecurring	1.687	0.454
		Recurring	1.550	0.414
		Total	**1.609**	**0.414**

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Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	Standard Deviation
I-405 North southbound	a.m.	Nonrecurring	3.534	1.879
		Recurring	2.254	1.320
		Total	**2.820**	**1.320**
I-405 North southbound	p.m.	Nonrecurring	1.239	0.558
		Recurring	1.084	0.220
		Total	**1.123**	**0.220**
I-405 South northbound	a.m.	Nonrecurring	1.320	0.526
		Recurring	1.222	0.210
		Total	**1.241**	**0.210**
I-405 South northbound	p.m.	Nonrecurring	2.810	1.008
		Recurring	2.420	0.719
		Total	**2.578**	**0.719**
I-405 South southbound	a.m.	Nonrecurring	1.566	0.736
		Recurring	1.425	0.433
		Total	**1.446**	**0.433**
I-405 South southbound	p.m.	Nonrecurring	1.807	0.981
		Recurring	1.447	0.497
		Total	**1.522**	**0.497**
I-5 Everett northbound	a.m.	Nonrecurring	1.053	0.344
		Recurring	1.015	0.090
		Total	**1.026**	**0.090**
I-5 Everett northbound	p.m.	Nonrecurring	2.253	1.337
		Recurring	1.483	0.895
		Total	**1.872**	**0.895**
I-5 Everett southbound	a.m.	Nonrecurring	1.306	0.734
		Recurring	1.072	0.280
		Total	**1.152**	**0.280**
I-5 Everett southbound	p.m.	Nonrecurring	1.167	0.416
		Recurring	1.069	0.192
		Total	**1.105**	**0.192**
I-5 Lynnwood northbound	a.m.	Nonrecurring	1.811	1.412
		Recurring	1.303	0.680
		Total	**1.443**	**0.680**
I-5 Lynnwood northbound	p.m.	Nonrecurring	1.483	0.717
		Recurring	1.171	0.345
		Total	**1.312**	**0.345**

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Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	**Standard Deviation**
I-5 Lynnwood southbound	a.m.	Nonrecurring	2.238	1.151
		Recurring	1.572	0.641
		Total	**1.898**	**0.641**
I-5 Lynnwood southbound	p.m.	Nonrecurring	1.246	0.719
		Recurring	1.069	0.118
		Total	**1.117**	**0.118**
I-5 North King northbound	a.m.	Nonrecurring	1.002	0.012
		Recurring	1.001	0.010
		Total	**1.001**	**0.010**
I-5 North King northbound	p.m.	Nonrecurring	1.935	0.543
		Recurring	1.572	0.541
		Total	**1.791**	**0.541**
I-5 North King southbound	a.m.	Nonrecurring	2.547	1.068
		Recurring	1.856	0.669
		Total	**2.068**	**0.669**
I-5 North King southbound	p.m.	Nonrecurring	1.749	1.327
		Recurring	1.089	0.401
		Total	**1.345**	**0.401**
I-5 Seattle CBD northbound	a.m.	Nonrecurring	2.036	0.775
		Recurring	1.328	0.358
		Total	**1.913**	**0.358**
I-5 Seattle CBD northbound	p.m.	Nonrecurring	2.110	0.845
		Recurring	1.365	0.409
		Total	**1.961**	**0.409**
I-5 Seattle CBD southbound	a.m.	Nonrecurring	1.181	0.307
		Recurring	1.070	0.094
		Total	**1.127**	**0.094**
I-5 Seattle CBD southbound	p.m.	Nonrecurring	1.852	0.487
		Recurring	1.420	0.349
		Total	**1.721**	**0.349**
I-5 Seattle North northbound	a.m.	Nonrecurring	1.020	0.041
		Recurring	1.016	0.037
		Total	**1.017**	**0.037**
I-5 Seattle North northbound	p.m.	Nonrecurring	1.913	0.843
		Recurring	1.525	0.905
		Total	**1.741**	**0.905**

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Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	Standard Deviation
I-5 Seattle North southbound	a.m.	Nonrecurring	2.721	1.611
		Recurring	1.484	0.812
		Total	**2.157**	**0.812**
I-5 Seattle North southbound	p.m.	Nonrecurring	3.044	1.654
		Recurring	1.385	0.749
		Total	**2.560**	**0.749**
I-5 South northbound	a.m.	Nonrecurring	2.008	0.771
		Recurring	1.554	0.577
		Total	**1.764**	**0.577**
I-5 South northbound	p.m.	Nonrecurring	1.020	0.111
		Recurring	1.005	0.049
		Total	**1.014**	**0.049**
I-5 South southbound	a.m.	Nonrecurring	1.005	0.043
		Recurring	1.003	0.047
		Total	**1.004**	**0.047**
I-5 South southbound	p.m.	Nonrecurring	2.038	0.780
		Recurring	1.426	0.522
		Total	**1.761**	**0.522**
I-5 Tukwila northbound	a.m.	Nonrecurring	1.826	0.765
		Recurring	1.213	0.235
		Total	**1.502**	**0.235**
I-5 Tukwila northbound	p.m.	Nonrecurring	1.243	0.425
		Recurring	1.017	0.031
		Total	**1.082**	**0.031**
I-5 Tukwila southbound	a.m.	Nonrecurring	1.077	0.338
		Recurring	1.034	0.195
		Total	**1.042**	**0.195**
I-5 Tukwila southbound	p.m.	Nonrecurring	1.353	0.487
		Recurring	1.116	0.273
		Total	**1.205**	**0.273**
I-90 Bellevue eastbound	a.m.	Nonrecurring	1.003	0.024
		Recurring	1.008	0.051
		Total	**1.007**	**0.051**
I-90 Bellevue eastbound	p.m.	Nonrecurring	1.221	0.598
		Recurring	1.097	0.211
		Total	**1.117**	**0.211**

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Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	Standard Deviation
I-90 Bellevue westbound	a.m.	Nonrecurring	1.570	0.601
		Recurring	1.216	0.241
		Total	**1.307**	**0.241**
I-90 Bellevue westbound	p.m.	Nonrecurring	1.509	1.058
		Recurring	1.026	0.214
		Total	**1.305**	**0.214**
I-90 Bridge eastbound	a.m.	Nonrecurring	1.208	0.366
		Recurring	1.138	0.255
		Total	**1.190**	**0.255**
I-90 Bridge eastbound	p.m.	Nonrecurring	1.592	0.624
		Recurring	1.143	0.280
		Total	**1.414**	**0.280**
I-90 Bridge westbound	a.m.	Nonrecurring	1.373	0.435
		Recurring	1.116	0.238
		Total	**1.159**	**0.238**
I-90 Bridge westbound	p.m.	Nonrecurring	2.233	1.022
		Recurring	1.551	0.748
		Total	**1.739**	**0.748**
I-90 Issaquah eastbound	a.m.	Nonrecurring	1.000	0.008
		Recurring	1.001	0.017
		Total	**1.001**	**0.017**
I-90 Issaquah eastbound	p.m.	Nonrecurring	1.049	0.121
		Recurring	1.016	0.052
		Total	**1.023**	**0.052**
I-90 Issaquah westbound	a.m.	Nonrecurring	2.005	0.863
		Recurring	1.380	0.485
		Total	**1.476**	**0.485**
I-90 Issaquah westbound	p.m.	Nonrecurring	1.010	0.025
		Recurring	1.016	0.038
		Total	**1.015**	**0.038**
I-90 Seattle eastbound	a.m.	Nonrecurring	2.582	1.495
		Recurring	1.824	1.124
		Total	**1.957**	**1.124**
I-90 Seattle eastbound	p.m.	Nonrecurring	2.185	1.610
		Recurring	1.294	0.760
		Total	**1.432**	**0.760**

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Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	Standard Deviation
I-90 Seattle westbound	a.m.	Nonrecurring	1.423	0.527
		Recurring	1.095	0.288
		Total	**1.210**	**0.288**
I-90 Seattle westbound	p.m.	Nonrecurring	1.192	0.199
		Recurring	1.118	0.132
		Total	**1.140**	**0.132**
SR 167 Auburn northbound	a.m.	Nonrecurring	1.893	0.622
		Recurring	1.627	0.573
		Total	**1.685**	**0.573**
SR 167 Auburn northbound	p.m.	Nonrecurring	1.094	0.181
		Recurring	1.058	0.058
		Total	**1.067**	**0.058**
SR 167 Auburn southbound	a.m.	Nonrecurring	1.148	0.731
		Recurring	1.060	0.299
		Total	**1.072**	**0.299**
SR 167 Auburn southbound	p.m.	Nonrecurring	2.487	1.280
		Recurring	1.739	0.878
		Total	**1.961**	**0.878**
SR 167 Renton northbound	a.m.	Nonrecurring	1.802	1.124
		Recurring	1.325	0.356
		Total	**1.624**	**0.356**
SR 167 Renton northbound	p.m.	Nonrecurring	1.244	0.465
		Recurring	1.032	0.106
		Total	**1.172**	**0.106**
SR 167 Renton southbound	a.m.	Nonrecurring	1.060	0.063
		Recurring	1.055	0.064
		Total	**1.056**	**0.064**
SR 167 Renton southbound	p.m.	Nonrecurring	2.163	1.054
		Recurring	1.423	0.541
		Total	**1.637**	**0.541**
SR 520 Redmond eastbound	a.m.	Nonrecurring	1.017	0.053
		Recurring	1.010	0.014
		Total	**1.011**	**0.014**
SR 520 Redmond eastbound	p.m.	Nonrecurring	2.148	0.951
		Recurring	1.595	0.483
		Total	**1.869**	**0.483**

(continued on next page)

Table 7.4. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections During Peak Periods (continued)

Section	Time of Peak	Congestion Type	TTI	
			Mean	Standard Deviation
SR 520 Redmond westbound	a.m.	Nonrecurring	1.088	0.271
		Recurring	1.022	0.119
		Total	**1.037**	**0.119**
SR 520 Redmond westbound	p.m.	Nonrecurring	1.764	1.307
		Recurring	1.163	0.628
		Total	**1.498**	**0.628**
SR 520 Seattle eastbound	a.m.	Nonrecurring	1.967	0.687
		Recurring	1.555	0.526
		Total	**1.695**	**0.526**
SR 520 Seattle eastbound	p.m.	Nonrecurring	1.632	0.595
		Recurring	1.370	0.378
		Total	**1.483**	**0.378**
SR 520 Seattle westbound	a.m.	Nonrecurring	1.843	0.780
		Recurring	1.353	0.487
		Total	**1.509**	**0.487**
SR 520 Seattle westbound	p.m.	Nonrecurring	3.004	1.003
		Recurring	2.370	0.994
		Total	**2.722**	**0.994**
I-405 Bellevue southbound	a.m.	Nonrecurring	1.311	0.545
		Recurring	1.130	0.587
		Total	**1.169**	**0.587**
I-405 Bellevue southbound	p.m.	Nonrecurring	4.163	1.562
		Recurring	2.006	0.975
		Total	**3.731**	**0.975**
I-405 Eastgate northbound	a.m.	Nonrecurring	1.798	0.445
		Recurring	1.616	0.456
		Total	**1.667**	**0.456**
I-405 Eastgate northbound	p.m.	Nonrecurring	1.104	0.283
		Recurring	1.042	0.124
		Total	**1.058**	**0.124**
I-405 Eastgate southbound	a.m.	Nonrecurring	1.228	0.901
		Recurring	1.035	0.189
		Total	**1.064**	**0.189**
I-405 Eastgate southbound	p.m.	Nonrecurring	3.048	1.265
		Recurring	2.581	0.786
		Total	**2.728**	**0.786**
	Total Nonrecurring	**1.733**		
	Total Recurring	**1.347**		
	Overall Total	**1.522**		

Table 7.5. Recurring, Nonrecurring, and Total TTIs for Seattle Study Sections on Midday Periods and Weekends and Holidays

Time Period	Congestion Type	TTI
Midday	Recurring	1.121
	Nonrecurring	1.227
	Total	**1.153**
Weekend and Holiday	Recurring	1.034
	Nonrecurring	1.142
	Total	**1.058**

Note: Midday was defined in the Seattle analysis as from 9:00 a.m. to 3:00 p.m. Weekend and holiday excludes midnight to 4:00 a.m.

$$\text{95th percentile TTI} = \text{mean TTI}^{1.8834}$$

$$(\text{RMSE} = 15.7\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.5)$$

$$\text{90th percentile TTI} = \text{mean TTI}^{1.6424}$$

$$(\text{RMSE} = 9.4\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.6)$$

$$\text{80th percentile TTI} = \text{mean TTI}^{1.365}$$

$$(\text{RMSE} = 4.5\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.7)$$

$$\text{median TTI} = \text{mean TTI}^{0.8601}$$

$$(\text{RMSE} = 6.3\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.8)$$

$$\text{10th percentile TTI} = \text{mean TTI}^{0.1524}$$

$$(\text{RMSE} = 5.4\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.9)$$

$$\text{PctTripsOnTime10} = 1 - \left(0.4396 * [\text{mean TTI} - 1]^{0.4361}\right)$$

$$(\text{RMSE} = 8.4\%) \quad (7.10)$$

where PctTripsOnTime10 is the percentage of trips that occur below the threshold of 1.1 * median TTI.

$$\text{PctTripsOnTime25} = 1 - \left(0.2861 * [\text{mean TTI} - 1]^{0.5251}\right)$$

$$(\text{RMSE} = 7.5\%) \quad (7.11)$$

where PctTripsOnTime25 is the percentage of trips that occur below the threshold of 1.25 * median TTI.

$$\text{PctTripsOnTime50mph} = 1 - \left(0.8985 * [\text{mean TTI} - 1]^{0.6387}\right)$$

$$(\text{RMSE} = 18.0\%) \quad (7.12)$$

where PctTripsOnTime50mph is the percentage of trips that occur at space mean speeds above the threshold of 50 mph.

$$\text{PctTripsOnTime45mph} = 1 - \left(0.8203 * [\text{mean TTI} - 1]^{0.7692}\right)$$

$$(\text{RMSE} = 14.0\%) \quad (7.13)$$

where PctTripsOnTime45mph is the percentage of trips that occur at space mean speeds above the threshold of 45 mph.

$$\text{PctTripsOnTime30mph} = 1 - \left(0.4139 * [\text{mean TTI} - 1]^{1.5527}\right)$$

$$(\text{RMSE} = 4.4\%) \quad (7.14)$$

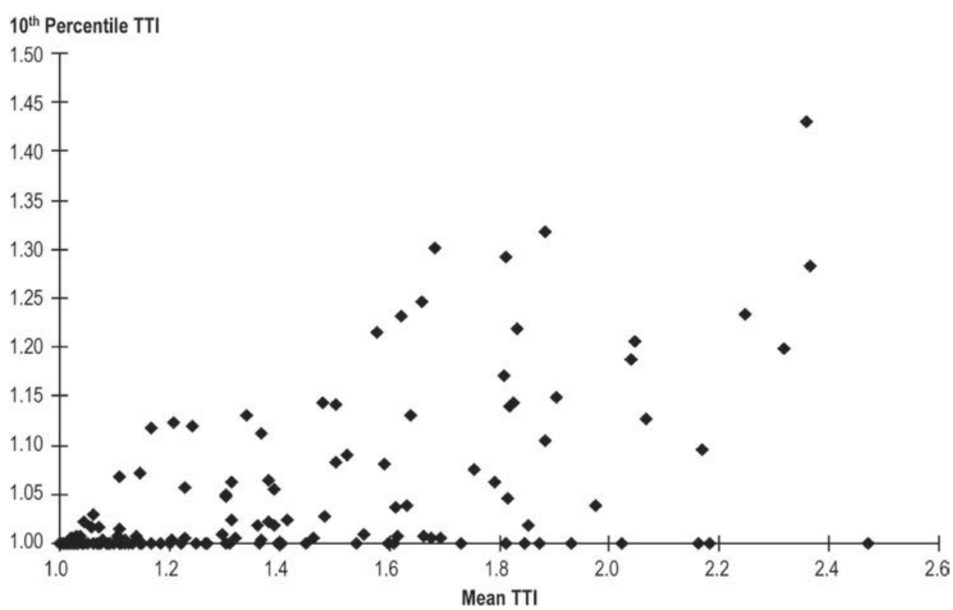

Figure 7.7. Section-level relationship for mean and 10th percentile TTI.

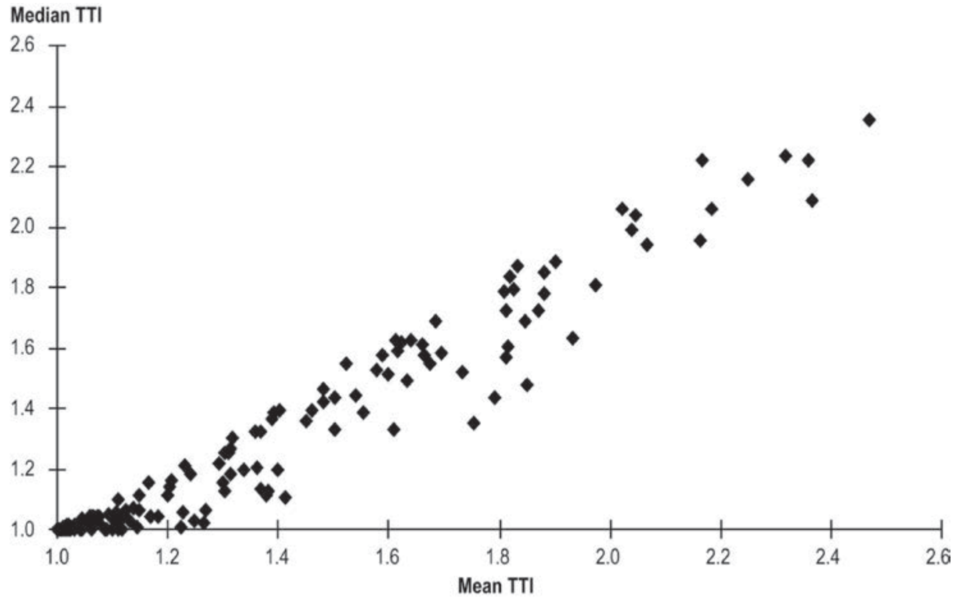

Figure 7.8. Section-level relationship for mean and median TTI.

where PctTripsOnTime30mph is the percentage of trips that occur at space mean speeds above the threshold of 30 mph.

$$\text{standard deviation} = 0.6182 * (\text{mean TTI} - 1)^{0.5404}$$

$$\left(R^2 = .781;\ \text{alpha levels of coefficients} < 0.0001\right) \quad (7.15)$$

As with the link level, if the recurring-only mean TTI is available, it must be factored with Equation 3.

Appendix H presents a revised set of section-level equations for the prediction of the 80th, 95th, and 99th percentile TTIs, standard deviation, and on-time metrics. These were fit to the same data described in this section, but different model forms were selected.

Signalized Arterials

The predictive equations for reliability metrics as a function of the mean for signalized arterials were obtained from the

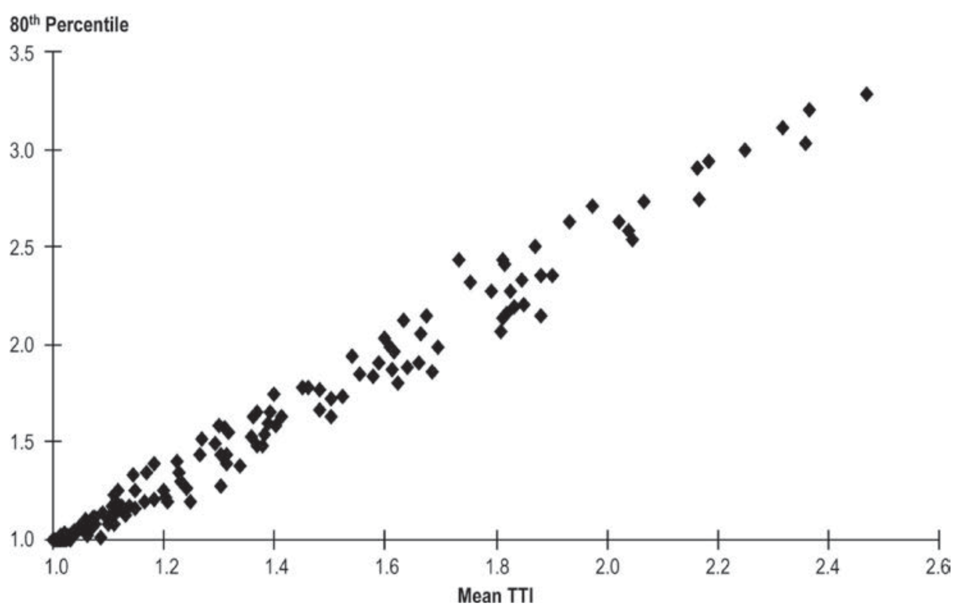

Figure 7.9. Section-level relationship for mean TTI and 80th percentile.

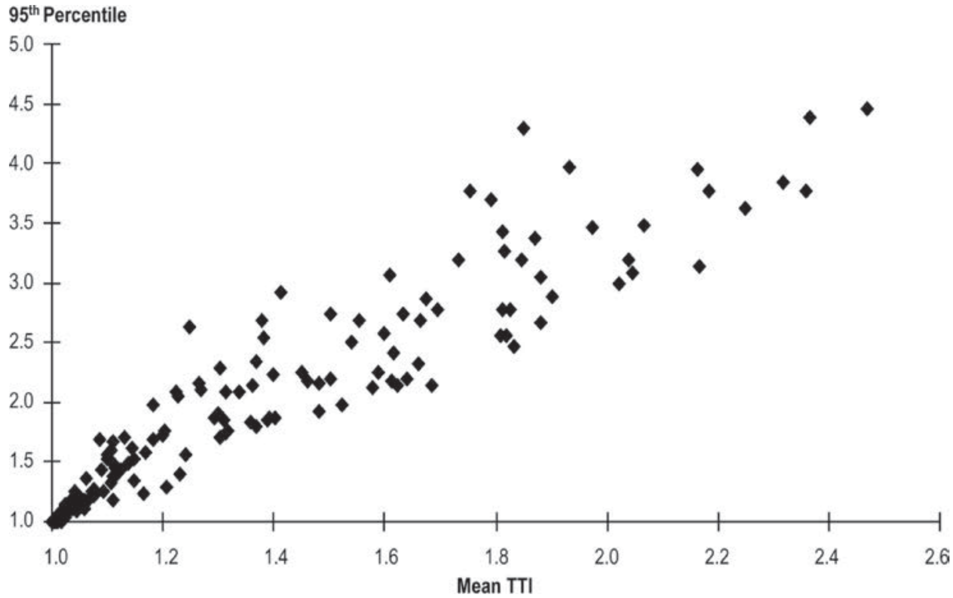

Figure 7.10. Section-level relationship for mean TTI and 95th percentile.

six Orlando study sections. Unlike urban freeways, on the signalized arterials there was no apparent relationship between mean TTI and the on-time reliability metrics.

$$\text{99th percentile TTI} = \text{mean TTI}^{2.2120}$$
$$(\text{RMSE} = 12.7\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.16)$$

$$\text{97.5th percentile TTI} = \text{mean TTI}^{2.0845}$$
$$(\text{RMSE} = 10.2\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.17)$$

$$\text{95th percentile TTI} = \text{mean TTI}^{1.9125}$$
$$(\text{RMSE} = 7.1\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.18)$$

$$\text{80th percentile TTI} = \text{mean TTI}^{1.4067}$$
$$(\text{RMSE} = 2.1\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.19)$$

$$\text{median TTI} = \text{mean TTI}^{0.9149}$$
$$(\text{RMSE} = 1.9\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.20)$$

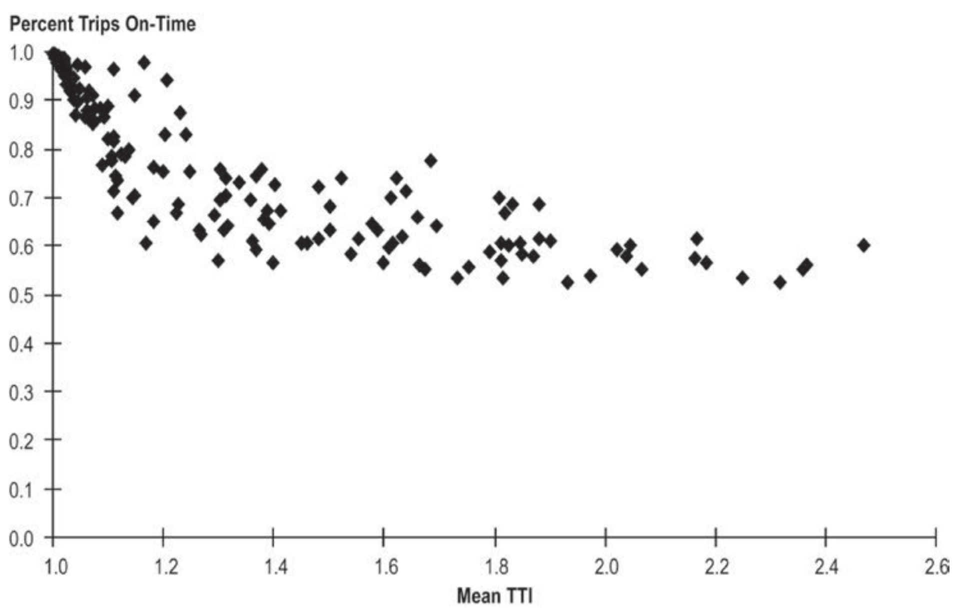

Figure 7.11. Section-level relationship for mean TTI and on-time at median plus 10%.

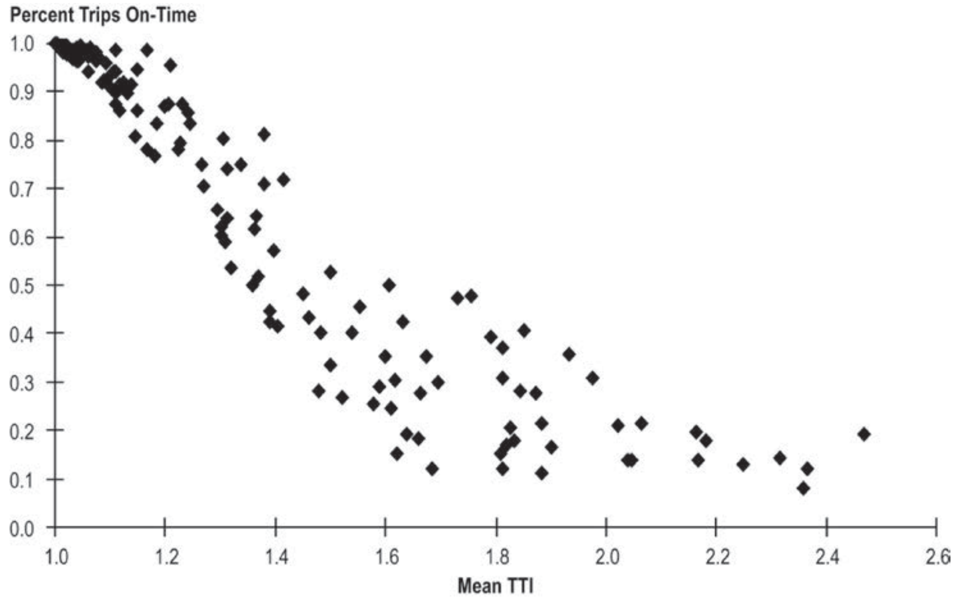

Figure 7.12. Section-level relationship for mean TTI and on-time at 45 mph threshold.

$$10\text{th percentile TTI} = \text{mean TTI}^{0.2689}$$

$$\left(\text{RMSE} = 4.0\%;\ \text{alpha level of coefficient} < 0.0001\right) \quad (7.21)$$

Rural Freeways

The predictive equations for reliability metrics as a function of mean TTI for rural freeways were derived using data from I-45 in Texas and I-95 in South Carolina. Four sections were used, two routes in each direction. The travel times used were for the entire segment (and, therefore, are long) and were derived using the vehicle trajectory method. These sections are not influenced by major urban areas or bottlenecks; examination of long-distance trips that pass through or otherwise touch urban areas is likely to reveal different patterns. An additional metric, the 97.5th percentile, was added because of the extreme skew in the travel time distributions for long-distance rural trips. Note that the 10th percentile TTI

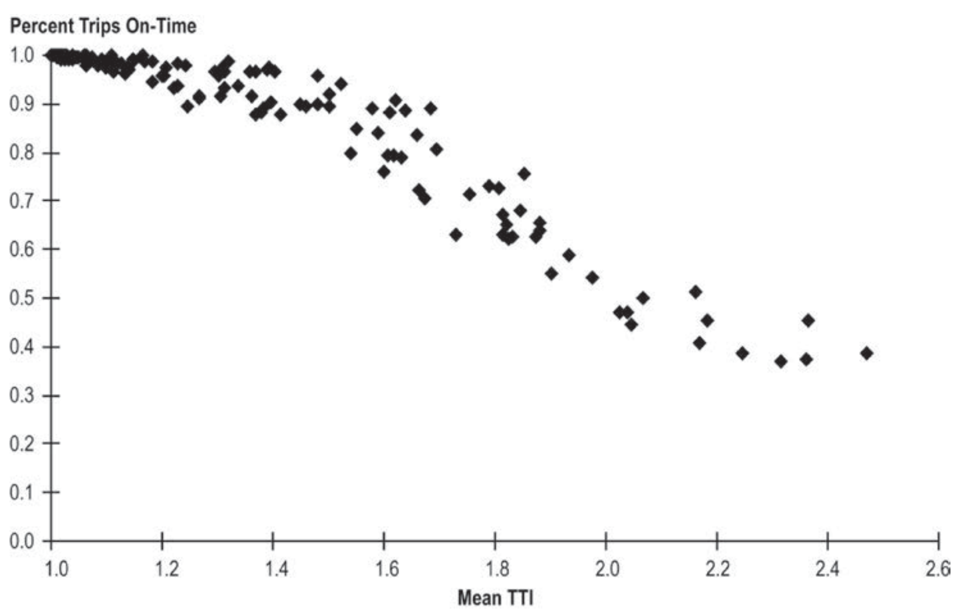

Figure 7.13. Section-level relationship for mean TTI and on-time at 30 mph threshold.

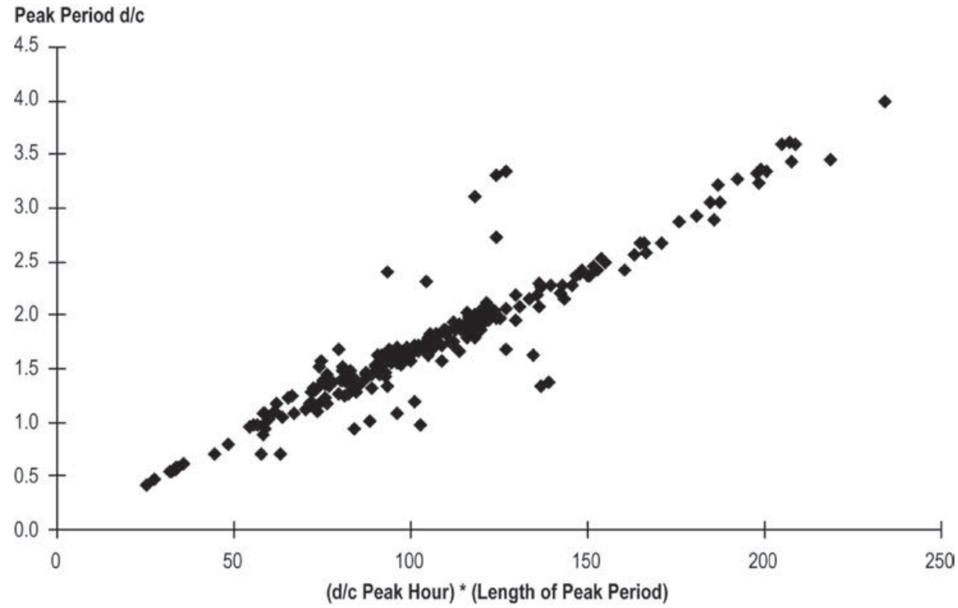

Figure 7.14. Predicting peak period d/c ratio.

was found to be 1.0, which is to be expected under routinely uncongested conditions. It also is worth noting that for these rural sections, mean TTI ranged from 1.025 to 1.045, extremely low values compared with the urban sections studied.

$$\text{99th percentile TTI} = \text{mean TTI}^{4.2584}$$

$$(\text{RMSE} = 4.2\%;\ \text{alpha level of coefficient} = 0.0052) \quad (7.22)$$

$$\text{97.5th percentile TTI} = \text{mean TTI}^{2.6723}$$

$$(\text{RMSE} = 0.3\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.23)$$

$$\text{95th percentile TTI} = \text{mean TTI}^{2.1365}$$

$$(\text{RMSE} = 0.4\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.24)$$

$$\text{80th percentile TTI} = \text{mean TTI}^{1.4923}$$

$$(\text{RMSE} = 0.1\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.25)$$

$$\text{median TTI} = \text{mean TTI}^{0.8763}$$

$$(\text{RMSE} = 0.1\%;\ \text{alpha level of coefficient} < 0.0001) \quad (7.26)$$

$$\text{10th percentile TTI} = 1.0 \quad (7.27)$$

Statistical Modeling of Reliability

The research team followed the modeling approach for the data-rich model form as closely as possible (see further discussion at the beginning of this chapter). The concept was to build a chain of relationships that are deterministic in nature rather than merely searching for a single predictive equation from the large set of independent variables available. Several observations should be made about the data set that have implications for applications of the models:

- The study sections routinely experience relatively high levels of congestion.
- Operations activities, particularly incident management, were well developed in the areas studied. Although it would have been interesting to study locations without such advanced activities, such locations in all likelihood would not have the data available for the research.
- The study sections had wide cross-sections, three or more lanes per direction, and number of lanes generally influences the impact of lane closures. (The average number of lanes on the study sections was 3.6.) However, number of lanes in the statistical models was not shown to be statistically significant. This may be a function of the reduced sample sizes in each number of lanes category.
- Minneapolis–St. Paul was the only location with any substantial winter weather conditions. For this reason, frozen precipitation was not used as a potential predictor of reliability. Even in Minneapolis–St. Paul, the number of days with snowfall or icing was relatively limited throughout the course of a year, making it difficult for frozen precipitation to show up as statistically significant. Further, on days when snow or ice is forecast, it is likely that demand will be dramatically lowered: travelers seek other modes or decide not to travel. For these reasons, the reliability measures explored in this research are not useful descriptors of winter weather impacts.

- The above discussion points out an issue with statistical modeling of reliability. Rare events that cause extreme disruptions are difficult to relate to the percentiles of an annual travel time distribution; the more common occurrences (e.g., bottleneck congestion, incidents, rainfall) tend to produce the statistically significant results. Further, diversion of demand during extreme disruptions will lessen the observed travel time impacts below what they would have been in the face of full demand.

The dependent variables used in the statistical analysis were derived from the distributions of the TTI for each analysis section. TTI was chosen because, as a unitless index, it is normalized for different section lengths. An alternative would have been to use the travel rate (measured in minutes per mile). Since TTI is computed as the actual travel rate divided by the ideal travel rate (i.e., the travel rate at the free-flow speed), the two measures are related. Several dependent variables based on the key moments of the TTI distributions were used: mean TTI, as well as the 10th, 50th (median), 80th, 95th, and 99th percentile TTIs. From these statistics, both the Buffer Index and skew statistic were computed (see the formulas in Table 4.4). Note that no adjustment for recurring-only conditions was necessary because the mean TTI predicted here includes both recurring and nonrecurring sources.

The first stage of this model form is to link reliability measures to lane hours lost due to incidents and work zones, d/c ratio, and weather conditions. During initial investigations, the project team noticed that including only incident lane hours lost as opposed to the sum of incidents and work zones produced more reliable models. This observation spurred a review of the original data used in the analysis. Members of the team talked with personnel at the Atlanta traffic management center (TMC), as well as with personnel from Traffic.com. Both groups admitted that work zone data are currently difficult to obtain and to code with accuracy. In Atlanta's case, the work zone units sometimes report their activities to the TMC; at other times, the TMC enters work zone data they had not been notified of by viewing it through their closed-circuit cameras. Further complicating matters is that the lane-blocking characteristics of a work zone usually change over time, but the work zone units report only a single number representing the general condition. TMC personnel try to compensate by visually observing the work zone periodically, but this means that the work zone information was not updated frequently, resulting in coded durations that were longer than the actual ones. Finally, in the highly congested sections used in the analysis, lane closures during peak times are avoided whenever possible. In the case of Traffic.com, the number of reported work zones was extremely low.

For these reasons, the team chose to include only incident lane hours lost in the statistical models as the major event— or disruption-related variable. In the case of Atlanta, if an active work zone with lane closures occurred during the time period of interest (e.g., the peak period), that day was excluded when compiling the final analysis data set. In applying the models, it was expected that lane hours lost due to short-term work zones would have roughly the same impact as incidents. Long-term work zones will usually affect demand and result in shifts to other routes, modes, and times of travel.

A variety of equation forms were tried, including natural logarithmic, Cobb–Douglas (multiplicative with exponents), and polynomials. The natural logarithmic form was selected because it has the feature of predicting a TTI of 1.0 when the independent variables are zero. As with the simple models, RMSE was used as the primary goodness-of-fit measure. Because the models were fit with no intercept term, to ensure continuity at the zero point, R^2 values could not be calculated. For the significance of the coefficients, a generous alpha level of 0.1 was used to allow variables to stay in the equations.

First-Stage Models

A large combination of independent variables was tested, with a focus on capturing the factors hypothesized to influence reliability (Figure 7.1), where reliability is measured over the course of a year. The results for the first-stage equations, the most important because they established that reliability can be predicted from congestion-causing conditions, appear below. Separate equations were fit for the peak hour, peak period, midday, and weekday time periods. Summary statistics for the base data appear in Table 7.6.

Peak Period

$$\text{mean TTI} = e^{(0.09677 * \text{dc}_{\text{crit}} + 0.00862 * \text{ILHL} + 0.00904 * \text{Rain05Hrs})} \tag{7.28}$$

RMSE = 18.8%; alpha level of coefficients: <0.0001, <0.0001, 0.0189 (in order of appearance in the equations).

$$\text{99th percentile TTI} = e^{(0.33477 * \text{dc}_{\text{crit}} + 0.012350 * \text{ILHL} + 0.025315 * \text{Rain05Hrs})} \tag{7.29}$$

RMSE = 39.8%; alpha level of coefficients: <0.0001, 0.0002, 0.0022.

$$\text{95th percentile TTI} = e^{(0.23233 * \text{dc}_{\text{crit}} + 0.01222 * \text{ILHL} + 0.01777 * \text{Rain05Hrs})} \tag{7.30}$$

RMSE = 32.3%; alpha level of coefficients: <0.0001, <0.0001, 0.0078.

Table 7.6. Summary Statistics for the Statistical Analysis

		Mean			
			Annual Incident		
	Section Years			TTI	
Time Slice	No. of Observations	dc_{crit}	Lane Hours Lost	Average	95th Percentile
Peak period	85	1.98	18.11	1.53	2.41
Peak hour	70	0.86	5.69	1.62	2.50
Midday	91	2.13	13.15	1.06	1.21
Weekday	89	11.98	67.91	1.16	1.84

Note: midday = 11:00 a.m. to 2:00 p.m., weekdays.

$$\text{80th percentile TTI} = e^{(0.13992*dc_{crit}+0.01118*ILHL+0.01271*Rain05Hrs)} \quad (7.31)$$

RMSE = 25.8%; alpha level of coefficients: <0.0001, <0.0001, 0.0163.

$$\text{50th percentile TTI} = e^{(0.09335*dc_{crit}+0.00932*ILHL)} \quad (7.32)$$

RMSE = 20.5%; alpha level of coefficients: <0.0001, <0.0001.

$$\text{10th percentile TTI} = e^{(0.01180*dc_{crit}+0.00145*ILHL)} \quad (7.33)$$

RMSE = 6.7%; alpha level of coefficients: 0.0169, 0.0060.

Peak Hour

$$\text{mean TTI} = e^{(0.27886*dc_{crit}+0.01089*ILHL+0.02935*Rain05Hrs)} \quad (7.34)$$

RMSE = 26.4%; alpha level of coefficients: 0.0008, 0.0094, 0.0838.

$$\text{99th percentile TTI} = e^{(1.13062*dc_{crit}+0.01242*ILHL)} \quad (7.35)$$

RMSE = 41.3%; alpha level of coefficients: <0.0001, 0.0477.

$$\text{95th percentile TTI} = e^{(0.63071*dc_{crit}+0.01219*ILHL+0.04744*Rain05Hrs)} \quad (7.36)$$

RMSE = 38.3%; alpha level of coefficients: <0.0001, 0.0436, 0.0553.

$$\text{80th percentile TTI} = e^{(0.52013*dc_{crit}+0.01544*ILHL)} \quad (7.37)$$

RMSE = 34.1%; alpha level of coefficients: <0.0001, 0.0031.

$$\text{50th percentile TTI} = e^{(0.29097*dc_{crit}+0.01380*ILHL)} \quad (7.38)$$

RMSE = 28.3%; alpha level of coefficients: <0.0001, 0.0015.

$$\text{10th percentile TTI} = e^{(0.07643*dc_{crit}+0.00405*ILHL)} \quad (7.39)$$

RMSE = 15.2%; alpha level of coefficients: 0.0081, 0.0748.

Midday (11:00 a.m. to 2:00 p.m., Weekdays)

$$\text{mean TTI} = e^{(0.02599*dc_{crit})} \quad (7.40)$$

RMSE = 7.5%; alpha level of coefficient: <0.0001.

$$\text{99th percentile TTI} = e^{(0.19167*dc_{crit})} \quad (7.41)$$

RMSE = 33.4%; alpha level of coefficient: <0.0001.

$$\text{95th percentile TTI} = e^{(0.07812*dc_{crit})} \quad (7.42)$$

RMSE = 21.8%; alpha level of coefficient: <0.0001.

$$\text{80th percentile TTI} = e^{(0.02612*dc_{crit})} \quad (7.43)$$

RMSE = 9.2%; alpha level of coefficient: <0.0001.

$$\text{50th percentile TTI} = e^{(0.01134*dc_{crit})} \quad (7.44)$$

RMSE = 21.8%; alpha level of coefficient: <0.0001.

$$\text{10th percentile TTI} = e^{(0.00389*dc_{crit})} \quad (7.45)$$

RMSE = 5.1%; alpha level of coefficient: <0.0016.

Weekday

$$\text{mean TTI} = e^{(0.00949*dc_{average}+0.00067*ILHL)} \quad (7.46)$$

RMSE = 29.3%; alpha level of coefficients: <0.0001, 0.0051.

$$\text{99th percentile TTI} = e^{(0.07028*dc_{average}+0.00222*ILHL)} \quad (7.47)$$

RMSE = 38.9%; alpha level of coefficients: <0.0001, 0.0261.

$$\text{95th percentile TTI} = e^{(0.03632*dc_{average}+0.00282*ILHL)} \quad (7.48)$$

RMSE = 31.8%; alpha level of coefficients: <0.0001, 0.0007.

$$\text{80th percentile TTI} = e^{(0.00842*dc_{average}+0.00117*ILHL)} \quad (7.49)$$

RMSE = 14.7%; alpha level of coefficients: 0.0004, 0.0023.

$$\text{50th percentile TTI} = e^{(0.0021 * dc_{average})} \quad (7.50)$$

RMSE = 4.7%; alpha level of coefficients: <0.0001.

$$\text{10th percentile TTI} = e^{(0.00047 * dc_{average})} \quad (7.51)$$

RMSE = 2.0%; alpha level of coefficients: 0.0121.

where

dc_{crit} = critical demand-to-capacity ratio on the study section (i.e., highest d/c ratio for all links on the section),

$dc_{average}$ = average d/c ratio on the study section (i.e., the mean of the d/c ratio for all the links on the section),

ILHL = annual lane hours lost due to incidents that occur within the time slice of interest (e.g., the peak period), and

Rain05Hrs = hours in the year during which rainfall is ≥0.05 inches that occur within the time slice of interest.

Several interaction terms involving volume or d/c ratio with event characteristics were also tried, but they failed to be significant in the regressions. It was expected that these terms would be important determinants of reliability, especially given the results of the exploratory research showing the strong effect of volume. However, it must be remembered that the models do not attempt to predict congestion on any given day, when these interactions are very likely to be significant. Rather, over the course of a year (over which reliability is determined), the interaction affects appear to be negligible.

Similarly, there were not enough cases of extreme or rare weather events (e.g., fog, snow) in the data to influence the annual summary metrics in a statistical sense. In the case of winter weather, unless the precipitation is unexpected, demand is likely to be lower as travelers forego trips or seek transit service. On an individual day, however, there is no denying that such events exert a strong influence on congestion. The predictive equations balance these variations by relying on a relatively common weather event, hourly rainfall ≥0.05 inches, to explain weather effects on annual reliability.

For reasons discussed above, the lane hours lost factor was limited to those related to incidents. The study sections were all located on high-volume, multilane roadways with significant congestion. Work zones during peak times were very likely not to involve lane closures, as it is common practice to keep all lanes open during the peak periods and to close them during off-peak times. Also, the coding of work zones, especially changes in lane closures over their duration, was found to be inconsistent in the data sets. Work zones are also rare events in general; some sections will have little or no work activity during a year, but incidents happen continuously. Finally, long-term work zones involving continuous lane closures will shift demand away from the facility. For these reasons, making a statistical connection with work zone–related lane closures proved difficult. However, the team still believes that lane closures due to short-term work zones are roughly equal to incidents in their effect on traffic. For this reason, it is recommended that if short-term work zones close lanes during peak periods, then an estimate of the annual lane hours lost due to them should be made and added to the ILHL factor used in the equations. Table 7.7 presents several analysis of variance statistics from the model development.

It is revealing that the midday models do not include the effect of either incidents or rain. Midday periods typically show reduced demand and little overall congestion. The fact that events do not show up as statistically relevant may indicate that demand (volume) is low enough that there is enough buffer to absorb the effect of most events.

The importance of demand and capacity to predicting reliability measures cannot be overstated. Examination of the Type I (sequential) and Type III (marginal) sums of squares for the peak models reveals the relative contribution of the independent variables. Type I sums of squares estimate the contribution of adding the variables in sequence. Type III sums of squares show the additional contribution of a variable given that the other variables are already in the model. Higher values indicate greater contribution to the model's explanatory power. For the 80th, 95th, and 99th percentile TTIs, the Type III sums of squares all show that the marginal contribution of the d/c ratio is higher than the other factors.

Second-Stage Models

Estimating D/C Ratio

The demand used in developing the models was the volume that occurred for the entire length of the study period, adjusted for any potential queuing affects as discussed in Chapter 4. Because the data were continuously collected for an entire year, the 99th percentile demand volume was selected. This was done to correspond to the usual way that traffic data are developed for highway capacity analysis, as follows. For the peak hour, the 99th percentile demand volume is close to the volume determined by the traditional *K*-factor, the 30th-highest hour of the year. Table 7.8 shows a comparison of these values for detectors (stations) in Atlanta for 2008. Note that the 99th percentile hourly volume was taken from a distribution of the actual peak hour volumes (nonholiday weekdays) for the year; that is, it was developed from all weekdays. The 30th-highest hourly volumes (*K*-factor volumes) are derived in the usual way by rank ordering all hours in the year.

Table 7.7. Analysis of Variance Statistics for Peak Models

Model	Dependent Variable	Independent Variable	Type I SS	Type III SS
Peak period	Mean TTI	d/c	13.16	0.97
		ILHL	1.40	1.18
		HrsRain05	0.20	0.20
	Median TTI	d/c	9.54	1.66
		ILHL	1.47	1.47
	80th Percentile TTI	d/c	25.51	2.02
		ILHL	2.39	1.99
		HrsRain05	0.40	0.40
	95th Percentile TTI	d/c	53.54	5.58
		ILHL	2.97	2.38
		HrsRain05	0.78	0.78
	99th Percentile TTI	d/c	96.56	11.59
		ILHL	3.27	2.42
		HrsRain05	1.58	1.58
Peak hour	Mean TTI	d/c	14.22	0.86
		ILHL	0.65	0.50
		HrsRain05	0.21	0.21
	Median TTI	d/c	11.66	2.46
		ILHL	0.87	0.87
	80th Percentile TTI	d/c	29.17	7.87
		ILHL	1.09	1.09
	95th Percentile TTI	d/c	49.60	4.37
		ILHL	0.89	0.62
		HrsRain05	0.56	0.56
	99th Percentile TTI	d/c	102.60	37.17
		ILHL	0.71	0.71

Note: SS = sums of squares.

The lengths of the time periods differ: the peak hour is 1 hour long, the midday period is 3 hours long (11:00 a.m. to 2:00 p.m.), and the peak period is variable as defined in Chapter 4. To develop demand volume, users should rely on local data to the extent possible, using the guidance above. In the absence of local data, the following default procedure is offered, based on the assumption that the 99th percentile of the peak hour volumes is equivalent to the *K*-factor volumes. Figure 7.15 shows the relationship between peak period d/c and the product of peak hour d/c times the length of the peak period assembled from the urban freeway study sections. A linear regression was performed on the data and produced the following equation:

$$(d/c)_{pp} = \{(d/c)_{ph} * \text{peak period length}\} * 0.01648 \qquad (7.52)$$

where

$(d/c)_{pp}$ = peak period d/c,
$(d/c)_{ph}$ = peak hour d/c,
$(d/c)_{ph}$ = peak hour volume to capacity (usually developed from travel demand forecasting models or by applying K- and D-factors to AADT), and
peak period length = length of peak period (min; see Chapter 4).

The maximum peak period length in the data was 200 minutes. Therefore, it is recommended that this equation be used only for peak period lengths up to 200 minutes.

The peak hour volume-to-capacity (v/c) ratio is computed either from empirical (factored daily traffic) data or model

Table 7.8. Comparison of 99th Percentile Hourly Volumes and K-Factor Volumes

Station ID	Hourly Volume		Ratio	Station ID	Hourly Volume		Ratio
	99th Percentile	30th Highest			99th Percentile	30th Highest	
200511	8,558	7,756	0.91	751488	9,873	9,648	0.98
200512	6,115	5,698	0.93	751491	12,394	12,369	1.00
200516	8,067	7,697	0.95	751495	14,396	14,027	0.97
200517	8,095	7,600	0.94	751496	12,494	12,551	1.00
200520	2,524	2,986	1.18	2850002	4,110	3,880	0.94
750502	11,931	11,278	0.95	2850003	8,028	7,945	0.99
750503	14,848	14,385	0.97	2850004	12,823	12,634	0.99
750505	11,377	11,631	1.02	2850005	10,688	10,585	0.99
750506	11,210	11,612	1.04	2850008	9,552	9,129	0.96
750508	12,119	11,987	0.99	2850009	9,649	9,290	0.96
750509	11,795	11,955	1.01	2850010	10,308	10,094	0.98
750510	8,939	9,542	1.07	2850011	10,270	10,069	0.98
750511	9,325	10,020	1.07	2850012	10,063	9,935	0.99
750512	8,613	8,907	1.03	2850013	10,112	10,015	0.99
750513	9,298	9,435	1.01	2850014	12,370	12,046	0.97
750515	8,446	8,730	1.03	2850015	10,309	10,048	0.97
750516	8,548	8,833	1.03	2850016	10,345	10,077	0.97
750517	6,791	6,342	0.93	2850017	8,897	8,684	0.98
750518	9,904	9,864	1.00	2850020	6,813	6,880	1.01
750519	10,012	10,001	1.00	2850021	8,399	9,692	1.15
750520	10,457	10,188	0.97	2850023	9,529	9,257	0.97
750521	10,081	10,037	1.00	2850024	7,736	8,314	1.07
750522	9,582	9,296	0.97	2850025	8,307	8,589	1.03
750523	7,846	7,490	0.95	2850026	9,402	9,820	1.04
750524	9,882	9,646	0.98	2850028	7,930	9,056	1.14
750526	6,930	6,968	1.01	2850029	7,911	8,384	1.06
751472	5,706	6,439	1.13	2850031	8,020	8,707	1.09
751473	5,872	6,073	1.03	2850032	7,935	8,503	1.07
751475	8,458	8,209	0.97	2850033	8,256	8,748	1.06
751476	8,176	8,184	1.00	2850034	8,233	8,960	1.09
751477	8,327	8,181	0.98	2850035	8,786	9,633	1.10
751479	9,380	9,805	1.05	2850036	9,130	9,348	1.02
751480	10,096	9,510	0.94	2850042	3,705	3,983	1.08
751481	9,000	9,669	1.07	2851004	4,457	4,796	1.08
751482	9,390	9,476	1.01	2851005	5,204	5,330	1.02
751484	9,750	10,185	1.04	2851006	8,343	8,027	0.96
751486	9,880	9,926	1.00	2851007	11,484	11,980	1.04
751487	9,775	10,075	1.03	2851008	13,046	13,553	1.04

(continued on next page)

Table 7.8. Comparison of 99th Percentile Hourly Volumes and K-Factor Volumes (continued)

Station ID	Hourly Volume		Ratio
	99th Percentile	30th Highest	
2851009	9,424	9,916	1.05
2851010	8,815	8,831	1.00
2851011	11,198	11,305	1.01
2851012	11,023	11,141	1.01
2851013	11,389	10,942	0.96
2851014	10,371	10,352	1.00
2851015	11,536	10,472	0.91
2851016	10,581	10,564	1.00
2851018	12,597	12,155	0.96
2851020	10,428	10,278	0.99
2851021	9,930	9,743	0.98
2851022	11,255	11,096	0.99
2851023	9,545	8,975	0.94
2851026	12,935	13,354	1.03
2851027	8,847	10,051	1.14
2851028	9,190	9,746	1.06
2851029	9,879	10,410	1.05
2851030	9,842	9,817	1.00
2851031	9,131	9,647	1.06
2851033	8,118	7,999	0.99
2851034	10,065	10,960	1.09
2851035	9,107	9,673	1.06
2851036	8,440	8,899	1.05
2851037	8,451	8,925	1.06
2851038	8,441	9,101	1.08
2851039	9,017	9,402	1.04
2851041	9,123	8,579	0.94
2851043	3,687	3,815	1.03
		Average	**1.01**

output. Using the HCM to calculate hourly capacity, a typical way to compute the v/c ratio from empirical data is

$$v/c = (\text{AADT} * K\text{-factor} * D\text{-factor})/\text{hourly capacity} \qquad (7.53)$$

where
AADT = annual average daily traffic,
K-factor = 30th-highest hour of traffic in a year, and
D-factor = directional split of traffic in the 30th highest hour.

The weekday and midday (11:00 a.m. to 2:00 p.m.) time periods also use the 99th percentile demand volume. Local values for these are preferred, but if these are not available, then the following factors developed from the Atlanta study sections can be used:

$$\text{99th percentile weekday demand} = \text{AADT} * 1.251 \qquad (7.54)$$

$$\text{99th percentile midday demand} = \text{AADT} * 0.234 \qquad (7.55)$$

Capacity in the d/c ratio was defined in the analysis as the hourly capacity determined according to HCM methods. Capacity should include the effect of weaving sections and merge areas, as appropriate.

Estimating Lane Hours Lost

Total (annual) lane hours lost is the sum of lane hours lost due to incidents (ILHL) and work zones. Work zone lane hours lost must be estimated with local knowledge of the extent and characteristics of planned work zones. Incident lane hours lost are calculated as follows:

$$\text{ILHL} = \text{number incidents} * \text{lanes blocked} * \text{incident duration} \qquad (7.56)$$

$$\text{ILHL} = \text{incident rate} * \text{VMT} \qquad (7.57)$$

where
number incidents = number of annual incidents (incident rate and VMT should be computed for the particular time slice under study, e.g., the peak period);
lanes blocked = number of lanes blocked per incident;
incident duration = average incident duration (hours), defined as the time between when the incident started and when the last lane or shoulder is cleared; and
VMT = vehicle miles traveled.

If incident rate is unavailable locally, it can be estimated by multiplying the crash rate by 4.545, which assumes that crashes are 22% of all incidents; this factor was developed from analyzing the incident data in the analysis data set.

If lanes blocked per incident is unavailable locally, it can be estimated using the following factors, developed from 2 years of incident data from Atlanta:

- 0.476 if a usable shoulder is present and it is local policy to move lane-blocking incidents to the shoulder as rapidly as possible. A usable shoulder is capable of safely storing the disabled vehicle and emergency vehicles (this is the policy in Atlanta);

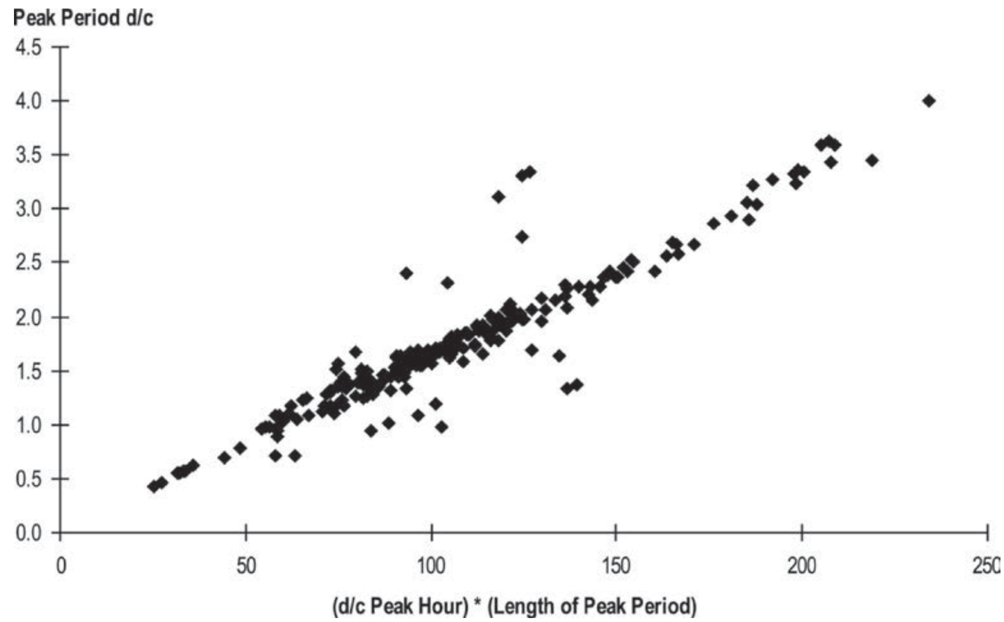

Figure 7.15. Predicting peak period d/c ratio.

- 0.580 if lane-blocking incidents are not moved to the shoulder. This factor was developed by considering lane-blocking incidents that were moved to the shoulder, and reassigning them back to lane-blocking status; and
- 1.140 if usable shoulders are unavailable.

Average incident duration is largely a function of incident management policies and actions. However, a statistical relationship from the data available proved elusive. The team had originally hoped to use Traffic Incident Management Self-Assessment scores as a way of quantitatively capturing the myriad of factors that comprise incident management programs, but these scores were available for only a few of the locations. As a means of guidance to practitioners, Table 7.9 provides peak period incident characteristics of the study locations.

Estimating Hours of Rainfall ≥0.05 Inches

The National Weather Service maintains hourly records of weather conditions that should be used to calculate this factor.

Graphical Display of Equations

Figures 7.16 through 7.18 graphically show the behavior of selected equations for predicting the 95th percentile TTI.

Table 7.9. Peak Period Incident Characteristics for Study Locations

Urban Area	Average Incident Duration[a] (min)	Quick-Clearance Law	PDO-Move-to-Shoulder Law	Fatality Removal Without Medical Examiner
Atlanta	43.5	Yes	Yes	Yes
Houston	43.2	Yes	Yes	Yes
Jacksonville	32.1[b]	Yes	Yes	Yes
Los Angeles	51.5	No	Yes	No
Minneapolis	47.3	No	No	No
San Diego	52.0	No	Yes	No

Note: PDO = property damage only.

[a] Average incident duration is defined as the time between when the incident started and when the last lane or shoulder is cleared.

[b] End time is defined as when the lane is cleared (incident may still be active on shoulder).

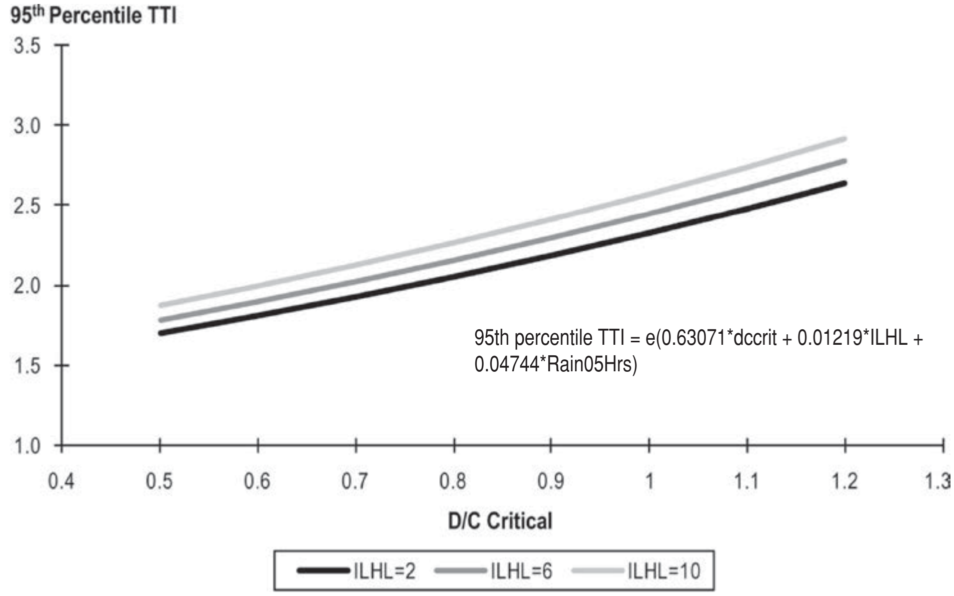

Figure 7.16. Effect of incident lane hours lost, peak hour equations.

Validation of Statistical Models

Data from the Seattle area, which were used in the congestion by source analysis in Chapter 5, were used to validate the statistical models. Travel time metrics and lane hours lost information were compiled directly from Seattle detector data and the Seattle incident data base, respectively. Data on demand and capacity were compiled from Highway Performance Monitoring System data for the Seattle study sections.

The results appear in Tables 7.10 and 7.11. For peak periods, the models tend to overpredict the key metrics when actual congestion is fairly low and underpredict when actual congestion is high (e.g., mean TTIs greater than 2.5). Low congestion during the peak period was rare in the data on which the models were fit, so a recommendation for their application would be to apply the peak period models only in situations in which at least a modest amount of congestion exists. (The rainfall factor was set to 4 hours for peak hour and 8 hours for the peak period.)

For weekdays (all 24 hours), the models tended to underpredict Seattle conditions, especially the 95th percentile TTIs. This may be due to the lack of a weather or rain variable in the weekday models, which proved to be insignificant for the model data set, but rain was shown in Chapter 5 to be an

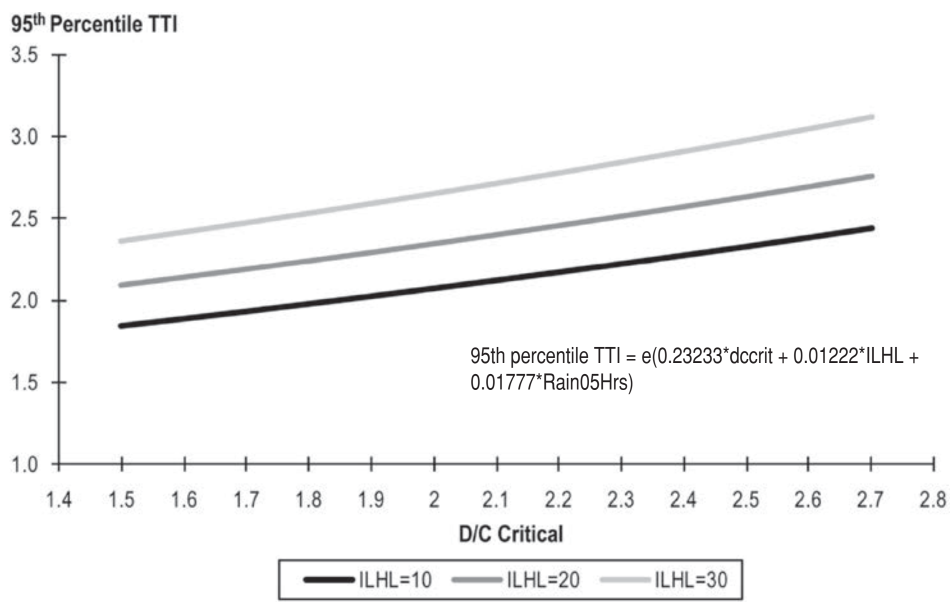

Figure 7.17. Effect of incident lane hours lost, peak period equations.

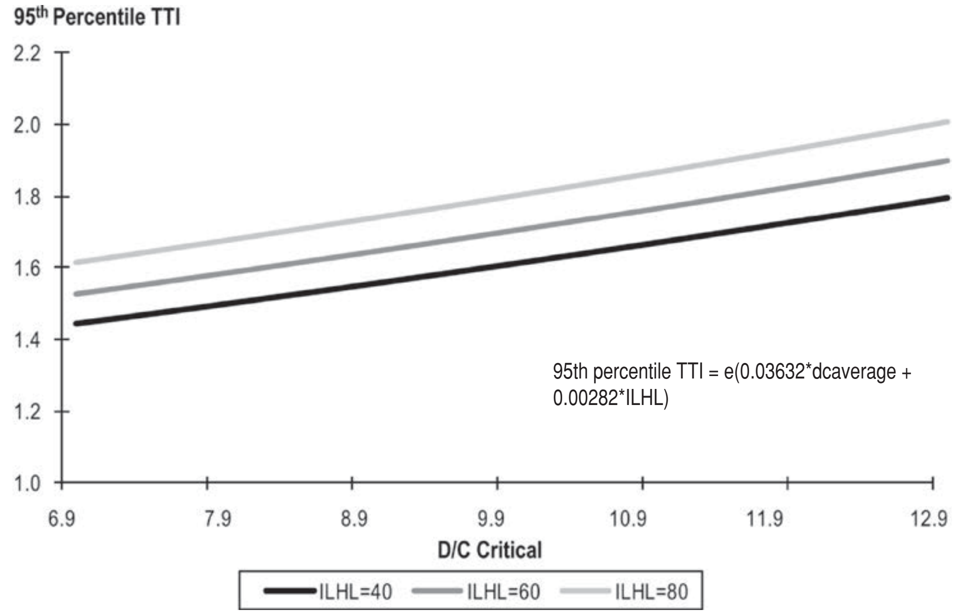

Figure 7.18. Effect of incident lane hours lost, weekday equations.

Table 7.10. Peak Period Model Validation for Seattle

	Mean TTI			80th Percentile TTI			95th Percentile TTI		
Section	**Actual**	**Predicted**	**Error (%)**	**Actual**	**Predicted**	**Error (%)**	**Actual**	**Predicted**	**Error (%)**
I-405 Bellevue northbound	1.346	1.810	34.5	1.507	2.301	52.7	2.314	3.369	45.6
I-405 Eastgate northbound	1.667	1.835	10.0	1.981	2.372	19.7	2.720	3.740	37.5
I-405 Eastgate southbound	2.728	1.955	–28.4	3.227	2.575	–20.2	4.209	4.091	–2.8
I-405 Kennydale southbound	1.898	1.677	–11.6	2.313	2.077	–10.2	3.376	2.958	–12.4
I-405 Kirkland northbound	1.995	2.019	1.2	2.408	2.640	9.6	3.132	3.827	22.2
I-405 Kirkland southbound	1.766	1.748	–1.0	2.147	2.189	2.0	2.673	3.119	16.7
I-405 North northbound	1.609	1.654	2.8	1.876	2.031	8.3	2.236	2.822	26.2
I-405 North southbound	2.820	1.792	–36.4	4.090	2.254	–44.9	6.272	3.161	–49.6
I-405 South northbound	2.578	1.609	–37.6	3.080	1.960	–36.4	3.756	2.707	–27.9
I-405 South southbound	1.522	1.607	5.6	1.797	1.957	8.9	2.406	2.703	12.3
I-5 Everett northbound	1.872	1.976	5.5	2.777	2.570	–7.5	4.294	3.740	–12.9
I-5 Everett southbound	1.520	1.843	21.2	1.850	2.348	26.9	2.590	3.387	30.8
I-5 Lynnwood northbound	1.443	1.722	19.4	1.667	2.163	29.8	3.539	3.198	–9.6
I-5 Lynnwood southbound	1.898	1.829	–3.6	2.448	2.338	–4.5	3.968	3.481	–12.3
I-5 South northbound	1.764	2.084	18.2	2.313	2.782	20.3	3.184	4.318	35.6
I-5 South southbound	1.762	1.964	11.5	2.350	2.576	9.6	3.251	3.969	22.1
I-5 Tukwila northbound	1.502	1.819	21.1	1.811	2.054	13.4	2.582	2.840	10.0
I-5 Tukwila southbound	1.205	1.858	54.2	1.265	2.111	66.8	1.933	2.926	51.3
I-90 Bellevue westbound	1.307	1.609	23.1	1.453	1.961	35.0	1.998	2.716	35.9
I-90 Bridge eastbound	1.414	1.636	15.7	1.868	2.008	7.5	2.622	2.832	8.0

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Table 7.10. Peak Period Model Validation for Seattle (continued)

Section	Mean TTI			80th Percentile TTI			95th Percentile TTI		
	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)
I-90 Bridge westbound	1.739	1.687	–3.0	2.608	2.091	–19.8	3.483	2.960	–15.0
I-90 Issaquah westbound	1.476	1.679	13.8	1.880	2.090	11.2	2.635	3.051	15.8
SR 167 Auburn northbound	1.685	1.615	–4.2	2.057	1.976	–3.9	2.567	2.795	8.9
SR 167 Auburn southbound	1.961	1.681	–14.3	2.693	2.082	–22.7	4.162	2.958	–28.9
SR 167 Renton northbound	1.623	1.689	4.0	1.744	2.100	20.4	3.361	3.026	–10.0
SR 167 Renton southbound	1.637	1.675	2.3	2.029	2.078	2.4	3.357	2.991	–10.9
Average error (%)			4.8			6.7			7.2

Table 7.11. Weekday Model Validation for Seattle

Section	Mean TTI			80th Percentile TTI			95th Percentile TTI		
	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)	Actual	Predicted	Error (%)
I-405 Bellevue northbound	1.186	1.130	–4.7	1.285	1.127	–12.3	1.865	1.606	–13.9
I-405 Eastgate northbound	1.177	1.177	0.0	1.232	1.158	–6.0	1.964	1.867	–4.9
I-405 Eastgate southbound	1.369	1.190	–13.1	1.399	1.181	–15.5	2.432	1.959	–19.4
I-405 Kennydale southbound	1.357	1.119	–17.5	1.642	1.113	–32.2	2.491	1.544	–38.0
I-405 Kirkland northbound	1.196	1.133	–5.3	1.123	1.146	2.1	2.227	1.633	–26.7
I-405 Kirkland southbound	1.162	1.123	–3.3	1.133	1.128	–0.4	2.000	1.572	–21.4
I-405 North northbound	1.135	1.124	–0.9	1.137	1.116	–1.9	1.784	1.568	–12.1
I-405 North southbound	1.105	1.136	2.8	1.318	1.137	–13.8	2.121	1.640	–22.7
I-405 South northbound	1.476	1.121	–24.1	1.933	1.110	–42.6	2.967	1.549	–47.8
I-405 South southbound	1.270	1.122	–11.6	1.446	1.112	–23.1	1.904	1.556	–18.3
I-5 Everett northbound	1.192	1.119	–6.1	1.031	1.129	9.5	2.514	1.553	–38.2
I-5 Everett southbound	1.054	1.122	6.4	1.012	1.134	12.1	1.216	1.570	29.1
I-5 Lynnwood northbound	1.134	1.112	–2.0	1.085	1.106	1.9	1.730	1.504	–13.1
I-5 Lynnwood southbound	1.165	1.116	–4.2	1.100	1.113	1.2	1.978	1.528	–22.7
I-5 South northbound	1.117	1.142	2.3	1.033	1.155	11.8	1.859	1.684	–9.4
I-5 South southbound	1.154	1.127	–2.3	1.061	1.129	6.3	2.123	1.592	–25.0
I-5 Tukwila northbound	1.111	1.117	0.6	1.066	1.118	4.8	1.680	1.536	–8.5
I-5 Tukwila southbound	1.060	1.114	5.1	1.043	1.112	6.6	1.207	1.517	25.7
I-90 Bellevue westbound	1.101	1.076	–2.2	1.000	1.076	7.6	1.516	1.330	–12.3
I-90 Bridge eastbound	1.118	1.078	–3.6	1.075	1.074	–0.1	1.876	1.335	–28.8
I-90 Bridge westbound	1.161	1.080	–7.0	1.053	1.078	2.4	1.547	1.346	–13.0
I-90 Issaquah westbound	1.077	1.062	–1.4	1.043	1.056	1.3	1.454	1.260	–13.4
SR 167 Auburn northbound	1.168	1.084	–7.2	1.248	1.078	–13.6	1.759	1.363	–22.5
SR 167 Auburn southbound	1.189	1.084	–8.8	1.265	1.078	–14.7	1.954	1.365	–30.1
SR 167 Renton northbound	1.201	1.093	–9.0	1.213	1.087	–10.4	1.916	1.406	–26.6
SR 167 Renton southbound	1.123	1.090	–3.0	1.144	1.083	–5.4	1.581	1.392	–12.0
Average error (%)			–4.6			–4.8			–17.2

Table 7.12. Application of Data-Poor Model to Seattle Weekday Data

Section	Mean TTI	80th Percentile TTI			95th Percentile TTI		
		Actual	Predicted	Error (%)	Actual	Predicted	Error (%)
I-405 Bellevue northbound	1.186	1.285	1.262	–1.8	1.865	1.379	–26.0
I-405 Eastgate northbound	1.177	1.232	1.249	1.4	1.964	1.358	–30.8
I-405 Eastgate southbound	1.369	1.399	1.536	9.8	2.432	1.807	–25.7
I-405 Kennydale southbound	1.357	1.642	1.516	–7.7	2.491	1.776	–28.7
I-405 Kirkland northbound	1.196	1.123	1.277	13.8	2.227	1.402	–37.1
I-405 Kirkland southbound	1.162	1.133	1.228	8.4	2.000	1.327	–33.6
I-405 North northbound	1.135	1.137	1.188	4.5	1.784	1.269	–28.9
I-405 North southbound	1.105	1.318	1.146	–13.0	2.121	1.207	–43.1
I-405 South northbound	1.476	1.933	1.702	–11.9	2.967	2.083	–29.8
I-405 South southbound	1.270	1.446	1.385	–4.2	1.904	1.568	–17.7
I-5 Everett northbound	1.192	1.031	1.271	23.3	2.514	1.393	–44.6
I-5 Everett southbound	1.054	1.012	1.075	6.2	1.216	1.105	–9.1
I-5 Lynnwood northbound	1.134	1.085	1.188	9.5	1.730	1.268	–26.7
I-5 Lynnwood southbound	1.165	1.100	1.232	12.1	1.978	1.334	–32.5
I-5 South northbound	1.117	1.033	1.163	12.6	1.859	1.232	–33.7
I-5 South southbound	1.154	1.061	1.217	14.6	2.123	1.311	–38.3
I-5 Tukwila northbound	1.111	1.066	1.154	8.2	1.680	1.218	–27.5
I-5 Tukwila southbound	1.060	1.043	1.083	3.8	1.207	1.116	–7.6
I-90 Bellevue westbound	1.101	1.000	1.140	14.0	1.516	1.199	–20.9
I-90 Bridge eastbound	1.118	1.075	1.164	8.3	1.876	1.233	–34.3
I-90 Bridge westbound	1.161	1.053	1.226	16.4	1.547	1.324	–14.4
I-90 Issaquah westbound	1.077	1.043	1.107	6.1	1.454	1.150	–20.9
SR 167 Auburn northbound	1.168	1.248	1.236	–1.0	1.759	1.339	–23.9
SR 167 Auburn southbound	1.189	1.265	1.267	0.1	1.954	1.385	–29.1
SR 167 Renton northbound	1.201	1.213	1.284	5.9	1.916	1.412	–26.3
SR 167 Renton southbound	1.123	1.144	1.172	2.4	1.581	1.244	–21.3
Average error (%)				5.5			–27.4

extremely important factor in Seattle congestion. Without testing another city, it is not known if Seattle is an exception or if rainfall has a universal influence on total weekday congestion. The problem may lie in the fact that Seattle weekday 95th percentile TTIs do not behave in the same way as those of the other cities. Table 7.12 shows the prediction of the 95th percentile TTI from the mean TTI using the data-poor model. The predicted 95th percentiles are consistently lower than the actual ones, yet the data-poor relationship had an excellent goodness-of-fit. The team is not sure why the 95th percentile TTIs in Seattle are so much higher compared with their means, but this indicates that further validation of the models with data from other cities is warranted.

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CHAPTER 8

Application Guidelines

Introduction

The predictive models that can be used in transportation modeling and analysis applications are of three kinds:

1. Adjustment factors (percentage reduction) derived from the before-and-after studies;
2. Relationships between the mean Travel Time Index (TTI) and reliability metrics (i.e., the simple or data-poor model); and
3. Direct prediction of reliability metrics as a function of demand, capacity, and disruption characteristics (i.e., the statistical or data-rich model).

This chapter provides general guidance on how to apply these relationships. Implementation of the methods within a specific application (e.g., the *Highway Capacity Manual* [HCM]) will require greater adaptation to the requirements of those methods.

Selecting the Appropriate Relationship

The most direct relationships developed for the impact of improvements on reliability are the adjustment factors from the before-and-after studies. However, as with adjustment factors for other forms of transportation analysis (e.g., safety analysis), care must be exercised in their application. Specifically, the base conditions for the before-and-after case studies should roughly match the conditions for the situation at hand. Therefore, the analyst should examine the details provided in Appendix B for the improvement type of interest and decide if the conditions of the case study are relevant. Only then can the adjustment factors be applied.

For many planning-level applications, the data-poor models can be used to generate reliability statistics. Because the relationships are based on first knowing the overall mean TTI (i.e., the average TTI over the course of a year that includes all possible sources of recurring and nonrecurring variation), analysts must identify how many nonrecurring events are included in the estimate of the overall TTI produced by their model. Usually, the overall TTI from planning models includes only recurring congestion, so the adjustment provided in Chapter 7 can be used directly.

The basic response variable used in this research is the TTI. In some cases, analysts will want different response metrics. TTI can be converted to other measures if the section length and free-flow speed are known. TTI is the result of dividing the actual travel time by the travel time at the free-flow speed. For example, consider a section 1.5 miles long with a TTI of 1.3. The free-flow travel time (at 60 mph, the free-flow speed in this research) is 1.5 minutes, and the actual travel time is 30% higher, or 1.95 minutes. The travel rate is therefore 1.95 divided by 1.5, or 1.3 minutes per mile.

Linking Improvements to Model Variables

The final stage of model application is to develop linkages between improvement types and the variables in the data-rich model. Table 8.1 presents a general discussion of how the improvements are to be considered and how their effects are to be accommodated by the models. Basically, the effect of improvements is traced to the changes in the independent variables and their determinants. Within the models, improvements can affect

- Demand (volume for the time period considered);
- Capacity (physical capacity, as determined by the HCM);
- Lane hours lost due to incidents and work zones. Work zone lane hours lost must be entered directly. Incident lane hours lost can be entered directly or as changes to
  - Incident frequency, a function of both
    - Incident rate, and
    - Vehicle miles traveled (VMT) (demand);

Table 8.1. General Linkages Between Improvements and Model Variables

Action to Improve Reliability	Effect on Reliability	Model Variable Affected
Add Capacity		
Add new through lanes	Increases design capacity.	d/c ratio
Add other geometric improvements (lane widening, shoulders, and lower grades)	Increases design capacity.	d/c ratio
Modify interchange (new configuration, longer, or additional ramps)	Increases design capacity.	d/c ratio
Add or modify access control, median barriers	Modest design capacity increase, significant reduction in probability of incidents (collisions).	d/c ratio; primary incident rate
Add managed lane (truck climbing lanes, high-occupancy vehicle [HOV] and high-occupancy toll lanes)	Increases capacity in unmanaged lanes by removing trucks, HOVs, toll payers from stream. Improves reliability for vehicles able to switch to managed lanes (d/c of managed lanes will usually be lower than for unmanaged lanes).	d/c ratio
Add auxiliary lanes	Increases capacity by allowing nonthrough vehicles to use auxiliary lanes.	d/c ratio
Add new interchange	Changes demand by changing access to facility; minor effect on design capacity.	d/c ratio
Add turn lanes	Increases capacity by shifting demand out of through lanes and increasing design capacity of through lanes.	d/c ratio
Convert two-way to one-way streets	Reduces demand by shifting one direction of demand to other streets. Increases design capacity for remaining allowed direction.	d/c ratio
Add safety improvements (median barriers, eliminate visual obstructions, lighting, and wider lanes)	Reduces likelihood of collisions and reduces incident frequency.	Primary crash rate
Operational Improvements		
Incident Management		
Improved equipment for incident detection and verification (CCTV)	Reduces incident duration.	Average incident duration
Improved interagency communications for incident detection and verification	Reduces incident duration.	Average incident duration
Improved equipment and service for incident response	Reduces incident duration.	Average incident duration
Improved interagency incident management coordination	Reduces incident duration.	Average incident duration
Improved responder training	Reduces incident duration.	Average incident duration
Incident command system	Reduces incident duration.	Average incident duration
Crash investigation sites	Reduces lane blockage.	Shoulder usability factor (in the lanes blocked per incident calculation)
Weather Management		
More effective deployment of snow and ice resources	Reduces impact of weather events on pavement and crashes.	Capacity reduction not as severe; primary crash rate
Snow and ice pretreatment	Reduces impact of weather events on pavement and crashes.	Capacity reduction not as severe; primary crash rate

(continued on next page)

Table 8.1. General Linkages Between Improvements and Model Variables (continued)

Action to Improve Reliability	Effect on Reliability	Model Variable Affected
Weather Management (continued)		
Microlevel weather forecasting	Reduces impact of weather events on pavement and crashes.	Primary crash rate
Weather monitoring	Reduces crash rates due to better traveler information.	Primary crash rate
Fog warning system	Reduces crash rates due to better traveler information.	Primary crash rate
Work Zone Management		
Scheduling (accelerated schedules, night time activities)	Reduces work zone duration.	Work zone duration
Use of more durable materials	Reduces frequency of work zone occurrence.	Work zone duration
Improved signing	Increases design capacity; decreases crashes.	d/c ratio; primary crash rate
Increased enforcement	Decreases crashes.	Primary crash rate
Full road and lane closures	Decreases design capacity but reduce work zone duration.	d/c ratio; work zone duration
Traffic control plan development	Increases design capacity.	d/c ratio
Active Traffic Management		
Traffic signal coordination	More green time; responsive cycle increases capacity.	d/c ratio
Traffic adaptive signal control	Through capacity is increased as demand increases.	d/c ratio
Ramp metering (fixed time, traffic responsive)	Increases design capacity.	d/c ratio
Integrated corridor management	Problematic; current FHWA research may reveal impacts; probably reduces demand and/or increases capacity (d/c).	
Traveler information system improvements (pretrip, roadside, and in-vehicle)	Problematic; probably reduces demand.	d/c ratio
Variable speed limits	Increases design capacity.	d/c ratio
Lane controls	Increases design capacity.	d/c ratio
Queue warning	Increases design capacity.	d/c ratio
Truck lane restrictions	Increases design capacity of nontruck lanes.	d/c ratio
Hard shoulder running during peak	Increases design capacity, but also increases incident impacts.	d/c ratio; shoulder usability factor
Access management	Increases design capacity.	d/c ratio
Traveler Information		
511	Reduces demand on event-stricken facilities.	d/c ratio
Variable message signs (VMS)	Reduces demand on event-stricken facilities.	d/c ratio
In-vehicle guidance	Reduces demand on event-stricken facilities.	d/c ratio
Demand Management		
Telecommuting	Reduces demand.	d/c ratio
Alternative work hours	Shifts demand (changes temporal traffic distribution).	d/c ratio
Land use controls	Reduces demand.	d/c ratio
Road pricing	Reduces demand on priced facility.	d/c ratio
Parking pricing	Reduces demand.	d/c ratio
Shifts to nonauto modes	Reduces demand.	d/c ratio

  - Lanes blocked per incident, a function of
    - Presence of shoulders, and
    - Local policy concerning moving lane-blocking incidents to the shoulder; or
- Average incident duration.

Improvements or strategies that affect demand are accounted for twice in the model: in the demand-to-capacity (d/c) ratio and in the incident frequency calculations.

The research team also undertook a review of recent studies of reliability improvements. Although none of them deal directly with estimating reliability, they can still be used in the modeling framework presented above (Tables 8.2 through 8.4). In some cases, a recommendation has been provided on how to adapt these results to the modeling framework. In others, the team has not provided a recommendation, but the results are presented because some practitioners might find them useful. As new research becomes available, especially other SHRP 2

Table 8.2. Incident Management Impacts

Improvement	Impact
Improving from no formal IM program to a program that includes detection, verification, and service patrols	**Atlanta**—Average time between first report and incident verification reduced by 74%. Average time between verification and response initiation reduced by 50%. Average time between incident verification and clearance of traffic lanes reduced by 38%. Maximum time between incident verification and clearance of traffic lanes reduced by 60% (*1*).
	Houston—Average 30-minute incident duration reduction (*2*).
RECOMMENDATION	*IDAS model recommends a default reduction in incident duration of 9% for incident detection, 39% for incident response systems, and 51% for combination incident detection and response systems* (*3*).
	Georgia (NaviGAtor)—Incident clearance time reduced by an average of 23 minutes. Incident response time reduced by 30% (*4*).
	Maryland (CHART)—Blockage duration from incidents reduced by 36%. This translates to a reduction in highway user delay time of about 42,000 hours per incident (*5*). 15% to 38% reduction in all secondary crashes, 4% to 30% reduction in rear-end crashes, and 21% to 43% reduction in severe secondary crashes (*4*).
RECOMMENDATION	*Based on CHART, reduce incident lane hours lost by 36%.*
Improved equipment for incident detection and verification (CCTV)	**Brooklyn**—Average time required to clear incident from roadway reduced by 66% (*6*).
	San Antonio (TransGuide)—20% improvement in response time (21% reduction for major incidents and 19% for minor incidents) (*7*).
RECOMMENDATION	*Based on TransGuide and assuming that incident response time is 20% of incident duration time, reduce incident duration by 4%.*
Improved interagency communications for incident detection and verification	**Minneapolis–St. Paul (Highway Helper)**—Automatic tow truck dispatch program is credited with a 20-minute reduction in incident response and removal times (85% improvement) (*8*).
RECOMMENDATION	*Assuming that response time is 20% of incident duration time, reduce incident duration by 17%.*
Improved equipment and service for incident response	**Hayward, California**—38% reduction in incident duration, 57% reduction in breakdown duration (*9*).
	Northern Virginia—Reduction in duration for all incidents is 2 to 5 minutes for cell phone in response vehicles, 2 to 5 minutes for CAD screens in response vehicles, and 4 to 7 minutes for GPS location for response vehicles (*10*).
	Oregon—Duration of delay-causing incidents decreased by approximately 30% on Highway 18 and 15% on Interstate 5 (service patrol addition) (*11*).
	Pittsburgh—Service patrol reduced response time to incidents from 17 to 8.7 minutes (*12*).
	Washington State—Average freeway incident clearance time for large trucks reduced to 1.5 hours from 5 to 7 hours without incident response team (*13*).
RECOMMENDATION	*For implementation of service patrols, reduce incident duration by 38%.*

Table 8.3. Weather Management Impacts

Improvement	Impact
More effective deployment of snow and ice resources	**Idaho DOT, U.S. Route 12**—Mobile anti-icing operations reduced average winter accident frequency by 83% compared with the past 3 years (*14*).
Snow and ice pretreatment	**Finland (Finnish National Road Administration)**—Duration of slippery road conditions estimated to decrease by 10 to 30 minutes per deicing activity, decreasing the chance for accidents caused by slipperiness. Estimated average time saved was 23 minutes per deicing activity (*15*).
	Minneapolis, I-35W and Mississippi River Bridge—2000–2001 season had a 50% reduction in total number of crashes over comparison season (1996–1997), even with an increase in average daily traffic of 9.3% (*16*).
Microlevel Weather Forecasting[a]	
Weather monitoring	**Idaho Storm Warning System**—Mean speeds in southbound lanes drop from 47.0 mph without dynamic message signs (DMS) to 41.2 mph with DMS warnings (~12% reduction). When high winds occurred with snow-covered pavement, mean speeds in southbound lanes dropped 35% from 54.7 mph to 35.4 mph compared with a 9% decline from 48.4 to 44.1 mph in northbound lanes (*17*).
Fog warning system	**London Orbital Motorway, M25**—Fog messages were followed by a statistically significant overall net reduction in mean vehicle speeds of about 1.8 mph. (*18*).
	Utah Fog Warning System, I-215—Average vehicle speed measured during fog events increased from 54 to 62 mph after system was deployed. Speed increase was partly attributable to reduction in the number of excessively slow drivers during fog events (*19*).
	Salt Lake Valley—15% increase in speeds and 22% decrease in standard deviation of those speeds under foggy conditions (*20*).

[a] No recommendations made for weather strategies' impacts on reliability.

research projects currently underway, their results can be adapted to the modeling framework in a similar manner.

Relationship Between Incident Management Efficiency and Model Variables

The incident management factors in Table 8.2 relate primarily to the technological (physical) aspects of incident management (i.e., equipment deployed to detect, verify, and respond to incidents). However, effective incident management depends not only on equipment but how efficiently the equipment is used and how well responders work together on the incident scene; institutional arrangements and programmatic aspects will determine the level of efficiency. Although it is thought that these attributes influence incident duration, quantifying them for inclusion in a statistical model is a challenging task. Originally it was thought that Traffic Incident Management Self-Assessment scores, which rank the level of sophistication and/or aggressiveness of incident management programs, could be used for this purpose.

However, these self-assessment scores were available from only three of the cities used in the urban freeway analysis. A few other key aspects of incident management programs were identified; these were available for six locations. Table 8.5 presents the results; cities are not identified because to obtain this information the research team had to maintain anonymity. There appears to be a loose relationship between self-assessment scores and incident duration: higher scores, which indicate greater sophistication or aggressiveness, generally correspond to lower incident duration. However, the sample size here is so small that it is impossible to say with certainty that a mathematical relationship exists. These limited results do suggest that additional work including many more locations is warranted.

Induced Demand Effects of Improvements

It has long been observed that transportation improvements that reduce travel times, especially those related to capacity expansion, become victims of their own success: lower travel times spur increased demand for the improved facility. This phenomenon, known as induced demand, has both short-run and long-run components. In the short run, trips will divert from nearby congested facilities to take advantage of the new lower travel times, and travelers who previously avoided a congested peak period will be drawn back to the peak. In the long run, reductions in travel time are thought to increase the amount of travel (VMT) as lower congestion allows both

Table 8.4. Active Traffic Management Impacts

Improvement	Impact
Traffic signal coordination	**Phoenix**—6.2% to 8% average increase in trip speeds (*21*).
	IDAS model uses a capacity increase of 14 to 20%. Actual increase value is sensitive to traffic variability and frequency of retiming (*3*).
RECOMMENDATION	*Decrease mean TTI by 7%.*
Traffic adaptive signal control	**Los Angeles (ATSAC)**—Travel time reduced by 12% to 18%, delay reduced by 44%, speed increased by 16% (*22*).
	Minneapolis (SCOOT)—Installation in 56 intersections showed 19% reduction in delay during special events, 8% during peaks (*12*).
	Oakland County, Michigan (SCATS)—Corridor travel time reduced from 7% to 32% over optimized fixed-time signal control. Average travel time reduction of 8% (average speed increased from 25 to 27 mph) (*12*).
	IDAS model recommends a default capacity increase of 8 to 14%. Actual increase value is sensitive to traffic variability. Assumes upgrade from coordinated preset timing (*3*).
	Dallas (North Central Expressway)—15% increase in speed, 15% decrease in delay (*23*).
RECOMMENDATION	*Reduce mean TTI by 12%.*
Ramp metering (fixed time)	**Portlan, Oregon**—25% increase in volume (*24*).
	Portland, Oregon—43% reduction in peak period accidents (*13*).
	Houston—29% increase in speed (*25*).
	IDAS model uses a default mainline capacity increase of 9.5% offset by a ramp capacity decrease of 33%. IDAS also suggests a reduction in accidents of 30% on ramp and adjacent freeway links (*3*).
	Minneapolis–St. Paul—14% average increase in throughput, 7% increase in corridor speed, 26% decrease in peak period accidents (*26*).
	Denver—19% increase in volume (*24*).
	Seattle (I-405 in 1997)—5% to 6% increase in volume (*24*).
	IDAS model uses a default mainline capacity increase of 13.5% offset by a ramp capacity decrease of 28%. IDAS also suggests a reduction in accidents of 30% on ramp and adjacent freeway links (*3*).
RECOMMENDATION	*Based on the Seattle before and after study presented in Chapter 6, use the following adjustments: 11% reduction in average travel time and 12% reduction in Planning Time Index.*
VMS/DMS	**Austin**—7% to 12% reduction in upstream lane volumes of an incident (*13*).
RECOMMENDATION	*For peak hour and peak period only, reduce demand volume by 3.5% (assumes 9% reduction in volumes during an incident and that incidents comprise 40% of total delay).*

longer and more trips to be made. Longer trips can result from the location decisions for place of residence and business. The converse is that congestion suppresses these aspects of travel.

Short-run induced demand can be studied via travel demand models that account for diversion of traffic from parallel facilities to an improved highway, shifts of travelers from other modes, and (depending on how the models are applied) the role of improved highways in causing people to shift the destinations of their trips. However, the models usually do not account for the effects of highway improvements on the total number of trips made and shifts in the locations of households, businesses, and other activities.

In previous studies, the induced demand effect has been quantified as elasticities of VMT with respect to highway travel time or lane miles. Travel time elasticities have been used in sketch planning analyses to estimate the aggregate response of travelers to transportation system improvements that provide time savings. The elasticities indicate the percentage change in VMT expected to result from a 1% change in travel time or lane miles. Cohen provided a summary of these studies (Table 8.6) (*27*). The results of Barr and Gorina are especially relevant because of the use of travel time as the causal factor. Their elasticities were in the –0.1 to –0.4 range, indicating that a 10% decrease in travel rate would cause a 1% to 4% increase in household VMT. These increases in VMT include the effects of modal diversion, trip distribution (in this case, substituting longer trips for shorter trips), and increases in the total number of person trips made.

For an individual facility, it would be expected that time savings would cause a greater increase in VMT than those suggested by the above elasticities. VMT increases occur because traffic increases on individual facilities include not only the

Table 8.5. Institutional and Programmatic Characteristics on Incident Management Programs in Study Locations

Urban Area	Traffic Incident Management Self-Assessment: Overall Score	Programmatic and Institutional	Operational	Communications and Technology	Quick-Clearance Law	Property Damage Only Move-to-Shoulder Law	Can a Fatality Be Moved with Medical Examiner Present?	Average Peak Period Incident Duration (min)
1	85.9	27.5	32.1	26.3	Yes	Yes	Yes	32.1
2	82.0	25.5	32.1	24.4	Yes	Yes	Yes	43.5
3	74.0	21.3	29.3	23.4	Yes	Yes	Yes	45.0
4	NA	NA	NA	NA	No	No	No	47.3
5	NA	NA	NA	NA	No	Yes	No	52.0
6	NA	NA	NA	NA	No	Yes	No	61.5

Note: NA = not available.

three effects noted above (modal diversion, trip distribution, and trip frequency), but also route diversion (in which travelers shift the routes they use but do not alter their origins or destinations).

These previous studies considered only changes in average travel times and did not include the effect of reliability on induced demand. However, it has been noted that travel time reliability has additional value to travelers beyond consideration of average or typical conditions (*28*). To the extent this is true, improvements in reliability may have an additional effect on induced demand. One approach to this issue may be to convert reliability improvements to equivalent travel time units. For example, Bates et al. measured variability as the standard deviation of travel time and found the value of variability reductions to be equal to 0.8 to 1.3 times the value of mean travel time reductions (*29*). Brownstone and Small measured variability as the difference between the 90th and 50th percentile travel times and found the value of variability reductions to be roughly equal to the value of mean travel time reductions (*30*).

However, the merit of adding a reliability factor to changes in mean travel time may be dubious. If elasticities are based on empirical data collected over a sufficiently long period of time so that they include the effect of disruptions, then adding a reliability factor would be double counting. That is, to the extent that observed travel times are overall mean travel times that include both recurring and nonrecurring sources, then the relationships identified in Chapter 7 indicate that an improvement in the overall mean also means that reliability has improved. If this is the case, then the reliability effect is already embedded in the observed increases in travel activity.

Table 8.6. Summary of Elasticities Used for Induced Demand (27)

Study	Primary Data Source	Change in Long-Run VMT Elasticity (%): Travel Time	Lane Miles	Comment
Barr and Gorina	1990 and 1995 Nationwide Personal Transportation Survey (NPTS)	–0.3 to –0.5	NA	Elasticities may be overstated because of the tendency for longer trips to have higher average speeds than shorter trips. Reanalysis suggests elasticities of –0.1 to –0.4.
SACTRA	Fuel price elasticities	–1.0	NA	Elasticity may be overstated because of differences in opportunities available to motorists to reduce travel time and fuel costs.
Noland	Highway statistics	NA	–0.8	Elasticity may be overstated because (*a*) of shifts of VMT and lane miles among highway systems and (*b*) highways that are widened have more VMT/lane mile than other highways.
Strathman	1995 NPTS, TTI Urban Mobility Study data set	NA	–0.32	Elasticity includes direct effects of lane miles on household VMT and indirect effects due to changes in density.
Marshall	TTI Urban Mobility Study data set	NA	–0.76 to –0.85	Elasticity may be overstated because of roadway classification issues and diversion from outside urban areas.

The situation is further clouded because no empirical studies have been done on the induced demand effect of operational treatments. Unlike capacity expansions (the basis of previous elasticity work), which improve recurring congestion every day, operational treatments only affect those conditions when disruptions occur (e.g., incidents and work zones). Although the effect of operational treatments can be tracked to a reduction in overall mean travel times, which in theory should have an induced demand effect, it is still not known if an improvement in travel times on a few days affects travel behavior in the same way as travel time improvements that affect every day.

These issues are sufficiently complex to warrant additional study. This project did not attempt to address these issues, but focused on the immediate or first-order impacts of improvement strategies on reliability. As new research becomes available that quantifies induced demand effects, it can be incorporated with the relationships developed in the present study. This process would involve three steps:

1. Estimate the first-order change in mean travel time and reliability measures.
2. Increase demand using elasticities from new research. The pivot point formulation is a convenient way to implement elasticities; for example,

   $$V = V_0 * \left(T/T_0\right)^{\beta}$$

   where

   V = new volume, including induced demand;
   V_0 = original volume, before the improvement;
   T = travel time after the improvement;
   T_0 = travel time before the improvement; and
   β = elasticity.

3. Reestimate the mean travel time and reliability measures using the new (increased) demand values.

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CHAPTER 9

Conclusions and Recommendations

Findings and Products of the Research

Data Set Compilation and Usage

A large and comprehensive data set was compiled with which to conduct the research. The data set will be of use for future research and the SHRP 2 data archive being constructed with the L03 data set as its core. The data set includes many levels of aggregation and summarization. The traffic data from urban freeways, which are the largest portion of the data set, include the original measurements from roadway detectors (5-minute intervals by lane) and number in the hundreds of millions of records. The traffic data also are summarized at several spatial and temporal aggregation levels. The most-summarized portion of the data set is the one used for the cross-sectional statistical analysis: every record is an annual summary of traffic and reliability characteristics, with annual event characteristics and roadway features merged into it. The data processing included new procedures that the research team created specifically for the project.

The sources of the data were primarily from state departments of transportation; data included continuous traffic measurements, incidents, work zones, intelligent transportation system equipment, operating policies, and geometric characteristics. In addition, the team purchased a limited amount of private-vendor vehicle probe data for rural freeways and signalized arterials; the rural freeway data were adequate to establish reliability, but the signalized arterial data did not appear to have enough samples, and local signal timing data were not available for the time period of the probe data. Incident data from a second private vendor also were available without a fee; these provided the needed lane blockage data in several locations where public agencies did not collect this type of information.

Fusion and integration of the various data proved to be a daunting and time-consuming task. The data sets had different georeferencing, which complicated the matching of traffic data, incidents, improvements, and geometric characteristics. Much of the matching had to be done manually. A large amount of testing, quality control, and development of new processing procedures had to be conducted.

The utility of the data set as a research resource was proven several times during the project. Often, the team needed to investigate new areas or compute factors, and these tasks were easily accomplished because the data were analysis ready. It is expected that future researchers will appreciate this feature.

In addition to supporting research, the data set represents an excellent model for practitioners to use in developing performance monitoring systems for congestion and reliability. Specifically, the different levels of temporal and spatial aggregation can be used to support many local requirements. The fusion of traffic, event, and geometric data provides the basis for tracking reliability trends, and it also includes the data required to explain those trends (e.g., demand and events). Data processing for performance monitoring is not trivial, and many different methods and assumptions can be used. The L03 research provides a basis for standardizing those procedures.

Exploratory Analyses

A large variety of exploratory analyses were undertaken before the main analyses to test assumptions and develop data processing methods and as an aid in understanding reliability in general. The highlights of these exploratory analyses follow.

Recommended Reliability Metrics

Empirical testing revealed that the performance metrics defined in the early stages of the research were sensitive to the effects of improvements. However, the team noticed that the 95th percentile Travel Time Index (TTI) may be too extreme a value to be influenced significantly by operations strategies and that

Table 9.1. Recommended Reliability Metrics

Reliability Performance Metric	Definition	Units
Buffer Index	Difference between 95th percentile TTI and average travel time, normalized by average travel time. Difference between 95th percentile TTI and median travel time (MTT), normalized by MTT.	%
Failure and on-time measures	Percentage of trips with travel times <1.1 MTT and <1.25 MTT. Percentage of trips with space mean speed less than 50, 45, and 30 mph.	%
Planning Time Index	95th percentile TTI.	None
80th percentile TTI	Self-explanatory.	None
Skew statistic	(90th percentile TTI – median)/(median – 10th percentile TTI).	None
Misery Index (modified)	Average of highest 5% of travel times divided by free-flow travel time.	None

the 80th percentile was more sensitive to these improvements. As a result, the 80th percentile TTI was added to the list of reliability performance metrics for the remainder of the research. The final set of reliability metrics, which also are appropriate for general practice, appears in Table 9.1.

Travel Time Distributions

Development of travel time distributions is the starting point for defining reliability metrics and a convenient way to visualize general congestion and reliability patterns for a highway section or trip. Examination of the distributions from the study sections used in this research reveals several characteristics:

- The shape of the travel time distribution for congested peak times (nonholiday weekdays) is much broader than the sharp spike evident in uncongested conditions. The breadth of this broad shoulder of travel times decreases as congestion level decreases;
- Similarly, the tails of the distributions (to the right) appear more exaggerated for the uncongested time slices. However, note that the highest travel times occur during the peaks; and
- Despite the fact that peaks have been defined, some trips occur at close to free flow. More trips are at free-flow speeds in the peak period than in the peak hour, probably because the peak times actually shift slightly from day to day, as traffic demand can be shifted by events. Also, there are probably some days when overall demand is lower than other days.

Data Requirements for Establishing Reliability

Because reliability is defined by the variability of travel conditions (travel time), it must be measured over a substantial portion of time to allow all of the influences of random events to be exerted. The optimal question here is, how much data are enough? Tests showed that an absolute minimum of 6 months of data is required to establish reliability within a small error rate in areas where winter weather is not a major factor. A full year of data is preferred.

Trends in Reliability

A study was undertaken using the Atlanta study sections to track performance for 2006, 2007, and 2008. Between 2006 and 2007, average congestion increased and reliability decreased, using the Planning Time Index and the Buffer Index to measure reliability. However, between 2007 and 2008, average congestion levels fell on all study sections as demand fell in response to the reduction in overall economic activity; this decrease corresponded to many anecdotal stories and other analyses about congestion in 2008. However, on most study sections, the Buffer Index showed an increase or a very marginal decrease, which would indicate that reliability worsened in most cases. In contrast, the Planning Time Index decreased on all sections. This discrepancy between the indices raised doubts about the use of the Buffer Index as the primary metric for tracking trends in reliability. The problem comes from way the Buffer Index is calculated: it is the buffer time (difference between the 95th percentile and the mean) normalized by the mean. In this experiment the 95th percentile decreased less than the mean, resulting in a higher Buffer Index. In other words, the decreased demand affected all points on the travel time distribution, not just the upper tail. The team believes the mechanism for these changes was a reduction in demand that led to across-the-board decreases in congestion, including days with and without roadway events (disruptions). However, conditions on the worst days, which are primarily a result of severe disruptions, were improved to a lower degree than typical or average conditions. The team expects that operations strategies would have a more pronounced effect on the times influenced by severe events.

The result of this experiment was that the Buffer Index is considered too erratic or unstable for use as the primary reliability metric for tracking performance trends or for studying the effects of improvements. However, as a secondary metric, it provides useful information and should be included in a suite of reliability performance metrics. In Atlanta from 2007 to 2008, it might be said that from the perspective of the user, the new conditions of 2008 were indeed less reliable, if one assumes that the 2008 average congestion was the base level: the worst days (as measured by the 95th percentile) are still out there. If, however, one considers the base level of congestion to be 2007, then it is clear that overall, the user's experience was improved.

Defining Peak Hour and Peak Period

Most previous studies of reliability and congestion define fixed time periods for the peak hour and peak period. However, for this research, the team decided that the most appropriate method would be to define each term specifically for each study section. Several methods were tested, with the most effective using a definition based on the most typical start and end times of continuous congestion. The resulting time slices were reviewed against local anecdotal knowledge and required very little adjustment.

Estimating Demand in Oversaturated Conditions on Freeways

Because the study took an empirical approach to studying reliability, the team had to deal with the thorny issue of how to measure demand given that measured volumes under congested flow are actually less than capacity on freeways. A method for assigning the demand stored in queues during periods of flow breakdown was developed and used throughout the remainder of the research, particularly in defining the demand-to-capacity ratio for the statistical modeling.

Reliability Breakpoints on Freeways

It was shown that travel time reliability on a freeway is not a function of counted traffic volumes until a breakpoint volume is reached. At that breakpoint, travel time reliability decreases abruptly. Once the breakpoint volume is exceeded, the decrease in travel time reliability (increase in the variance) is extreme and so abrupt as to suggest it is a vertical function, with a nonsingular relationship to further volume increases. The breakpoint volume varies significantly between facilities and even within the same freeway facility (by location and direction of travel on the same facility), and it does not appear to be a fixed ratio of the theoretical capacity of the subject section of the facility. The breakpoint in reliability generally occurs at a counted volume significantly lower than the theoretical capacity of the facility computed according to the methodology of the *Highway Capacity Manual* (HCM). This is partly because the breakpoint volume computed in this analysis was the average hourly volume counted over a peak period, and not the peak 15-minute demand used in the HCM capacity calculation.

But this peaking effect does not entirely explain the difference between breakpoint and theoretical capacity. Part of the reason that the breakpoint volume is significantly lower than the theoretical capacity is that most sections of freeway are upstream of a bottleneck and, thus, are affected by downstream congestion backing up into the subject section long before the subject section's HCM capacity is reached. Further, traffic-influencing events, especially incidents, effectively lower capacity when they occur, and over time these events cause reliability to degrade. This effect manifests itself in lower breakpoint volumes than for capacity related strictly to physical features. Finally, even for bottlenecks, the data suggest that the reliability breakpoint occurs long before the theoretical HCM capacity of the bottleneck is reached.

Sustainable Service Rates on Freeways

Just as travel times vary over time, capacity is not a fixed value, but also varies over time. The same factors that influence reliability also affect capacity variability. Incidents and work zones reduce overall roadway capacity by blocking lanes and shoulders and by affecting driver behavior (e.g., lower speeds and variable following distances due to rubbernecking). Weather conditions affect driver behavior in similar ways. Capacity probably is not affected by the amount of demand (volume) as reliability is, but it is affected by the nature of that demand. That is, at a microlevel, when volumes are very close to theoretical capacity, variability in driver behavior, small bursts of demand at merge areas (e.g., on-ramps), and the distribution of trucks at specific places and times all probably cause flow to break down at different demand levels. The research did not specifically tease out these factors, but all of them are embedded in the final capacity distributions. The team developed a large set of capacity distributions that look roughly like travel time distributions, but reversed: the tail of the distribution is skewed to the left (lower capacity values) rather than to the right. Because these distributions were developed from year-long data measurements, they include the effect of many influencing factors, resulting in capacity values that could be used in a stochastic framework to model congestion and reliability. The set of capacity distributions also is a useful construct for accounting for reliability within future versions of the HCM.

Travel Time Distributions on Urban Freeways, Signalized Arterials, and Rural Freeways

An analysis of travel time distributions for different time slices and congestion levels revealed the following characteristics:

- All distributions feature a tail that is skewed to the right (i.e., higher travel times). Most of these abnormally high

travel times can be attributed to one or more of the sources of congestion; that is, they occur in the presence of an event(s) and/or high demand;
- Uncongested periods are characterized by a sharp peak of travel time frequencies near the free-flow speed;
- When congestion dominates the time slice (e.g., peak hour, peak period), the travel time distribution becomes more broad and less peaked;
- Travel time distributions on signalized arterials are uniformly broad in shape, even for relatively low levels of congestion, presumably because of signal delay at even low volumes and interference from side traffic; and
- As trips become longer, travel time distributions assume the typical uncongested shape.

Vulnerability to Flow Breakdown

Examination of the 5-minute data at individual stations (groups of detectors in a direction on a highway segment) reveals that there is an upsurge in the 95th percentile travel times 20 to 45 minutes before the start of what is considered the normal peak period. This upsurge begins before the uptick in average travel times and indicates that this window of time is vulnerable to flow breakdown. These windows are extremely important for operators to focus on as breakdowns during this time will strongly influence the duration and severity of the peak.

Reliability of Urban Trips Based on the Reliability of Links

For extended travel (trips of 10 to 12 miles) on urban freeways, the reliability of the entire trip can be predicted as a function of the reliability of the links that comprise the trip. Although not specifically tested, it should be possible to construct trip reliability for trips that include other types of highways in addition to freeways, subject to the issue of time dependency for long trips.

Before-and-After Studies on Selected Study Sections

The primary goal of the research was to develop relationships for predicting the change in reliability due to improvements. The best way to accomplish this was with controlled before-and-after studies. However, such analyses are substantially more challenging than what is typically done because of the data requirements: to establish reliability empirically, 6 to 12 months of data are required, with 12 months being the preferred data collection period. This means a long period of continuously collected data is required both before and after the improvement. So, instead of designing traditional before-and-after experiments, the team concentrated on collecting continuous traffic data from areas known from previous experience to have quality data, interesting congestion, and good records of event data. At a minimum, this method of data collection would provide the best data for developing cross-sectional statistical relationships. As it turned out, the team was able to identify 17 cases of improvements that coincided with identified data, although the types of improvements were somewhat limited.

The analysis produced reliability adjustment factors that can be applied to the various improvements. The adjustment factors for a specific type of improvement vary slightly, presumably because background (baseline) conditions are somewhat different. Users are directed to the detailed descriptions of the studies in Appendix B to select the conditions most appropriate for their situation.

A global finding from the before-and-after analyses was that all forms of improvements, including capacity expansion, affect both average congestion and reliability in a positive way (i.e., average congestion is reduced and reliability is improved). Conceptually, this makes sense: one of the seven sources of congestion and reliability identified earlier was the amount of base capacity. All things being equal, more capacity (in relation to demand) means that the roadway is able to absorb the effects of some events that would otherwise cause disruption. The size of this effect was greater than the team had originally anticipated (see Chapter 8 for a complete discussion). For transportation professionals, this significance of capacity means that to the extent that reliability is valued more highly than average travel time, a large part of the benefits of capacity-expansion projects has been missed in historical analyses.

Cross-Sectional Statistical Modeling

Going into the project, the team realized that only a limited number of before-and-after studies would be possible. Therefore, much of the effort for the study went into the creation of a cross-sectional data set from which statistical models could be developed. The final analysis data set for the statistical modeling is highly aggregated: each record represents reliability, traffic, and event data summarized for a section for a year. This structure is necessary because reliability is measured as the variability in travel times over the course of a year. As such, the cross-sectional model is a macroscale model. It does not seek to predict the travel time for a particular set of circumstances; that is, it is not appropriate for real-time travel time prediction. Rather, it seeks to predict the overall travel time characteristics of a highway section in terms of both mean and reliability performance. It is, therefore, appropriate for adaptation to many existing models and applications that seek to do the same, and it can serve as the basis for conducting cost–benefit analyses.

Two model forms were developed: simple and complex. The simple model form relates all of the reliability metrics to the mean TTI for all three highway types studied (urban freeways, rural freeways, and signalized arterials). These relationships are convenient for many applications that produce mean travel time–based measures as output (e.g., traditional travel demand forecasting models, HCM). Because the mean TTI developed from the research data includes the effects of all possible influences of congestion, which produces a mean value greater than model results (which usually are for typical non-extreme conditions), an adjustment factor was developed to convert model output to the overall mean TTI so that the relationships can be applied.

A more detailed model form was developed that relates reliability measures to the factors that influence reliability. It has long been theorized that reliability is determined by demand, capacity, incidents, weather, and work zones. In fact, that is what the team found from analyzing the research data set. A tiered predictive model was developed that related the reliability metrics over highway sections (multiple links, usually 4 to 5 miles long) for different time slices to

- The critical demand-to-capacity ratio (maximum from the individual links);
- Lane hours lost due to incidents and work zones combined (annual); and
- Number of hours during which rainfall was ≥0.05 inch (annual).

The rainfall variable must be computed using weather records. Guidance was developed for how to develop the demand-to-capacity ratio. Lane hours lost was decomposed into a series of subrelationships that can be estimated using easily obtained data.

Congestion by Source

The research team had conducted congestion by source analyses in earlier projects, but the data available for those studies were incomplete. The L03 research offered an opportunity to assemble the data more carefully and to incorporate other data sources. The goal was to capture the contributions of the factors influencing congestion and reliability, as shown in Figure 9.1. The analysis was conducted at a microlevel: data at the 5-minute level were analyzed for possible effects by the sources.

An assignment of congestion causality was made for the measured delay in the Seattle data. Taken at face value, the analysis supports the commonly heard statement that “incidents and crashes cause between 40% and 60% of all delay.” In reality, a considerable portion of the delay associated with

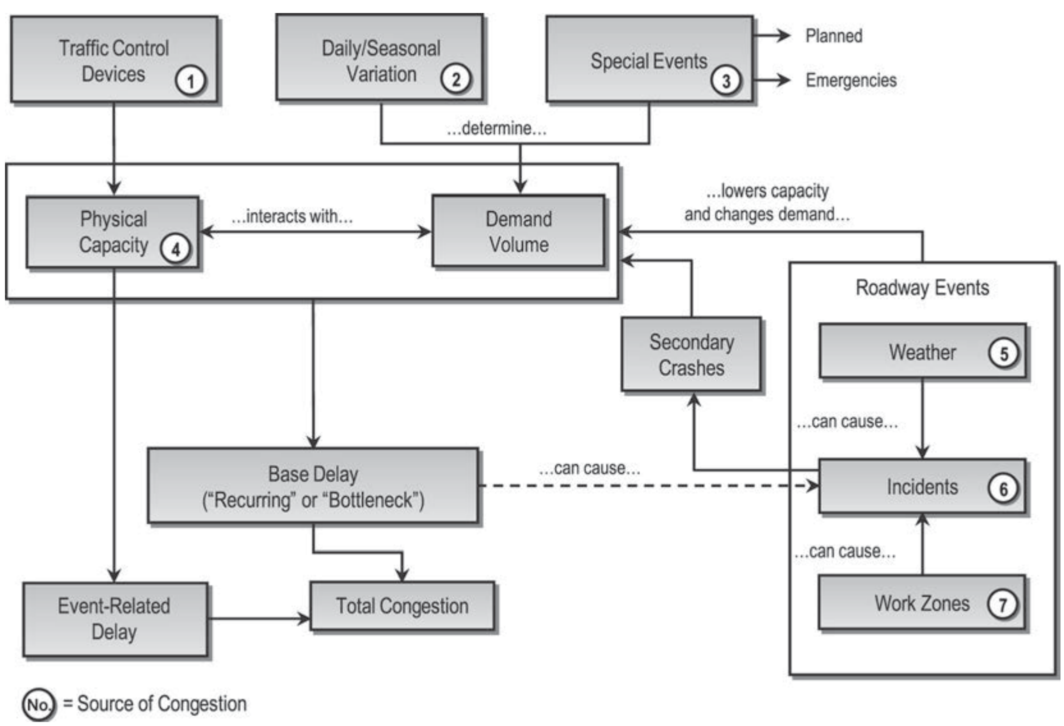

Figure 9.1. A model of congestion and its sources.

incidents and crashes is caused by large traffic volumes. Therefore, the amount of delay caused by incidents is actually less than can be reasonably assigned by simply observing the occurrence of events. There were numerous examples in the analysis data set of significant crashes and other incidents that caused little or no congestion because of when they occurred. These showed that without sufficient volume, an incident causes no measurable change in delay.

In the Seattle area, many incidents take place during peak periods, causing already existing congestion to grow worse, the result of the interwoven effects of incidents, bad weather, and traffic volumes on travel times. In addition, all types of disruptions to normal roadway performance (rain, crashes, noncrash incidents) cause congestion to start earlier and last longer during the peak period, while increasing travel times during the normally congested times. Incidents and other disruptions also can cause congestion to form during times of the day that are normally free from congestion. However, congestion only forms when the disruption lowers functional capacity below traffic demand. Thus volume, relative to roadway capacity, is a key component of congestion formation, and in urban areas it is likely to be the primary source of congestion. Disruptions then significantly increase the delay that the basic volume condition creates.

The fact that traffic volume is the basis of congestion also affects how various traffic disruptions alter travel patterns. Not only does traffic volume affect whether an incident causes congestion, but it affects how long that congestion lasts once the primary incident has been removed. The Seattle data showed that in the morning peaks, disruptions have a more noticeable effect on the timing of the end of the peak period, while in the evening the opposite is true.

In summary, analysis of 42 roadway segments in the Seattle metropolitan area showed that a majority of travel delay in the region is the direct result of traffic volume demand exceeding available roadway capacity. Whenever they occur, incidents, crashes, and bad weather add significantly to the delays that can be otherwise expected. The largest of these disruptions plays a significant role in the worst travel times that travelers experience on these roadways. However, the relative importance of any one type of disruption tends to vary considerably from corridor to corridor.

In peak periods, incidents add only marginally to total delay, but they shift when and where those delays occur, as well as who suffers from those delays. That is, many incidents shift where a normally occurring bottleneck occurs, freeing up some roadway sections, while causing others to suffer major increases in congestion. But taken as a total, if a section is already normally congested, the added delay from incidents is modest (at least in Seattle) compared with the daily delay from simply too many vehicles for the available physical capacity.

In congested urban areas, traffic incidents often cause unreliable traffic patterns more than increases in total delay. Although the total delay value does goes up, the big change is often the shift in who gets delayed. For a specific severe incident, many travelers may value the extra (unplanned) delay very highly, and they are very likely to remember these extreme cases. Some of that (total) delay is offset by other travelers who reach their destination early because their trip is downstream of the incident-caused bottleneck, and volume has probably been metered by that bottleneck.

Significance of Demand for Reliability Estimation

A major result of the research was the finding that demand (volume) is an extremely important determinant of reliability, especially in terms of its relation to capacity. As shown in Figure 9.1, demand's interaction with physical capacity is the starting point for determining congestion. The research team initially postulated that the effect of most events is determined by the level of demand under which those events occur. For example, if an incident or work zone blocks a traffic lane, the impact will only be felt if volumes are high enough to be affected by the lost capacity. However, the team did not expect demand to have as strong an effect as the analyses indicated. Throughout the different analyses conducted for the L03 research, demand kept emerging as a significant factor. The case for the strong effect of demand (volume) is summarized as follows:

- The Atlanta trend analysis revealed that roughly a 3% drop in demand significantly improved both average congestion level and reliability between 2007 and 2008.
- The before-and-after studies of capacity improvements produced a strong improvement in reliability, not just average congestion. The team believes the mechanism for this improvement is a simultaneous change in capacity in relation to demand (the demand-to-capacity or volume-to-capacity ratios), so a change in either will produce the same effect. This simultaneous effect was subsequently verified in the cross-sectional statistical models.
- The Seattle congestion by source analysis revealed that a substantial portion of delay could not be attributed to an event, even with careful consideration of off-section conditions and special events. This leaves demand as the sole cause. The Seattle analysis also shows that incidents during low-demand periods have only a small effect on congestion.
- The midday cross-sectional models did not show lane hours lost due to incidents and work zones as a statistically significant independent variable, indicating that under low-volume conditions (i.e., conditions in which volumes are low relative to the available physical capacity), the annual

effect of disruptions is small. Extreme disruptions (e.g., multiple lane closures) clearly will have an effect on an individual day, but over the course of a year these events are rare and do not appear to move the annualized reliability metrics very much at all.
- The peak hour and peak period cross-sectional models showed that the demand-to-capacity ratio was a stronger contributor to the model than lane hours lost.

The influence of demand is probably related not only to sheer volume of traffic but its characteristics. As volumes approach theoretical capacity, traffic flow becomes unstable and increasingly susceptible to breakdown due to small changes. These small changes can occur at a point substantially less than theoretical capacity, and when they occur near potential bottleneck areas such as on-ramps, weaving areas, and lane drops, the team postulates that their effect is enhanced.

In addition to variations in demand as a source of unreliable travel times, evidence exists that physical capacity is also variable. This variation in physical capacity, which results from disruptions and other factors that can occur on a highway segment, was observed by the research team throughout the course of a year. However, the work of Brilon and preliminary research conducted by other SHRP 2 contractors suggest that capacity varies even in the absence of disruptions (*1*).

Why would physical capacity vary? The team believes that fluctuations in traffic conditions at a microscale are the most likely causal factors. These small changes could be related to

- **Driver behavior**—One or a few vehicles can behave aberrantly (e.g., sudden unexplained stops);
- **Truck presence**—A small increase in trucks in the traffic stream at a given point in time and space could have a detrimental effect; and
- **Microbursts of merging traffic**—A small but intense influx of vehicles from an on-ramp could be enough to cause flow breakdown.

The finding that demand and capacity strongly influence travel time reliability has several implications:

- The mechanism for the influence of demand and capacity on travel time reliability can be seen in the before-and-after studies. Consider the distribution of travel times that occurs on a routinely congested highway segment over the course of a year. Capacity additions and demand reductions will reduce nearly all the travel times in the congested portion of the distribution and will improve congestion on nearly all days; capacity and demand are always present in the roadway environment. In contrast, strategies geared to disruptions (e.g., incident management) will only affect congestion when those disruptions occur, and disruptions will not appear during every congested period of every day. In other words, only selected travel times in the congested portion of the distribution will be reduced by strategies such as incident management;
- It is clear that traditional capacity projects improve reliability, and failure to account for this effect in economic analyses has excluded benefits to users; and
- Demand management strategies, such as pricing, also will lead to improvements in reliability.

Accounting for volumes in relation to available capacity can provide a tool for efficiently allocating operations strategies, particularly incident management. That is, times and locations that are most vulnerable to flow breakdowns can be targeted.

Reliability As a Feature of Congestion

The intertwined relationship between demand, capacity, and disruptions documented in the L03 research leads to another major conclusion: *reliability is a feature or attribute of congestion, not a distinct phenomenon.* Because any influence on congestion will lead to unreliable travel, reliability cannot be considered in isolation. Going into the research, the project team's thinking, like that of the profession in general, was that reliability related primarily to disruptions and the operational treatments aimed at those disruptions. The analysis showed that even in the absence of disruptions, a substantial amount of variability (i.e., unreliability) in travel times exists for recurring-only (bottleneck-related) conditions. Therefore, the most inclusive view of travel time reliability is that it is part of overall congestion. Just as congestion can be defined by extent and severity, it can also be defined by how it varies over time. Operational treatments are clearly effective in dealing with unreliable travel, but so are other congestion-relief measures.

Recommendations for Future Research

Based on the results of this study, the team offers the following suggestions for future research.

Detailed Examination of Reliability Causes and Prediction on Signalized Arterials

Because of data limitations in the number of signalized arterials with continuous travel time data, the amount of data on those that did, lack of continuous volume data to match against the available travel time data, and no information on incident and work zone characteristics, only simple analyses using travel time data from signalized arterials could be undertaken for this study. However, since the completion of data collection for this research, it is clear that data availability is about to increase dramatically. Private vendors of vehicle probe data have improved their data processing methods and increased their sources of travel time data in the past 18 months. As a result, many states already have purchased statewide private-vendor probe data, primarily for traveler information applications. Like freeway detector data, these data have value in developing performance measures and supplying research studies after the fact. This trend is expected to continue as new sources, perhaps even those from consumer sources, continue to be added to their products. In addition, new and relatively inexpensive technologies for collecting travel times on signalized highways, such as Bluetooth readers and vehicle signature detectors, offer great potential for new forms of traffic management applications by public agencies.

Effective Collection of Systemwide Demand Data

The study was possible because traditional urban freeway detectors collect both speeds and volumes. However, if the newer sources of speed and travel time data discussed above become widespread, there will be no companion volume measurements until the number of vehicles detected approaches 100%. The L03 research has shown that demand is a vital determinant of reliability. Further, from an operations viewpoint, emerging methods such as active traffic management are likely to require more, not less, data (travel times and volumes) to feed their control processes.

Consistency in Data Collection for Incidents and Work Zones

The research team labored mightily to find and process incident and work zone data to match against the traffic measurements. The duration of blockages (recognizing that the nature of blockages can change over the course of a single event) was the critical piece of data required. Also, consistency in geocoding of events, traffic detectors, and roadway features would greatly enhance future research. An extra complication is the fact that private vendors (at least the two used in this research) use the Traffic Message Channel standard for geolocation, a standard that is almost never used by public agencies. To avoid the large amount of manual intervention endured by the team (which would be even more onerous for public agencies trying to deal with the issues systemwide rather than on selected study sections), consideration should be given to how all of these data should be collected, organized, and related to each other. The development of new standards or the extension of existing ones may be required to accomplish this goal.

Development of Alternative Reliability Concepts for Extreme Events

As developed in this research, the concept of reliability is part of the urban congestion problem. That is, it has been studied on highways that experience routine congestion from both recurring and nonrecurring sources. The working definition used was that reliability is a description of how travel times vary over time. It was noted that extreme events (disruptions) such as major snow or ice storms, hurricane evacuations, and full highway closures do not have a statistical significance in trying to predict reliability, which, by definition, occurs over the course of a year. Because they are so rare, they only shift the annual travel time distribution by a small amount. However, these extreme events are extremely important to both transportation agencies and travelers, even if their occurrence is rare. If the urban congestion–based reliability concepts cannot describe these events, then an alternative should be explored.

Standard Data Processing Methods for Developing Congestion and Reliability Performance Measures

In order to conduct the research, data processing procedures had to be developed to develop reliability performance metrics. These metrics are likely to be used on their own in many other transportation applications. However, a large amount of leeway exists in how the metrics can be developed from field data. As congestion performance monitoring becomes more widespread, and perhaps even federally mandated, the need to produce consistent metrics will become critical.

Improved Methods for Microlevel Weather Data Collection

The locations of the weather observations used in the study relative to the study sections were admittedly crude. The assumption was that data from the closest National Weather Service station observations would apply to the study sections, when they could be several miles apart. This assumption probably led to misallocation of rainfall occurrence for at least some cases, but major weather fronts are most likely accounted for in the data. However, the team believes that better methods can be explored. In lieu of deploying weather stations at regular intervals, which would be prohibitively expensive, one promising method is the automated processing of time-lapse radar information to obtain precipitation data.

Reliability of Trips

At the beginning of the study the team selected the extended highway section as the basic unit of analysis. Relatively homogenous highway sections in terms of geometrics, typically covering 4 to 5 miles for urban sections (with much longer lengths for the few rural freeway sections), were chosen. These study sections were chosen because this is the level at which the data were available and because they can be used by many existing applications. However, for several reasons, calculating the reliability of an entire trip is likely to be quite different. First, with few exceptions, the study sections were selected because they had relatively high volumes and were moderately congested during peak times; that is, they represent the worst conditions that can be encountered for a user making an entire trip. This means that a trip-based travel time distribution is likely to gravitate toward one that shows less congestion and better overall reliability. An additional complication is the scheduling component: if a trip can start within a window of time as opposed to a specific time, users can in theory improve the travel time and reliability of their trip. Research is needed on these subjects, specifically how they affect investment decisions. That is, the facility focus as suggested by the L03 perspective leads to a certain set of investments (improvements). If the focus is changed to the entire trip (i.e., trips, as well as facilities, are managed), how do the investment decisions change?

Before-and-After Studies for Demand Management, Active Traffic Management, and Institutional Aspects of Incident Management

Reliability evaluations style (with long before-and-after periods) should be undertaken as these types of projects are deployed. In addition to observing changes in congestion and reliability, these future studies should report the changes in the independent variables for the L03 cross-sectional statistical models (demand, capacity, and the characteristics of incidents and work zones). The present study noted that various degrees of institutional arrangements and policies related to incident management should have a positive effect on incident duration, which can then be related to reliability via the statistical models. The idea is that, beyond the deployment of equipment, the success of incident management will be determined by how agency agreements and policies translate to reductions in incident duration in the field.

Real-Time Predictive Models

A potentially useful corollary to the macrolevel reliability relationships developed in the L03 effort is the development of models that would relate the congestion level on a specific day to the contributing factors. Such models would provide travel time prediction for a given set of circumstances rather than reliability prediction, but they would provide a useful tool for traffic managers. The L03 data set could be used as a starting point for this research, although based on the team's experiences with the congestion by source analysis, more microlevel data on traffic flow and events might be necessary (e.g., 30-second to 1-minute volumes and speeds). A microlevel examination of traffic flow breakdown would provide great insight into the causes of congestion.

Expand on the Concept of Whole-Year Capacity

The L03 research demonstrated that capacity varies substantially. The concept of whole-year capacity, touched on in the L03 exploratory analyses, is worth pursuing further. Because many predictive models (including travel demand forecasting and macroscopic and mesoscopic simulation models) use the concept of capacity as a starting point for determining congestion, whole-year capacity may be an entry point for incorporating reliability into these models. That is, instead of using a fixed capacity, model runs could use whole-year capacity distributions stochastically. Because the whole-year capacity distributions developed from empirical data include all of the possible influencing factors, they represent a more realistic picture of how capacity actually behaves.

Reference

1. Brilon, W., J. Geistefeldt, and H. Zurlinden. Implementing the Concept of Reliability for Highway Capacity Analysis. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2027*, Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 1–8. http://trb.metapress.com/content/u700713ur834410r/fulltext.pdf.

APPENDIX A

Data Elements and Structure for the Statistical Analysis Data Set

Table A.1. Area Operations

Category	Variable	Definition or Question
Location	URBAN_AREA	Name of urban area where site is located
	TIME_SPAN	Dates the data cover (typically 1 year)
Service patrol (SP)	AREA_SP_TRUCKS	Number of SP trucks in active duty
	AREA_SP_TRUCKS_ACTIVE	Percentage of total hours in a week when SP trucks are active
	AREA_SP_TRUCKS_MILE	Trucks per route mile
Incident management policies	TIM_SA_OVERALL	Traffic Incident Management Self-Assessment Score, Overall
	TIM_SA_PROGRAM_INSTITUTIONAL	Traffic Incident Management Self-Assessment Score, Section 1
	TIM_SA_OPERATIONAL_ISSUES	Traffic Incident Management Self-Assessment Score, Section 2
	TIM_SA_COMM_TECHNOLOGY	Traffic Incident Management Self-Assessment Score, Section 3
	QUICK_CLEARANCE_LAW	Is a quick-clearance law in effect?
	PDO_MOVE_TO_SHOULDER_LAW	Can property damage only (PDO) crashes be moved to shoulder by motorists?
	FATALITY_REMOVAL	Can fatalities be moved without medical examiner death certification?
Operations	TMC_STAFF_MILE	Number of traffic management center (TMC) staff divided by miles covered

Table A.2. Service Patrols

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	PERIOD	Time slice (1 = peak hour; 2 = peak period; 3 = midday; 4 = weekday; 5 = weekend/ holiday; 6 = counterpeak; 7 = peak shoulder; 8 = all days)
Service patrol	SERVICE_PATROL_TRUCKS	Number of SP trucks covering the section during the time period
	SERVICE_PATROL_SCHEDULE_PCT	Percentage of time period when SP trucks are active
	SERVICE_PATROL_HOURS_MILE	Truck hours per mile during time period

Table A.3. Bottleneck Off-Section

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	BOTTLENECK_NAME	Unique name for this bottleneck
	ROUTE_NORTH_APPROACH	Intersecting Route 1
	ROUTE_SOUTH_APPROACH	Intersecting Route 2
	ROUTE_EAST_APPROACH	Intersecting Route 3
	ROUTE_WEST_APPROACH	Intersecting Route 4
	NB_EXIT_AADT_C	Annual average daily traffic–to–capacity (AADT/C) ratio on the northbound exit to the bottleneck
	NB_EXIT_PEAK_PERIOD_D_C	Peak period demand-to-capacity (d/c) ratio on the northbound exit to the bottleneck
	NB_EXIT_PEAK_HOUR_D_C	Peak hour d/c ratio on the northbound exit to the bottleneck
	SB_EXIT_AADT_C	AADT/C ratio on the southbound exit to the bottleneck
	SB_EXIT_PEAK_PERIOD_D_C	Peak period d/c ratio on the southbound exit to the bottleneck
	SB_EXIT_PEAK_HOUR_D_C	Peak hour d/c ratio on the southbound exit to the bottleneck
	EB_EXIT_AADT_C	AADT/C ratio on the eastbound exit to the bottleneck
	EB_EXIT_PEAK_PERIOD_D_C	Peak period d/c ratio on the eastbound exit to the bottleneck
	EB_EXIT_PEAK_HOUR_D_C	Peak hour d/c ratio on the eastbound exit to the bottleneck
	WB_EXIT_AADT_C	AADT/C ratio on the westbound exit to the bottleneck
	WB_EXIT_PEAK_PERIOD_D_C	Peak period d/c ratio on the westbound exit to the bottleneck
	WB_EXIT_PEAK_HOUR_D_C	Peak hour d/c ratio on the westbound exit to the bottleneck

Table A.4. Section Characteristics

Category	Variable	Definition
Location	URBAN_AREA	Name of urban area where the site is located
	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	ROUTE	From TMC configuration file
	DIR_TXT	From TMC configuration file
	BEG_MILE_POINT	Beginning log mile
	END_MILE_POINT	Ending log mile
Geometrics	LNTH_QTY	Length (mi)
	LANE_WIDTH	Lane width (ft)
	AVG_NO_LANES	Number of lanes (weighted average if number changes on section)
	TOTAL_ON_RAMPS	Total number of on-ramps
	TOTAL_OFF_RAMPS	Total number of off-ramps
	NO_LINKS	Number of links comprising this section
Traffic flow	AADT_C_AVERAGE	Vehicle miles traveled (VMT)–weighted average of link AADT/C ratios
	AADT_C_CRITICAL	Maximum of link AADT/C ratios
	VMT_24_HOUR_TOTAL	24-hour VMT for entire time span
Intelligent transportation system equipment	NO_RAMP_METERS	Number of ramp meters
	NO_CCTV	Number of CCTV cameras
	NO_DMS	Number of dynamic message signs

Table A.5. Section Events

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	PERIOD	Time slice (1 = peak hour; 2 = peak period; 3 = midday; 4 = weekday; 5 = weekend/holiday; 6 = counterpeak; 7 = peak shoulder; 8 = all days)
Weather	PCT_HRS_RAIN_01	Percentage of hours when there was rain ≥0.01 inch
	PCT_HRS_RAIN_05	Percentage of hours when there was rain ≥0.05 inch
	PCT_HRS_RAIN_10	Percentage of hours when there was rain ≥0.1 inch
	PCT_HRS_RAIN_25	Percentage of hours when there was rain ≥0.25 inch
	PCT_HRS_RAIN_50	Percentage of hours when there was rain ≥0.50 inch
	PCT_HRS_RAIN_DRY_SPELL	Percentage of hours when there was rain ≥0.01 inch after +30 days of no rain
	PCT_HRS_SNOW	Percentage of hours when measurable snow fell
	PCT_HRS_UNFROZEN_PRECIP	Percentage of hours when some form of precipitation was present
	PCT_HOURS_FROZEN_PRECIP	Percentage of hours when snow, sleet, or freezing rain fell
	PCT_HOURS_FOG	Percentage of hours when fog was reported
Incidents	INCIDENT_SOURCE	Data source for incidents
	INCIDENT_LANE_HOURS_LOST	Lane hours lost due to incidents
	INCIDENT_SHOULDER_HOURS_LOST	Shoulder hours lost due to incidents
	INCIDENT_DURATION_AVERAGE	Average incident duration
	INCIDENT_DURATION P95	95th percentile of incident duration
	NO_INCIDENTS	Total number of incidents (all types)
	NO_CRASHES	Total number of crashes
	NO_FATAL_CRASHES	Number of fatal crashes
	NO_INJURY_CRASHES	Number of injury crashes
	NO_PDO_CRASHES	Number of PDO crashes
	NO_COMB_TRUCK_CRASHES	Number of combination truck crashes
Work zones	WZ_SOURCE	Data source for work zones
	WZ_LANE_HOURS_LOST	Lane hours lost due to work zones
	WZ_SHOULDER_HOURS_LOST	Shoulder hours lost due to work zones
	NO_WORK_ZONES	Number of newly initiated work zones
	WZ_DURATION_AVERAGE	Average work zone duration
	WZ_DURATION P95	95th percentile of work zone duration

Table A.6. Section Traffic Flow

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	PERIOD	Time slice (1 = peak hour; 2 = peak period; 3 = midday; 4 = weekday; 5 = weekend/holiday; 6 = counter peak; 7 = peak shoulder; 8 = all days)
Traffic flow	D_C_AVERAGE	VMT-weighted average of link d/c ratios
	D_C_CRITICAL	MAX (link d/c ratios)
	D_C_CRITICAL_DISTANCE	(Distance of critical d/c link from downstream end) divided by section length
	VMT_TOTAL	Sum of link VMT for this time span
	DVMT_AVERAGE	Average daily VMT
	DVMT_STD_DEV	Standard deviation of daily VMTs
	DVMT_HIGH_VARIABILITY_DAYS	Number of days when VMT > (1.1 * average daily VMT)

Table A.7. Link Characteristics[a]

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	LINK_ID	Link to which the station belongs
	ROUTE	From TMC configuration file
	DIR_TXT	From TMC configuration file
	BEG_MILE_POINT	Beginning log mile
	END_MILE_POINT	Ending log mile
Geometrics	LNTH_QTY	Length of detector zone (zone of influence) for computing travel times
	NO_LANES	Number of lanes
	LANE_WIDTH	Lane width (ft)
	RIGHT_SHOULDER_WIDTH	Right-shoulder width (ft)
	LEFT_SHOULDER_WIDTH	Left-shoulder width (ft)
	NO_ON_RAMPS	Number of on-ramps
	NO_OFF_RAMPS	Number of off-ramps
	WEAVING_TYPE	Type of weaving section
	SPEED_LIMIT	Speed limit (mph)
	HCM_CAPACITY	HCM capacity

(continued on next page)

Table A.7. Link Characteristics[a] (continued)

Category	Variable	Definition
Traffic summary[b]	AADT	AADT, computed from the data
	AADT_OTHER	AADT (secondary value)
	AADT_OTHER_SOURCE	Other sources of AADT (e.g., Highway Performance Monitoring System)
	AADT_STD_DEV	Standard deviation of directional average daily traffic (DADT) that goes into AADT calculation
	AWDT	Average weekday daily traffic (AWDT)
	AWDT_STD_DEV	Standard deviation of DADTs that go into AWDT calculation
	AWEHDT	Average weekend/holiday daily traffic
	AWEHDT_STD_DEV	Standard deviation of DADTs that go into average weekend/holiday daily traffic calculation
	K_FACTOR	Peak hour *K*-factor, computed from the data
	PCT_TRUCKS	Percentage trucks
	AADT_C	AADT/C ratio
	PHV_PPV	Peak hour demand volume divided by peak period demand volume
	PCT_IMPUTED	Percentage of original records for which volume has been imputed

[a] Data about the links (segments) and traffic summaries.
[b] If two detectors exist on a link, then one must be selected as the representative detector.

Table A.8. Link Traffic Flow[a]

Category	Variable	Definition
Location	SHRP_SECTION	Unique ID for this SHRP 2 study section
	TIME_SPAN	Dates the data cover (typically 1 year)
	LINK_ID	Link to which the station belongs
	PERIOD	Time slice (1 = peak hour; 2 = peak period; 3 = midday; 4 = weekday; 5 = weekend/ holiday; 6 = counter peak; 7 = peak shoulder; 8 = all days)
Traffic Statistics	VOLUME_MEASURED_AVERAGE	Straight average of measured volumes for this period
	VOLUME_DEMAND_AVERAGE	Average of demand volumes (calculated)
	VOLUME_MEASURED_STD_DEV	Standard deviation of measured volumes
	VOLUME_DEMAND_STD_DEV	Standard deviation of demand volumes
	VOLUME_HIGH_VARIABILITY_DAYS	Number of days when volume > (1.1 * average demand volume)
	PCT_AADT	Average demand volume divided by AADT
	D_C	Demand-to-capacity ratio

[a] Data on basic traffic flow by time period for each link.

APPENDIX B

Before-and-After Analyses of Reliability Improvements

Effect of Ramp Metering on Reliability on I-285 in Atlanta, Georgia

Background

The Georgia Department of Transportation (GDOT) has aggressively pursued ramp metering as a control strategy on Atlanta area freeways. GDOT started very limited deployment in 1996; by 2005 there were nine operating meters. In 2006, the FastForward program was initiated by the Governor. As part of this program, 161 ramp meters were installed, most of them in 2008.

All 10 of the SHRP 2 study sections in Atlanta now have ramp meters installed. Two sections, the northbound and southbound sections of I-75/I-85 (the downtown connector), already had ramp meters beginning in 2005. The four sections on I-285 had meters operating as of July 7, 2008, and the four sections on I-75 had meters operating as of October 2, 2008. It was decided to use the four I-285 sections for the analysis as there were sufficient before-and-after data when the analysis was initiated (i.e., approximately 6 months of data for each period). As shown in Chapter 4, 6 months of data provide acceptable estimates of annual reliability if winter weather is not a major factor.

The locations of the ramp meters for the analysis sections on I-285 (north side) are listed below. Their operating times expand slightly beyond the beginning and ending of the peak periods, as determined in Chapter 4.

- Eastbound between I-75/Cobb and Peachtree–Dunwoody Road—6:15 to 9:30 a.m. (Section 5)
    - New Northside Drive,
    - Riverside Drive,
    - Roswell Road, and
    - Peachtree–Dunwoody Road;
- Westbound between Buford Highway and GA 400—6:15 to 9:45 a.m. (Section 6)
    - Buford Highway,
    - Peachtree Industrial Boulevard,
    - Chamblee–Dunwoody Road, and
    - Ashford–Dunwoody Road;
- Westbound between GA 400 and I-75—3:30 to 6:30 p.m. (Section 7)
    - Glenridge Drive,
    - Roswell Road,
    - Riverside Drive, and
    - Northside Drive;
- Eastbound between Roswell Road and Spaghetti Junction—3:30 to 6:30 p.m. (Section 8)
    - Ashford–Dunwoody Road,
    - North Peachtree Road,
    - Peachtree Industrial Boulevard, and
    - Buford Highway.

Methodology

A before-and-after analysis was conducted. The before period was defined as January 1 through June 16, 2008. The after period was defined as July 16 through December 31, 2008. This allowed for a dead zone of 2 weeks before and after ramp meter turn-on to allow the system to stabilize. Two types of controls were used:

1. **Control sections—**Sections that did not have ramp meters installed. Because of the aggressiveness of Georgia DOT's program, it was difficult to locate sections with no ramp meters for the analysis period that had similarly high-base congestion levels, although four sections were located. In addition to these sections, a reduced before-and-after period of 75 days before June 16 and 75 days after July 16 was selected for all SHRP 2 sections. As shown in the

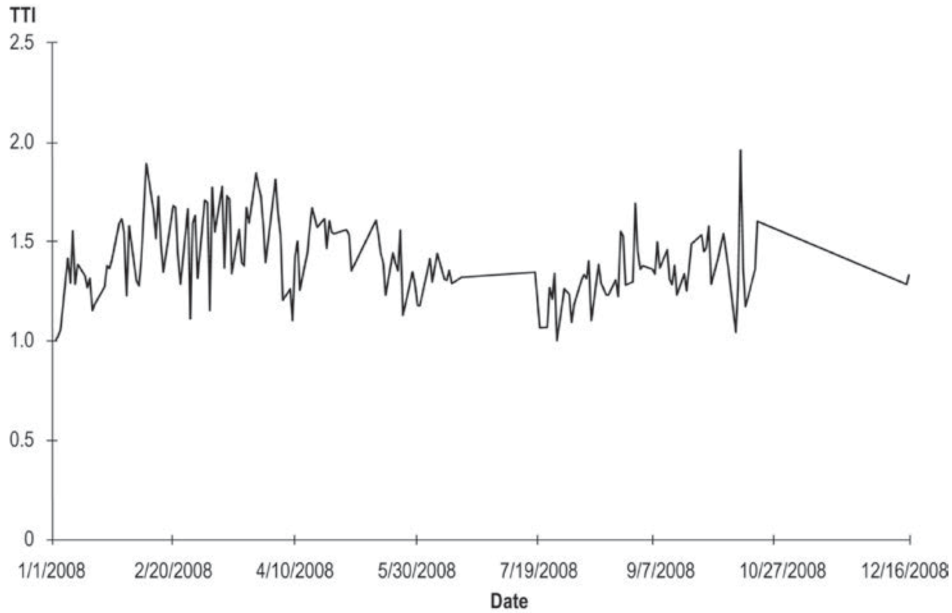

Figure B.1. Section 5 peak period TTIs.

Phase 2 report, a period of 75 days of data is insufficient to establish reliability, but is more than adequate to estimate average congestion, as measured by the Travel Time Index (TTI) here.

2. **Influencing factors—**Demand (vehicle miles traveled [VMT]) and lane hours lost due to incidents were compiled for the before-and-after periods to see to what degree they might be influencing results. The team was particularly concerned about demand changes; as shown in the Phase 2 report, gas price and availability in the summer of 2008 caused a temporarily sharp drop-off in demand.

Results

Figures B.1 through B.4 show the TTI for each daily peak period for the four sections receiving ramp metering. The self-imposed dead zone is readily apparent in the June 16 to

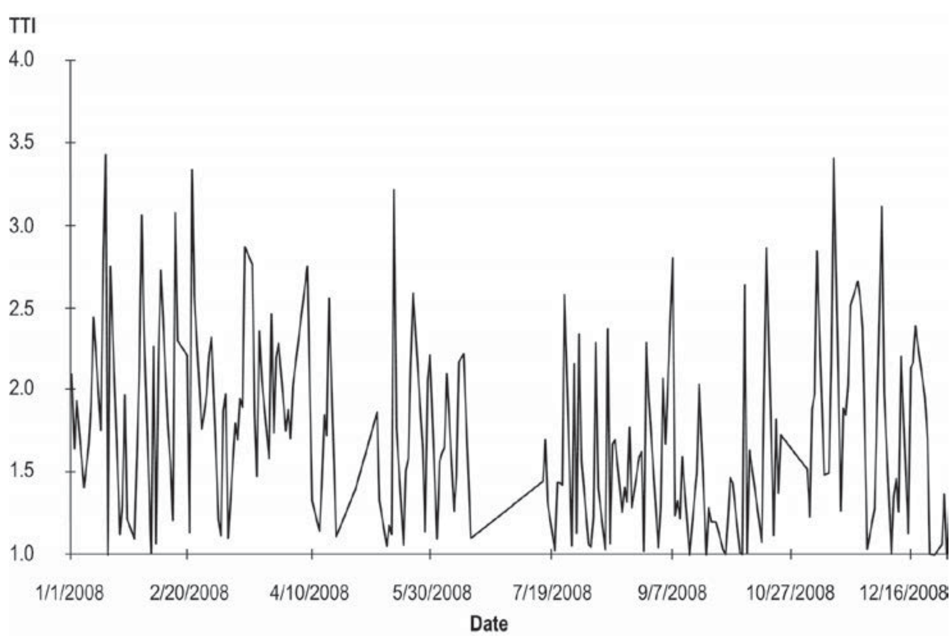

Figure B.2. Section 6 peak period TTIs.

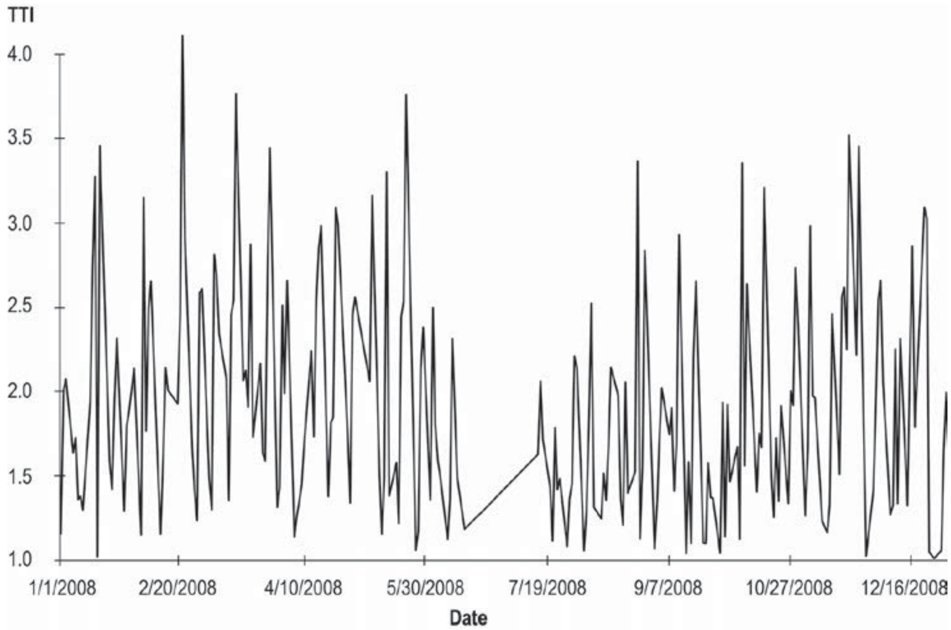

Figure B.3. Section 7 peak period TTIs.

July 16 period. Note that Section 5 had a data outage after October 15, which means that any results will be inconclusive for this section (although they have been reported). Tables B.1 through B.4 present the results of the before-and-after analysis on the four study sections. Multiple reliability metrics were used to characterize the before-and-after conditions. Also included is the sustainable service rate (SSR) developed in Chapter 4. Two estimates of daily vehicle miles traveled (DVMT) were used: the DVMT in the peak period and in an extended period, including 45-minute shoulders on each side of the peak period. These estimates were used to account for queuing in the peak period, which lowers observed VMT. These results reveal

- Base (average) congestion conditions as measured by TTI dropped between 7.5% and 13.4% for the period.

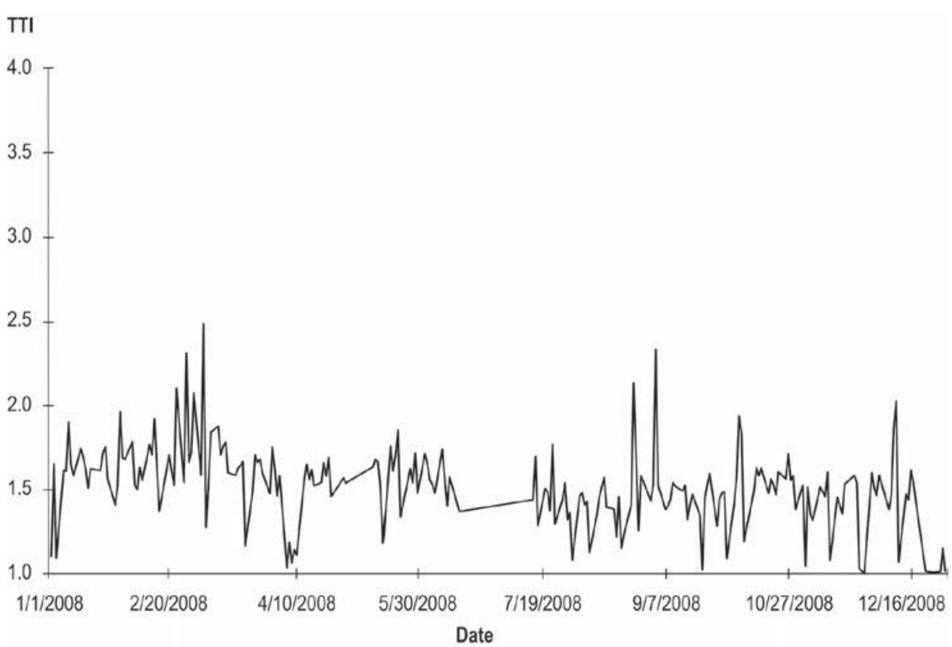

Figure B.4. Section 8 peak period TTIs.

Table B.1. Section 5: I-285 Eastbound from I-75 to GA 400 (Peak Period, 7:15 to 8:45 a.m.; Section Length, 6.860 mi)

	Before	After	Change (%)
Reliability Metric			
TTI	1.447	1.338	–7.5
Buffer Index	0.332	0.320	–3.6
Planning Time Index	1.927	1.744	–9.5
Skew statistic	.	.	–2.1
Misery Index	2.117	1.944	–8.2
On-time at 45 mph	34.0%	48.7%	43.2
Mean SSR	1,750	1,740	–0.6
Control Statistic			
Peak period DVMT	1,019,705	1,010,691	–0.9
Shoulder + peak DVMT	1,694,413	1,642,311	–3.1
Peak incident lane hours lost	7.63	6.22	–18.5
Peak incident shoulder hours lost	32.25	24.83	–23.0
Peak number of incidents	61	45	–26.2

Table B.2. Section 6: I-285 Westbound from I-75 to GA 400 (Peak Period, 4:30 to 6:30 p.m.; Section Length, 6.880 mi)

	Before	After	Change (%)
Reliability Metric			
TTI	1.814	1.571	–13.4
Buffer Index	0.708	0.766	8.2
Planning Time Index	3.099	2.774	–10.5
Skew statistic	1.231	2.559	107.9
Misery Index	3.528	3.227	–8.5
On-time at 45 mph	25.4%	44.9%	76.8
Mean SSR	1,720	1,755	2.0
Control Statistic			
Peak period DVMT	886,378	896,326	1.1
Shoulder + peak DVMT	2,100,381	2,105,177	0.2
Peak incident lane hours lost	26.77	15.24	–43.1
Peak incident shoulder hours lost	93.91	61.94	–34.0
Peak number of incidents	80	95	18.8

Table B.3. Section 7: I-285 Eastbound from GA 400 to I-85 (Peak Period, 4:00 to 6:30 p.m.; Section Length, 5.861 mi)

	Before	After	Change (%)
Reliability Metric			
TTI	1.958	1.735	–11.4
Buffer Index	0.766	0.843	10.1
Planning Time Index	3.458	3.197	–7.5
Skew statistic	1.855	2.603	40.3
Misery Index	3.963	3.631	–8.4
On-time at 45 mph	24.4%	34.9%	43.0
Mean SSR	1,690	1,740	3.0
Control Statistic			
Peak period DVMT	870,265	876,770	0.7
Shoulder + peak DVMT	2,440,655	2,461,321	0.8
Peak incident lane hours lost	31.65	30.88	–2.4
Peak incident shoulder hours lost	67.50	70.35	4.2
Peak number of incidents	117	139	18.8

Table B.4. Section 8: I-285 Westbound from GA 400 to I-85 (Peak Period, 7:15 to 9:00 a.m.; Section Length, 5.595 mi)

	Before	After	Change (%)
Reliability Metric			
TTI	1.602	1.453	–9.3
Buffer Index	0.287	0.313	9.1
Planning Time Index	2.061	1.909	–7.4
Skew statistic	0.557	0.707	26.9
Misery Index	2.470	2.267	–8.2
On-time at 45 mph	18.7%	34.7%	85.6
Mean SSR	1,920	1,910	–0.5
Control Statistic			
Peak period DVMT	924,065	923,262	–0.1
Shoulder + peak DVMT	1,758,676	1,713,866	–2.5
Peak incident lane hours lost	15.58	12.93	–17.0
Peak incident shoulder hours lost	31.70	45.63	43.9
Peak number of incidents	71	80	12.7

Table B.5. Performance of Control Sections

Period	Section	TTI	Buffer Index	Skew Statistic	Planning Time Index	On-Time at 45 mph (%)	Misery Index
Before	23	1.081	0.364	31.948	1.474	0.916	1.689
After	23	1.101	0.417	27.518	1.560	0.893	2.098
Before	26	1.349	0.568	3.995	2.115	0.616	2.803
After	26	1.350	0.532	3.167	2.068	0.598	2.632
Before	28	1.041	0.153	11.477	1.200	0.966	1.476
After	28	1.076	0.177	4.790	1.267	0.956	1.660
Before	29	1.243	0.528	7.928	1.899	0.684	2.120
After	29	1.204	0.384	4.080	1.666	0.783	2.134

- As demonstrated in Chapter 4, the Buffer Index and the skew statistic generally increased as TTI dropped; the Buffer Index increased approximately 10%, and the skew statistic increased on three of the sections as TTI dropped. Section 5 showed a 3.6% decrease in the Buffer Index, but this section also showed the lowest drop in TTI (7.5%). The skew statistic changed dramatically on some sections (up to 107% on Section 6). Further analyses may show that this fluctuation is an aberration, but it is potentially an unstable indicator of changes in reliability.
- The Planning Time Index decreased on all sections; decreases ranged from 7.4% to 9.5%. The Misery Index showed the most consistent pattern for the reliability metrics, decreasing between 8.2% and 8.5% on all sections.
- SSR was relatively stable on Sections 5 and 8 (morning peaks), exhibiting slight decreases of 0.5% and 0.6%, respectively. On the two afternoon peak sections, increases of 2.0% and 3.0% were observed. Note that the afternoon peak sections also had higher base congestion levels than the morning peak sections.
- Shoulder DVMT was either stable or increased slightly on the two afternoon peak sections. Shoulder DVMT on the morning peak sections decreased by 2.5% and 3.1%.
- As might be expected with only 6 months of data confined to weekday periods of approximately 1.5 to 2 hours, incident characteristics varied across the sections, sometimes increasing in severity, sometimes decreasing.
- Incident effects were relatively stable on Sections 5, 7, and 8. Section 6 showed a significant drop-off in the time lanes and shoulders were blocked.

Table B.5 shows the performance of the control sections for the entire before-and-after periods. These are sections that did not have ramp meters installed during 2008 and are not SHRP 2 study sections. The results show that congestion and reliability were relatively stable on the control sections in the before-and-after period, although their base congestion levels were generally lower than the SHRP 2 study sections.

Table B.6 shows the change in TTI for the reduced (75-day) before-and-after period. For the nontreatment sections, a general downward trend is apparent in average congestion levels. However, the decrease on three of the four sections with ramp metering was larger than the decrease on the untreated sections.

Conclusions

Both average congestion and reliability (as measured by the Planning Time Index) showed improvements for the time period after ramp meters became operational, with decreases

Table B.6. Change in Base Congestion for All Sections (±75 days from Ramp Meter Turn-On)

	TTI		
Section	Before	After	Change (%)
1	1.714	1.561	–8.9
2	1.345	1.251	–7.0
3	1.313	1.288	–1.9
4	2.253	2.247	–0.3
5	1.418	1.278	–9.8
6	1.757	1.510	–14.0
7	1.862	1.693	–9.1
8	1.530	1.520	–0.6
9	1.554	1.468	–5.5
10	1.633	1.522	–6.8
23	1.031	1.026	–0.4
26	1.138	1.276	12.1
28	1.034	1.065	3.0

Note: Sections 5 to 8 are the treatment sections.

of roughly 10% and 8%, respectively. The changes in demand probably explain a small amount of the decreases. Incident effects do not appear to be large enough to have a significant influence on the improvements in congestion and reliability. Therefore, the 10% and 8% decreases should be taken as an upper limit. Without a statistical model, it is difficult to know how much to adjust the decreases, but a reasonable estimate would be that ramp meters reduce average congestion by 8% to 9%, and improve reliability by 6% to 7%. Changes in year-long capacity, as measured by the SSR, are in the 2% to 3% range.

Effect of Adaptive Ramp Meter Control on I-210 in Los Angeles, California

The results show little change to slight degradation in congestion and reliability due to implementing the adaptive ramp meter control (Tables B.7 and B.8 and Figures B.5 and B.6). However, these results were obtained before adjustment of the metering algorithm. Therefore, these tests will be redone with a different after period. (Note: Travel time density is the frequency percentage for the travel time measurements.)

Effect of Implementing Rapid Clearance Policy for Large-Truck Crashes on I-710 in Los Angeles, California

Tables B.9 through B.12 and Figures B.7 through B.10 show the results of the analysis.

Table B.7. Summary Demand, Weather, and Incident Characteristics on I-210 Westbound in Los Angeles

		Before	After
Demand	Annual average daily traffic (AADT)	140	144
	K-factor	5%	5%
Weather (number of days)	Rain	8	0
	Fog	0	0
	Snow	0	0
	Wind	0	0
Incidents	No collision	100	113
	Collision, no injury	60	98
	Collision, injury and/or fatality	9	14

Effect of Ramp Meters in San Francisco Bay Area, California

Tables B.13 and B.14 and Figures B.11 and B.12 present the results of the analysis.

Effect of Freeway Service Patrol Implementation in San Diego, California

I-8 Westbound

Tables B.15 and B.16 and Figures B.13 and B.14 present the results of the analysis.

Table B.8. Performance Measure Comparisons for I-210 Westbound in Los Angeles

	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
Time Period	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Peak hour	25.7 **0.1**	26.5 **0.1**	0.246 **0.006**	0.245 **0.004**	0.051 **0.004**	0.046 **0.003**	2.358 **0.016**	2.410 **0.010**	1.062 **0.048**	0.932 **0.038**	0.391 **0.009**	0.389 **0.010**
Peak period	23.9 **0.1**	25.0 **0.1**	0.312 **0.005**	0.303 **0.003**	0.098 **0.003**	0.095 **0.003**	2.327 **0.009**	2.391 **0.010**	1.151 **0.030**	1.050 **0.028**	0.491 **0.007**	0.499 **0.009**
Counterpeak	15.9 **0.0**	16.8 **0.0**	0.152 **0.003**	0.210 **0.004**	0.039 **0.002**	0.052 **0.002**	1.399 **0.013**	1.530 **0.009**	4.374 **0.223**	2.895 **0.099**	0.466 **0.014**	0.491 **0.015**
Midday	14.8 **0.0**	15.1 **0.0**	0.040 **0.001**	0.064 **0.002**	0.002 **0.000**	0.016 **0.001**	1.114 **0.003**	1.186 **0.004**	2.989 **0.084**	4.350 **0.121**	0.147 **0.005**	0.286 **0.011**
Weekday	16.8 **0.0**	17.2 **0.0**	0.398 **0.004**	0.423 **0.003**	0.148 **0.001**	0.154 **0.001**	1.928 **0.005**	2.024 **0.005**	24.515 **0.280**	16.458 **0.201**	0.850 **0.003**	0.884 **0.003**
All year	16.1 **0.0**	16.5 **0.0**	0.294 **0.004**	0.331 **0.004**	0.124 **0.001**	0.130 **0.001**	1.810 **0.006**	1.899 **0.007**	34.160 **0.442**	19.620 **0.216**	0.844 **0.004**	0.886 **0.004**

Note: Standard errors are shown in boldface.

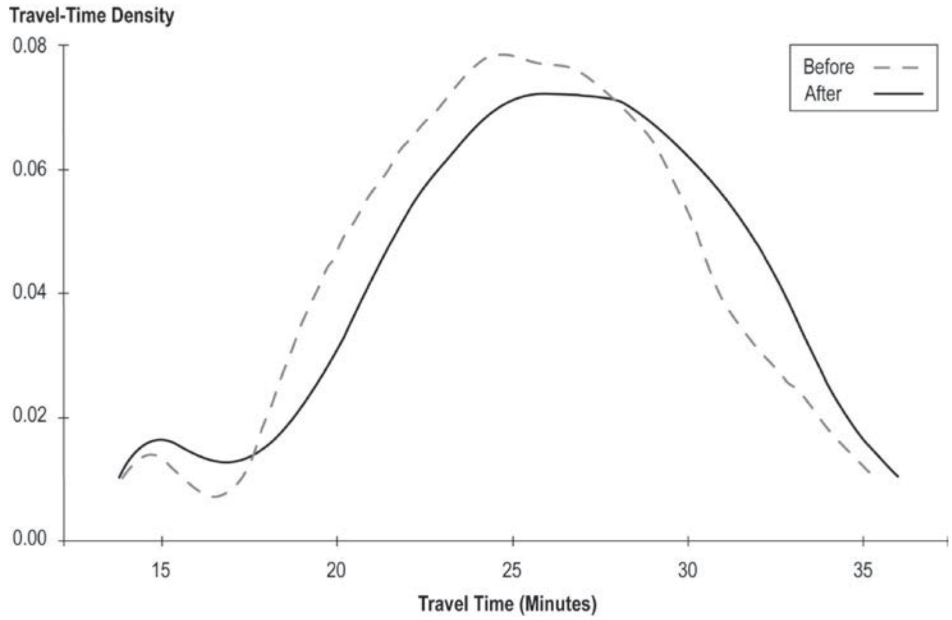

Figure B.5. Travel time density on I-210 westbound in Los Angeles, peak hour.

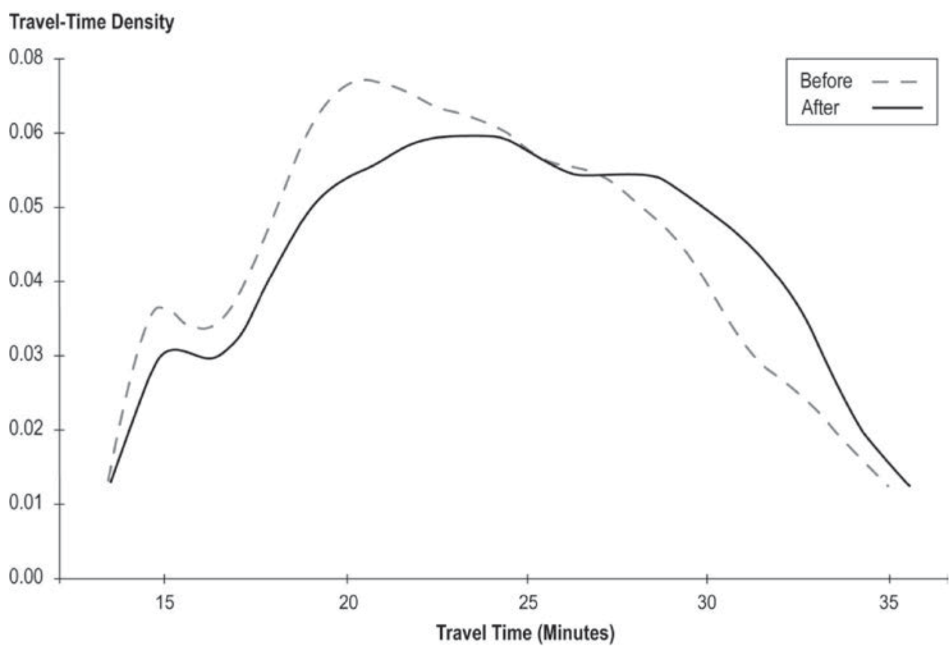

Figure B.6. Travel time density on I-210 westbound in Los Angeles, peak period.

Table B.9. Summary Demand, Weather, and Incident Characteristics on I-710 Northbound in Los Angeles

		Before	After
Demand	AADT	161	159
	K-factor	6%	6%
Weather (number of days)	Rain	11	6
	Fog	0	2
	Snow	0	0
	Wind	0	0
Incidents	No collision	196	162
	Collision, no injury	139	121
	Collision, injury and/or fatality	17	13

Table B.10. Performance Measure Comparisons for I-710 Northbound in Los Angeles

	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
Time Period	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Peak hour	19.9 **0.1**	17.0 **0.1**	0.337 **0.011**	0.238 **0.007**	0.098 **0.005**	0.065 **0.003**	2.330 **0.040**	1.874 **0.031**	2.401 **0.108**	1.940 **0.081**	0.754 **0.028**	0.682 **0.027**
Peak period	18.7 0.1	16.1 **0.0**	0.347 **0.009**	0.247 **0.007**	0.109 **0.003**	0.075 **0.002**	2.259 **0.026**	1.784 **0.017**	1.890 **0.055**	2.277 **0.078**	0.803 **0.017**	0.714 **0.020**
Counterpeak	19.1 **0.1**	18.9 **0.1**	0.358 **0.005**	0.319 **0.005**	0.126 **0.003**	0.100 **0.003**	2.185 **0.017**	2.082 **0.011**	1.721 **0.060**	1.476 0.043	0.625 **0.012**	0.538 **0.007**
Midday	15.3 **0.0**	14.7 **0.0**	0.169 **0.009**	0.124 **0.005**	0.063 **0.003**	0.040 **0.002**	1.657 **0.019**	1.444 **0.013**	4.006 **0.198**	2.305 **0.082**	0.645 **0.018**	0.497 **0.014**
Weekday	16.3 **0.0**	15.4 **0.0**	0.343 **0.003**	0.282 **0.002**	0.129 **0.001**	0.100 **0.001**	1.955 **0.006**	1.745 **0.005**	4.278 **0.043**	4.194 **0.039**	0.784 **0.005**	0.673 **0.004**
All year	15.5 **0.0**	14.8 **0.0**	0.325 **0.002**	0.257 **0.002**	0.129 **0.001**	0.097 **0.001**	1.855 **0.007**	1.659 **0.004**	6.328 **0.078**	8.684 **0.131**	0.797 **0.006**	0.671 **0.004**

Note: Standard errors are shown in boldface.

Table B.11. Summary Demand, Weather, and Incident Characteristics on I-710 Southbound in Los Angeles

		Before	After
Demand	AADT	167	148
	K-factor	5%	5%
Weather (number of days)	Rain	11	8
	Fog	3	5
	Snow	0	0
	Wind	0	0
Incidents	No collision	189	156
	Collision, no injury	165	165
	Collision, injury and/or fatality	12	14

Table B.12. Performance Measure Comparisons for I-710 Southbound in Los Angeles

Time Period	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	18.0 **0.1**	17.0 **0.0**	0.167 **0.006**	0.177 **0.004**	0.037 **0.004**	0.019 **0.002**	1.792 **0.016**	1.641 **0.008**	0.529 **0.028**	1.053 **0.042**	0.366 **0.009**	0.311 **0.008**
Peak period	17.4 0.0	16.5 **0.0**	0.194 **0.005**	0.199 **0.003**	0.043 **0.002**	0.028 **0.002**	1.750 **0.013**	1.622 **0.005**	0.690 **0.029**	1.041 **0.022**	0.399 **0.008**	0.342 **0.006**
Counterpeak	16.4 **0.1**	15.1 **0.0**	0.262 **0.007**	0.218 **0.007**	0.076 **0.003**	0.061 **0.003**	1.802 **0.021**	1.596 **0.011**	2.573 **0.099**	3.657 **0.138**	0.610 **0.016**	0.604 **0.018**
Midday	14.8 **0.0**	14.1 **0.0**	0.190 **0.007**	0.103 **0.003**	0.049 **0.002**	0.031 **0.001**	1.527 **0.015**	1.349 **0.011**	3.314 **0.116**	3.513 **0.103**	0.566 **0.022**	0.402 **0.010**
Weekday	15.2 **0.0**	14.5 **0.0**	0.272 **0.002**	0.225 **0.001**	0.084 **0.001**	0.066 **0.001**	1.644 **0.005**	1.503 **0.003**	4.457 **0.052**	5.739 **0.059**	0.570 **0.005**	0.475 **0.004**
All year	14.7 **0.0**	14.1 **0.0**	0.280 **0.001**	0.212 **0.002**	0.096 **0.001**	0.070 **0.001**	1.590 **0.004**	1.461 **0.002**	10.589 **0.231**	10.381 **0.101**	0.575 **0.004**	0.473 **0.003**

Note: Standard errors are shown in boldface.

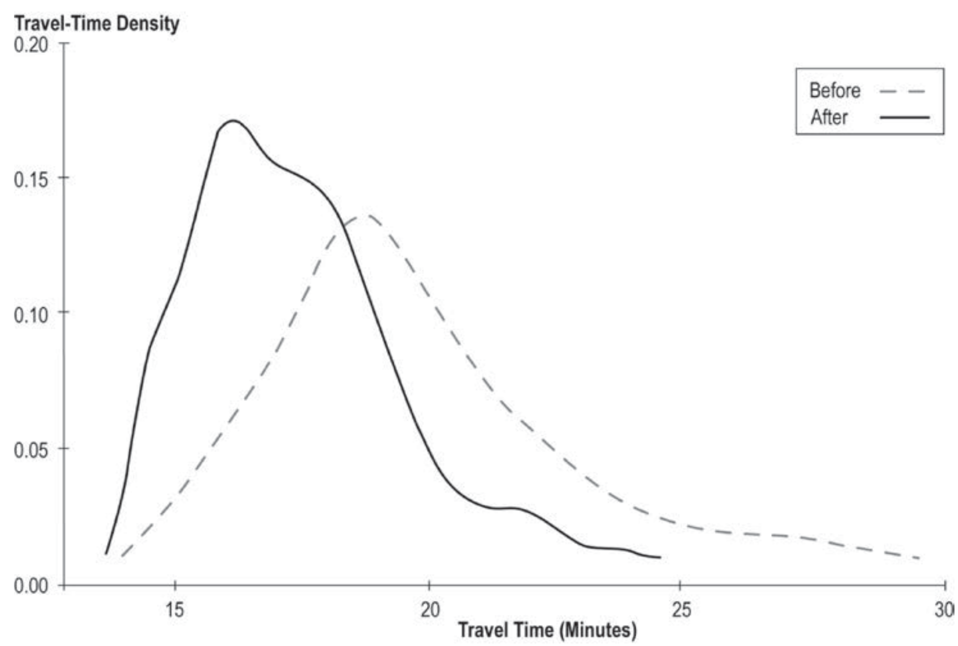

Figure B.7. Travel time density on I-710 northbound in Los Angeles, peak hour.

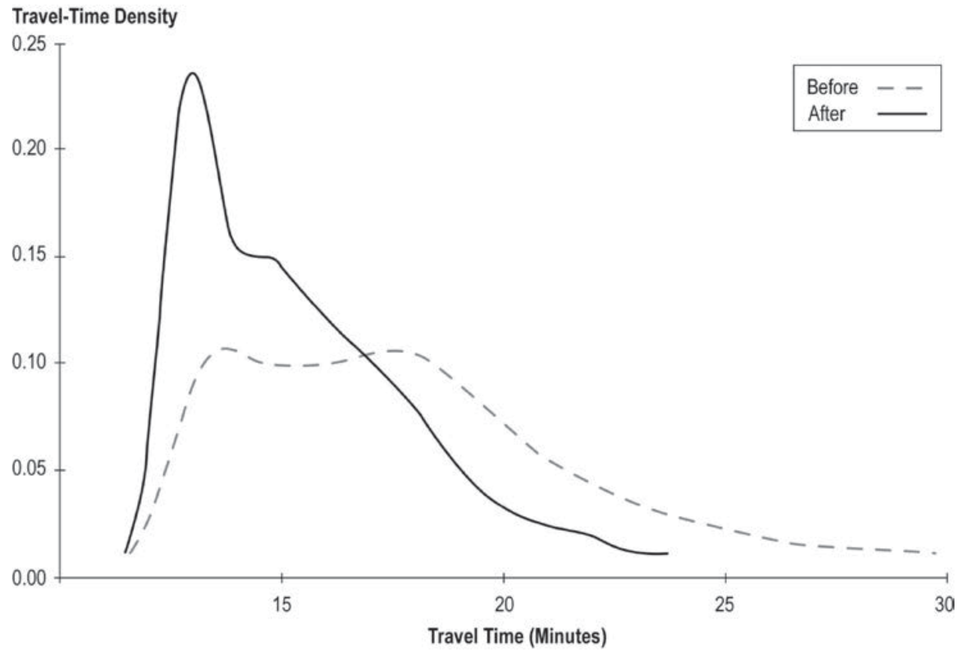

Figure B.8. Travel time density on I-710 northbound in Los Angeles, peak period.

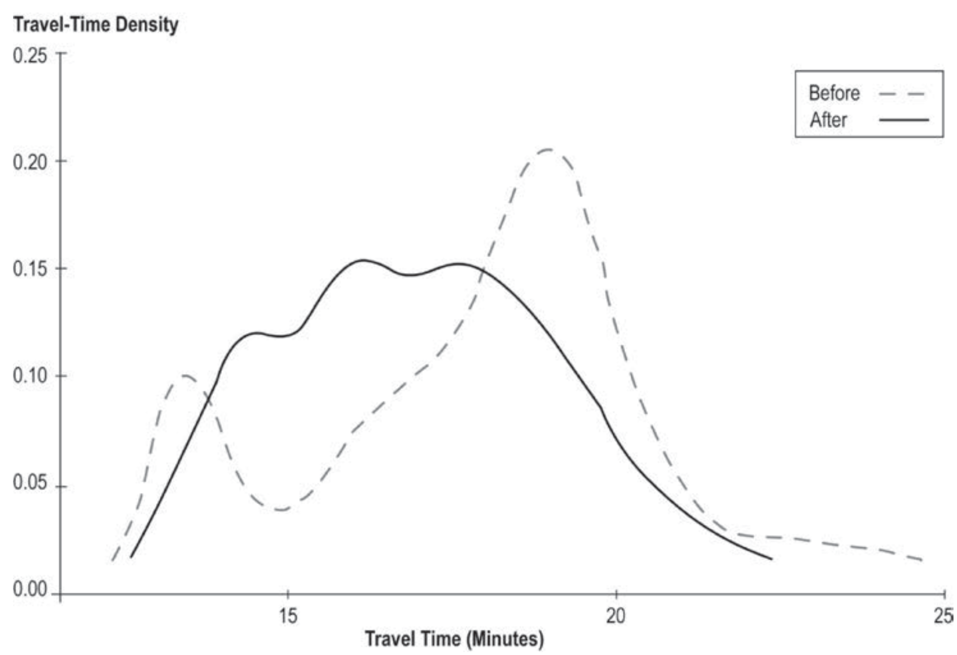

Figure B.9. Travel time density on I-710 southbound in Los Angeles, peak hour.

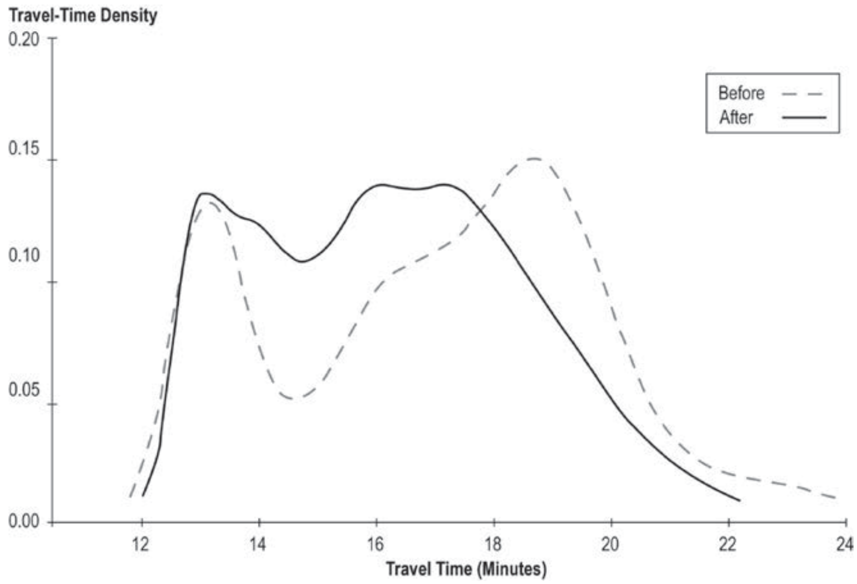

Figure B.10. Travel time density on I-710 southbound in Los Angeles, peak period.

I-8 Eastbound and SR 52 Westbound

Tables B.17 through B.20 and Figures B.15 through B.18 present the results of the analysis.

Effect of Capacity Improvements on Reliability in Minneapolis–St. Paul, Minnesota

Analytic Procedures for Determining the Impacts of Reliability Mitigation Strategies

Preliminary Investigation of the Before-and-After Study Sections

Five sites in the Minneapolis–St. Paul area were selected for the before-and-after study. A brief description of project type and duration is stated in Table B.21. The before study period for each site is approximately the year before the project start date, and the after study period is approximately the year after the project completion date. Due to lack of data for the first half of the after period of Project C, the after period was extended to ensure a full year's data for the analysis. Table B.22 lists the before-and-after periods for all before-and-after study sections.

Additional information about Projects E, G, and H includes the following:

- Project E's improvement work (adding an auxiliary lane) happened right after the operation of the HOT lane project on the same section of I-394. To isolate the effect of the HOT project from the effect of the new auxiliary lane, an additional section on I-394 was chosen to study HOT effects. In this additional section (I-394 eastbound from I-494 to Highway 169), the only improvement for the study period was the HOT project.
- All study sections, except Project G, were chosen at approximately the locations where improvement projects were located. Due to a lack of data at or near the Project G location, a southbound section, which is about 3 miles upstream of the project site and separated by a major bottle neck (I-494), was chosen for the analysis.
- For Project H, the northbound direction of the highway was selected as the study section. However, different improvement work was done on each side of the highway. The northbound section had a third lane added, and the southbound section had an auxiliary lane added. The interchange conversion from cloverleaf to a folded diamond affected both directions. Therefore, the treatment (as in a quasi-experimental design) for Project H was a combination of different improvement projects.

Table B.13. Summary Demand, Weather, and Incident Characteristics for I-580 Eastbound in San Francisco Bay Area

		Before	After
Demand	AADT	110	111
	K-factor	5%	5%
Weather (number of days)	Rain	16	18
	Fog	6	11
	Snow	0	0
	Wind	0	0
Incidents	No collision	182	131
	Collision, no injury	28	25
	Collision, injury and/or fatality	7	8

Table B.14. Performance Measure Comparisons for I-580 Eastbound in San Francisco Bay Area

	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
Time Period	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Peak hour	14.2 **0.2**	11.1 **0.1**	0.347 **0.014**	0.349 **0.007**	0.126 **0.014**	0.101 **0.004**	3.685 **0.064**	2.986 **0.036**	1.149 **0.120**	1.974 **0.076**	0.666 **0.047**	0.705 **0.018**
Peak period	13.1 **0.1**	10.2 **0.0**	0.426 **0.010**	0.337 **0.005**	0.166 **0.005**	0.101 **0.002**	3.738 **0.063**	2.800 **0.016**	1.273 **0.068**	1.621 **0.038**	0.822 **0.024**	0.738 **0.010**
Counterpeak	7.1 **0.0**	6.5 **0.0**	0.156 **0.004**	0.170 **0.005**	0.014 **0.004**	0.053 **0.002**	1.526 **0.011**	1.585 **0.025**	1.614 **0.119**	3.324 **0.108**	0.363 **0.032**	0.693 **0.028**
Midday	7.6 **0.1**	6.9 **0.0**	0.140 **0.010**	0.223 **0.006**	0.056 **0.006**	0.080 **0.002**	1.886 **0.081**	1.762 **0.024**	2.514 **0.174**	4.470 **0.129**	0.941 **0.095**	0.802 **0.024**
Weekday	8.6 **0.0**	7.5 **0.0**	0.686 **0.008**	0.461 **0.003**	0.207 **0.003**	0.178 **0.001**	3.050 **0.027**	2.263 **0.007**	5.693 **0.100**	5.527 **0.048**	1.329 **0.014**	0.990 **0.007**
All year	7.8 **0.0**	7.1 **0.0**	0.612 **0.012**	0.446 **0.002**	0.174 **0.002**	0.171 **0.001**	2.833 **0.019**	2.136 **0.006**	7.041 **0.132**	8.676 **0.073**	1.412 **0.014**	0.997 **0.005**

Note: Standard errors are shown in boldface.

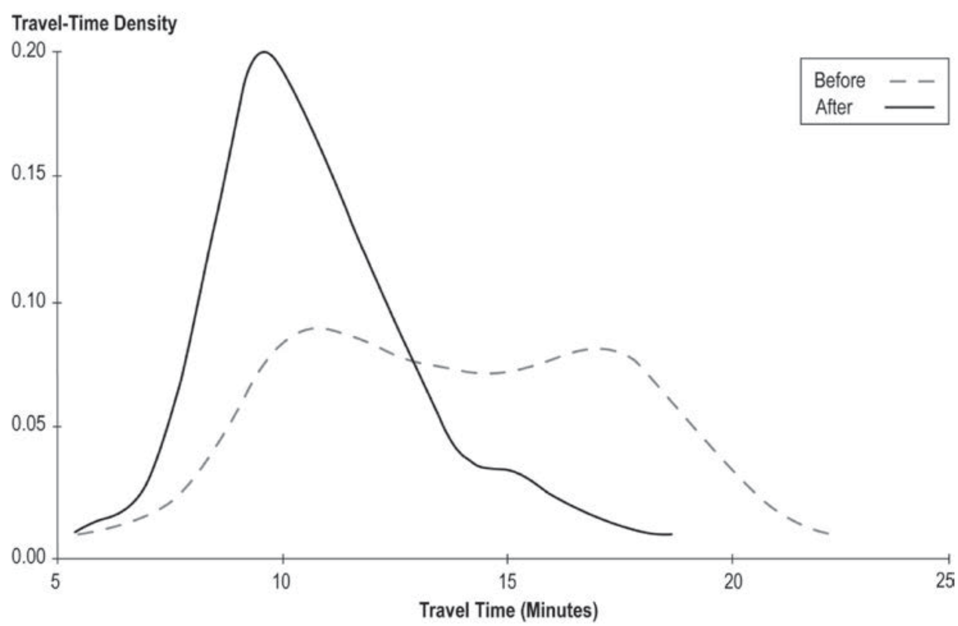

Figure B.11. Travel time density on I-580 eastbound in San Francisco Bay Area, peak hour.

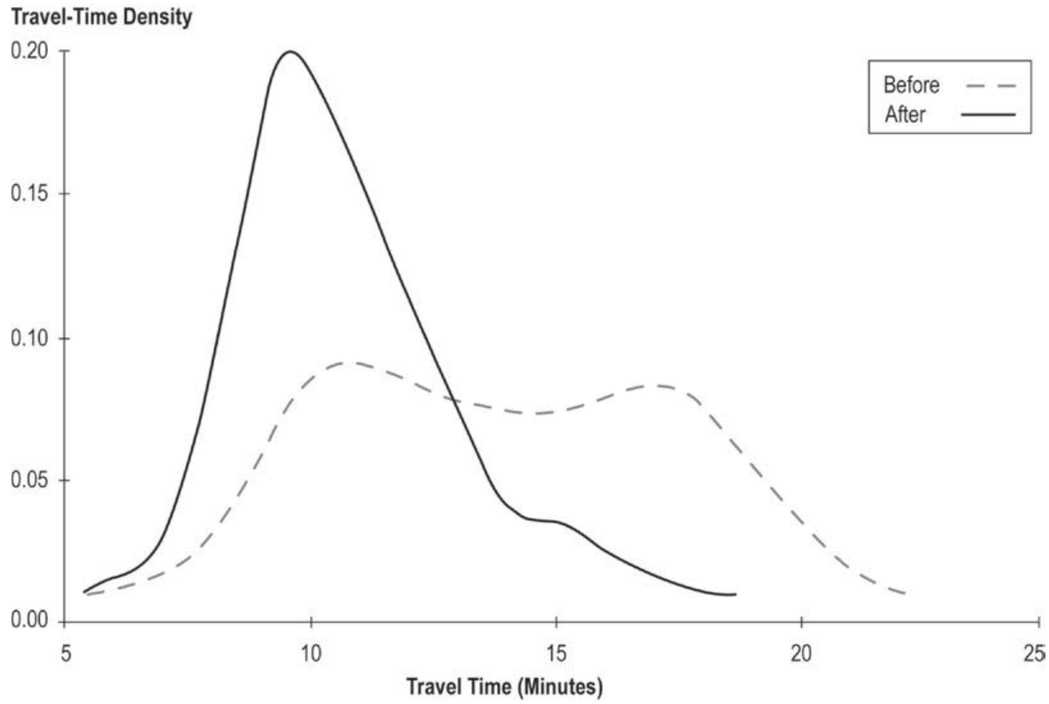

Figure B.12. Travel time density on I-580 eastbound in San Francisco Bay Area, peak period.

Peak hour travel time for both the before and after study periods of each section was plotted to examine the improvement effect on average travel time and reliability. The analyzed peak hour was specific to the study section; it was identified by an algorithm designed by the research team. The peak hour travel time frequency distribution for the before and after periods also was plotted to identify the shift in distribution.

Table B.15. Summary Demand, Weather, and Incident Characteristics for I-8 Westbound in San Diego

		Before	After
Demand	AADT	49	46
	K-factor	4%	5%
Weather (number of days)	Rain	9	5
	Fog	0	0
	Snow	0	0
	Wind	0	0
Incidents	No collision	6	4
	Collision, no injury	6	5
	Collision, injury and/or fatality	2	0

By examining the plots, the team observed the following general trends:

- Projects B, C, E, and E2 demonstrated reductions in average travel time and improvements in reliability of travel time;
- Project G showed increases in average travel time, but it also showed improvements in reliability of travel time; and
- Project H showed reductions in average travel time along with deteriorations in reliability of travel time.

Due to the relative locations of the study section and the improvement project site of Project G, this section was possibly subject to other influencing factors besides the improvement project itself. For example, if more traffic took southbound Highway 169 due to improved interchange and driving conditions, the study section may have experienced an increase in travel time because of the I-494 bottleneck. However, even with increases in average travel time, this section showed an improvement in travel time reliability.

Project H is another section that requires further investigation. Multiple improvement projects implemented at the same time could have different effects than the same projects implemented separately.

At this time, the effects of confounding factors (e.g., incidents and weather effects) have not been studied along with improvement project effects.

Table B.16. Performance Measure Comparisons for I-8 Westbound in San Diego

Time Period	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	6.1 **0.0**	6.1 **0.0**	–0.001 **0.000**	0.002 **0.002**	0.000 **0.000**	0.004 **0.001**	1.000 **0.000**	1.015 **0.001**	NA NA	NA NA	0.000 **0.000**	0.090 **0.015**
Peak period	6.1 **0.0**	6.1 **0.0**	–0.001 **0.000**	0.006 **0.000**	0.000 **0.000**	0.002 **0.000**	1.000 **0.000**	1.018 **0.000**	NA NA	NA NA	0.000 **0.000**	0.055 **0.005**
Counterpeak	6.6 **0.0**	6.6 **0.0**	0.106 **0.010**	0.103 **0.010**	0.061 **0.002**	0.056 **0.002**	1.505 **0.025**	1.440 **0.018**	NA NA	NA NA	0.892 **0.034**	0.811 **0.029**
Midday	6.1 **0.0**	6.1 **0.0**	–0.005 **0.001**	0.015 **0.000**	0.003 **0.001**	0.002 **0.000**	1.005 **0.001**	1.029 **0.000**	NA NA	NA NA	0.081 **0.010**	0.058 **0.005**
Weekday	6.2 **0.0**	6.2 **0.0**	–0.013 **0.000**	0.003 **0.000**	0.021 **0.001**	0.018 **0.001**	1.034 **0.001**	1.037 **0.001**	NA NA	NA NA	0.298 **0.007**	0.267 **0.006**
All year	6.2 **0.0**	6.2 **0.0**	–0.013 **0.000**	0.004 **0.000**	0.017 **0.000**	0.015 **0.000**	1.026 **0.000**	1.030 **0.000**	NA NA	NA NA	0.254 **0.005**	0.228 **0.005**

Note: Standard errors are shown in boldface. NA = Not available (skew statistics could not be computed because 10th and 50th percentile travel times were too close).

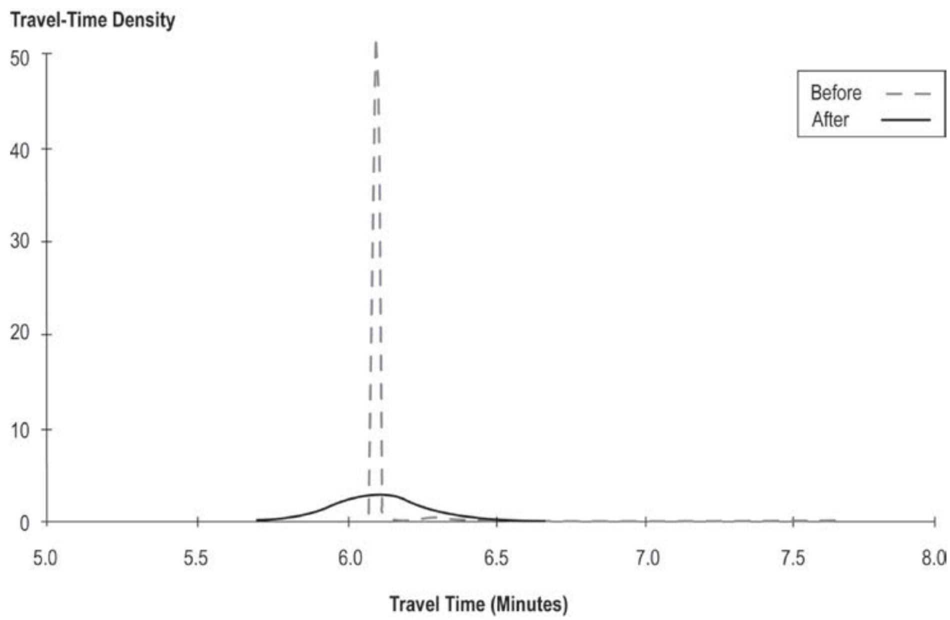

Figure B.13. Travel time density on I-8 westbound in San Diego, peak hour.

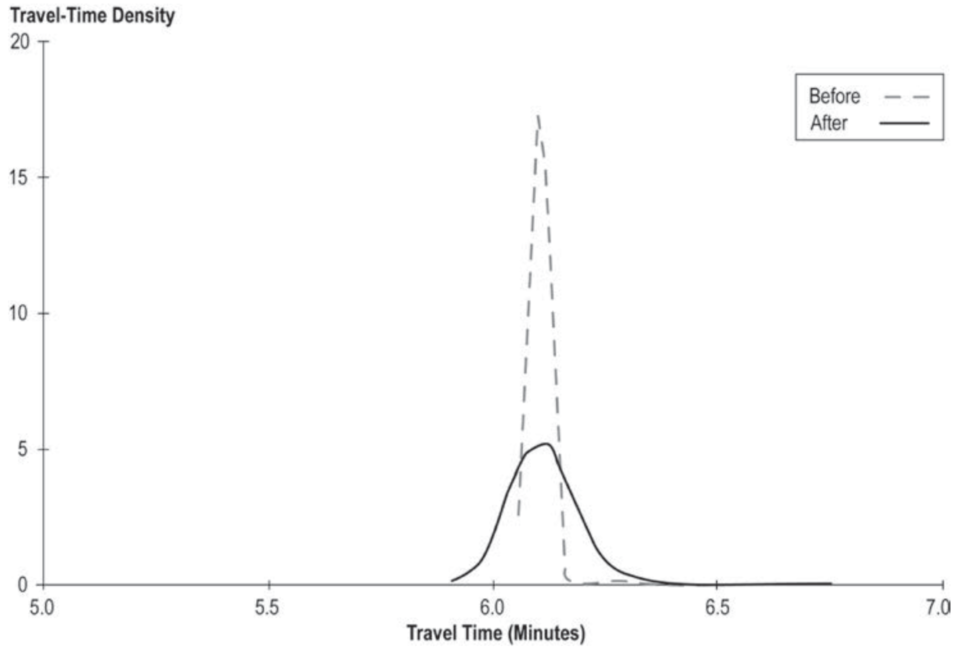

Figure B.14. Travel time density on I-8 westbound in San Diego, peak period.

Peak hour travel times and peak hour travel time frequency distributions for the study segments are shown in Figures B.19 through B.32. Performance measure comparisons for the study segments are provided in Tables B.23 through B.29.

Effect of Large-Truck Incident Rapid Clearance Policy in Atlanta, Georgia

Various public and private organizations in metro Atlanta work together as the Traffic Incident Management Enhancement (TIME) Task Force to improve the management of traffic incidents. In 2006, the TIME Task Force developed a strategic vision of initiatives to improve TIME services in metro Atlanta. One of several high-priority recommendations was to quickly and safely remove large-vehicle crashes from the roadways. The Georgia Towing and Recovery Incentive Program (TRIP) program was developed as part of this strategic vision.

TRIP is a recovery incentive program that pays heavy-duty recovery companies a monetary bonus for clearing commercial vehicle crashes quickly. TRIP helps to reduce the impact of major traffic incidents in metro Atlanta and to meet TIME's aggressive clearance goal of 90 minutes or less. The program, implemented in early 2008, covers the following roadways:

- I-285 (beltway) and all freeways inside its perimeter
  - I-75,
  - I-85,
  - I-20,
  - GA 400, and
  - GA 166; and
- Four hot spots outside of the I-285 perimeter
  - I-85 Northside from I-285 to Pleasantdale Exit,
  - I-75 Northside from I-285 to Windy Hill Exit,
  - I-20 Westside from I-285 to Fulton Industrial Exit, and
  - I-20 Eastside from I-285 to Wesley Chapel Exit.

The analysis of the TRIP program proceeded differently from the other before-and-after evaluations. Instead of tracking reliability measures directly, the team considered incident characteristics instead. This decision was due to two factors.

Table B.17. Summary Demand, Weather, and Incident Characteristics for I-8 Eastbound in San Diego

		Before	After
Demand	AADT	49	49
	K-factor	6%	6%
Weather (number of days)	Rain	13	8
	Fog	1	5
	Snow	0	0
	Wind	0	0
Incidents	No collision	6	7
	Collision, no injury	6	3
	Collision, injury and/or fatality	1	1

Table B.18. Performance Measure Comparisons for I-8 Eastbound in San Diego

	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
Time Period	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
Peak hour	7.3 **0.0**	7.1 **0.0**	0.283 **0.008**	0.266 **0.007**	0.085 **0.004**	0.077 **0.004**	1.737 **0.016**	1.647 **0.017**	3.136 **0.233**	7.800 **0.901**	0.575 **0.022**	0.604 **0.023**
Peak period	6.9 **0.0**	6.7 **0.0**	0.301 **0.004**	0.287 **0.003**	0.098 **0.002**	0.090 **0.002**	1.671 **0.007**	1.600 **0.008**	13.763 **0.641**	47.245 **3.115**	0.611 **0.013**	0.634 **0.012**
Counterpeak	6.0 **0.0**	6.0 **0.0**	–0.004 **0.001**	–0.006 **0.001**	0.007 **0.001**	0.033 **0.002**	1.018 **0.001**	1.035 **0.005**	NA NA	NA NA	0.187 **0.024**	0.279 **0.015**
Midday	6.0 **0.0**	5.9 **0.0**	0.003 **0.001**	–0.001 **0.001**	0.010 **0.001**	0.009 **0.001**	1.034 **0.002**	1.022 **0.001**	NA NA	NA NA	0.200 **0.017**	0.159 **0.012**
Weekday	6.3 **0.0**	6.2 **0.0**	0.169 **0.005**	0.120 **0.006**	0.091 **0.001**	0.080 **0.001**	1.462 **0.004**	1.405 **0.003**	NA NA	NA NA	0.579 **0.005**	0.535 **0.004**
All year	6.2 **0.0**	6.1 **0.0**	0.050 **0.003**	0.014 **0.001**	0.071 **0.001**	0.065 **0.001**	1.371 **0.005**	1.336 **0.003**	NA NA	NA NA	0.530 **0.004**	0.494 **0.004**

Note: Standard errors are shown in boldface. NA = Not available (skew statistics could not be computed because 10th and 50th percentile travel times were too close).

First, most TRIP coverage was on highways not previously identified as SHRP 2 study sections, and sufficient traffic data were not available. Second, the after period was 2008, which was already observed to have lower congestion levels due to decreased demand.

A comparison of incident statistics for the before (2007) and after (2008) periods is shown in Table B.30. Because of the TRIP incentive program, average incident duration for large-truck crashes fell almost 13%, and lane hours lost per crash dropped over 9%. During the same period, crashes not involving large trucks showed a slight decrease in average incident duration (3%), but large decreases in lane hours lost (14%). Further examination of the data reveals that in 2008 shoulder hours lost per nontruck crash increased 6% over 2007. This increase coincides with a more aggressive incident management policy instituted in 2008 to move lane-blocking vehicles to the shoulder as rapidly as possible.

Table B.19. Summary Demand, Weather, and Incident Characteristics for SR 52 Westbound in San Diego

		Before	After
Demand	AADT	65	60
	K-factor	8%	8%
Weather (number of days)	Rain	9	5
	Fog	0	0
	Snow	0	0
	Wind	0	0
Incidents	No collision	11	8
	Collision, no injury	2	3
	Collision, injury and/or fatality	2	1

Effect of Capacity Improvements near Seattle, Washington

I-405 Southbound in Kirkland, Washington

Background

The I-405 Kirkland Nickel Improvement Stage 1 project expanded the capacity of a bottleneck segment on a major urban north–south Interstate by adding an additional general-purpose (GP) lane. The project is the first stage of a multistage project to improve traffic conditions along a 7.6-mile segment of I-405 north of Bellevue, Washington, a major suburban city.

The project location was a 2-mile southbound freeway segment of I-405, located on the east side of Lake Washington (Seattle lies on the west side of Lake Washington). The segment is part of a freeway commute route that experiences heavy volumes and congestion during the a.m. peak period. Traffic on that route travels toward the Bellevue central business district. Just before reaching downtown Bellevue, the route also connects to an interchange with SR 520, a major east–west freeway that provides access to downtown Seattle (westbound) and the City of Redmond (eastbound); the latter

Table B.20. Performance Measure Comparisons for SR 52 Westbound in San Diego

Time Period	Average Travel Time		Buffer Index		Failure Rate		Planning Time Index		Skew Statistic		Misery Index	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	13.2 **0.1**	9.7 **0.0**	0.369 **0.012**	0.206 **0.006**	0.135 **0.005**	0.045 **0.004**	2.329 **0.053**	2.162 **0.021**	2.275 **0.142**	0.834 **0.041**	1.018 **0.038**	0.441 **0.017**
Peak period	13.0 **0.1**	9.3 **0.0**	0.427 **0.008**	0.257 **0.004**	0.163 **0.003**	0.068 **0.003**	2.414 **0.037**	2.177 **0.013**	7.613 **0.711**	0.662 **0.017**	1.223 **0.033**	0.524 **0.014**
Counterpeak	9.3 **0.0**	5.8 **0.0**	0.000 **0.000**	0.000 **0.000**	0.000 **0.000**	0.000 **0.000**	1.000 **0.000**	1.000 **0.000**	NA NA	NA NA	0.000 **0.000**	0.000 **0.000**
Midday	9.3 **0.0**	5.8 **0.0**	–0.002 **0.000**	0.001 **0.000**	0.000 **0.000**	0.000 **0.000**	1.009 **0.001**	1.008 **0.000**	NA NA	NA NA	0.045 **0.009**	0.042 **0.006**
Weekday	10.3 **0.0**	6.8 **0.0**	0.290 **0.007**	0.476 **0.002**	0.146 **0.001**	0.271 **0.001**	1.760 **0.005**	1.881 **0.004**	NA NA	NA NA	1.111 **0.010**	0.805 **0.006**
All year	10.1 **0.0**	6.6 **0.0**	0.072 **0.007**	0.454 **0.002**	0.130 **0.001**	0.254 **0.002**	1.668 **0.005**	1.834 **0.003**	NA NA	NA NA	1.042 **0.009**	0.813 **0.004**

Note: Standard errors are shown in boldface. NA = Not available (skew statistics could not be computed because 10th and 50th percentile travel times were too close).

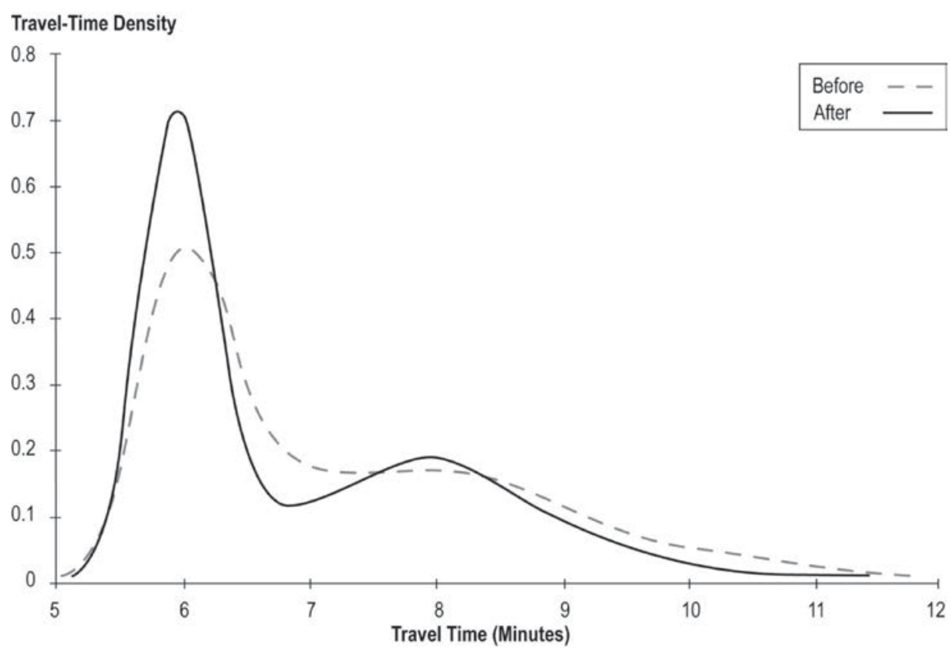

Figure B.15. Travel time density on I-8 eastbound in San Diego, peak hour.

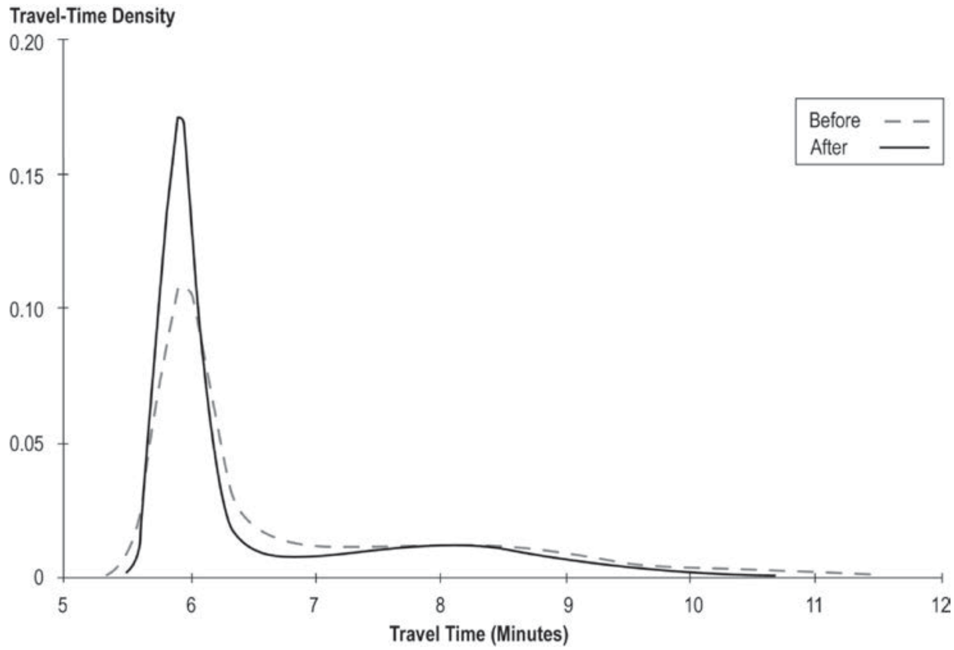

Figure B.16. Travel time density on I-8 eastbound in San Diego, peak period.

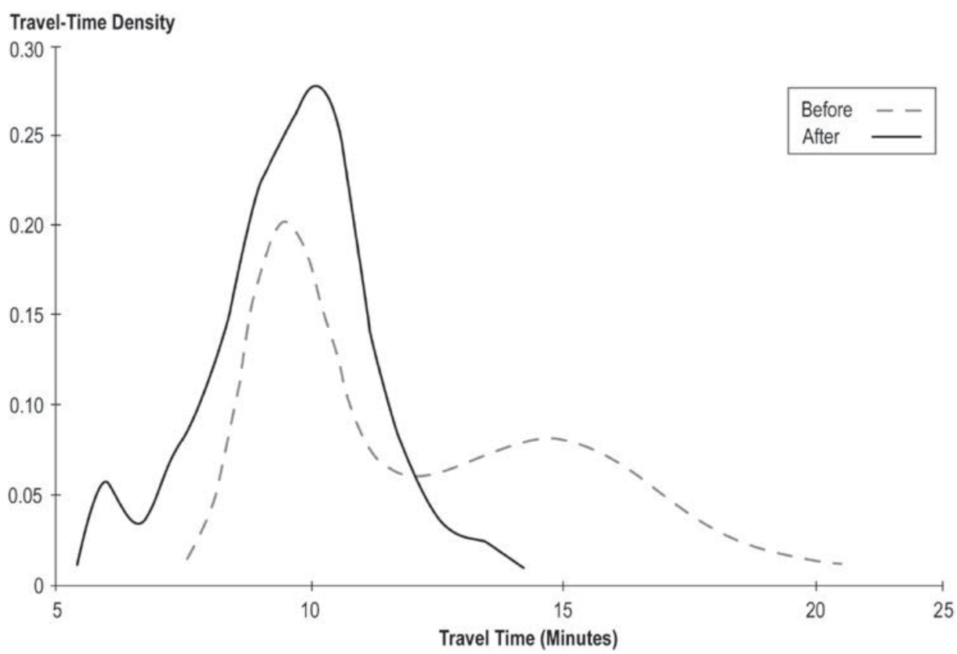

Figure B.17. Travel time density on SR 52 westbound in San Diego, peak hour.

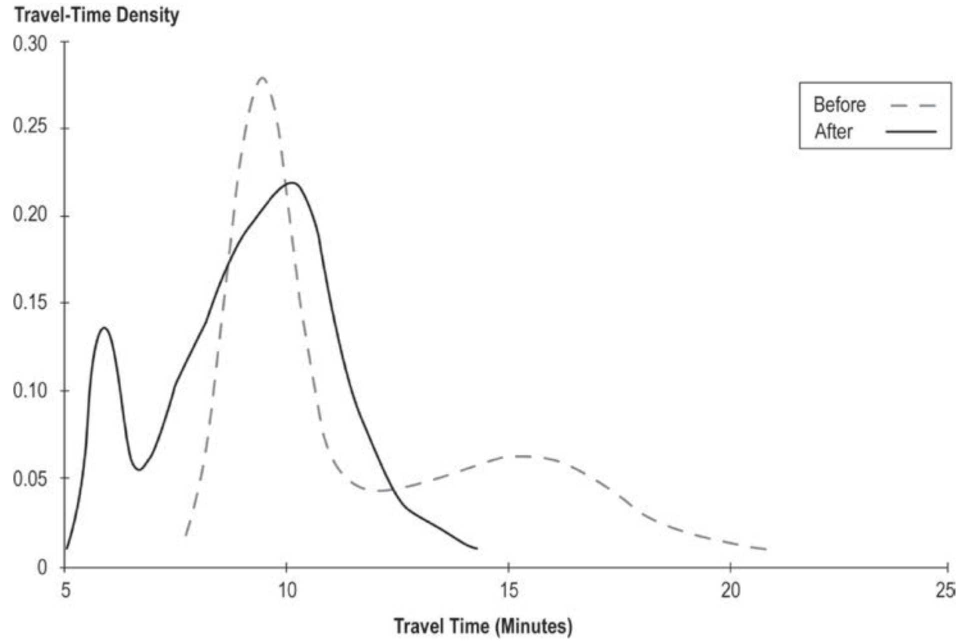

Figure B.18. Travel time density on SR 52 westbound in San Diego, peak period.

Table B.21. Before-and-After Study Sites in Minneapolis–St. Paul Area

Project ID	Highway	Location	Project Description	Project Cost	Approximate Start Date	Approximate Completion Date
B	I-94	Highway 100 to I-494	Add third lane in each direction.	$55M	September 2001	Fall 2004
C	I-494	Highway 100 to Highway 5	Add third lane in each direction.	$71M	May 2003	Fall 2005
E	I-394	Highway 100 to Highway 169	Add auxiliary lane westbound; high-occupancy toll (HOT) lane project (MnPass).	$2M	September 2005	October 2005
E2	I-394	I-494 to Highway 169	HOT lane project (MnPass).	NA	May 2005	August 2006
G	Highway 169	Anderson Lakes and Pioneer Trail	Convert signalized intersections to diamond interchanges.	$20M	Summer 2005	Fall 2006
H	Highway 100	Highway 7 to Minnetonka Boulevard	Add third lane northbound. Add auxiliary lane southbound. Convert Highway 7 interchange from cloverleaf to folded diamond.	$7M	June 2006	October 2006

Table B.22. Study Periods for Before-and-After Projects

Project ID	Route	Directions Covered	Beginning Landmark	Ending Landmark	Before Period	After Period
B	I-94	Eastbound	Highway 100	I-494	September 2000 to September 2001	November 2004 to November 2005
B	I-94	Westbound	I-494	Highway 100	September 2000 to September 2001	November 2004 to November 2005
C	I-494	Eastbound	Highway 5/312	Highway 100	April 2002 to April 2003	July 2006 to July 2007
E	I-394	Westbound	Highway 100	Highway 169	July 2004 to July 2005	November 2005 to November 2006
E2	I-394	Eastbound	I-494	Highway 169	July 2004 to July 2005	November 2005 to November 2006
G	Highway 169	Southbound	T.H. 62	I-494	June 2005 to June 2006	November 2006 to November 2007
H	Highway 100	Northbound	36th St	I-394	April 2005 to April 2006	November 2006 to November 2007

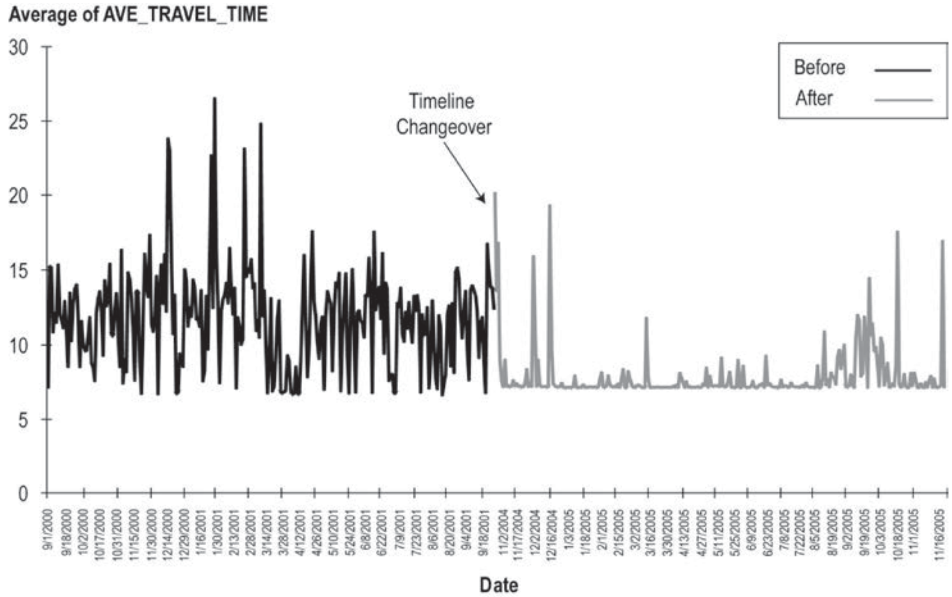

Figure B.19. Peak hour travel time for Project B eastbound.

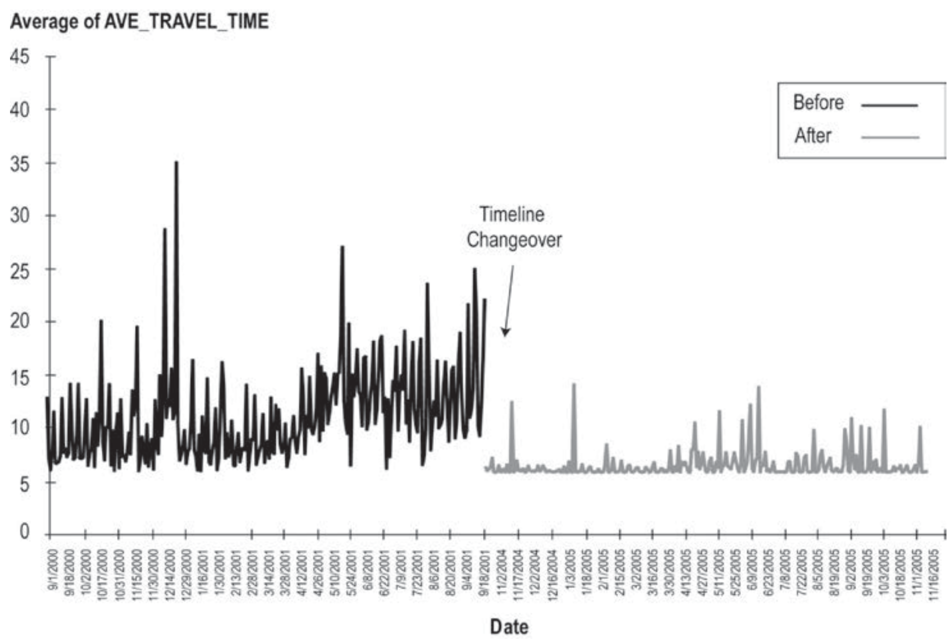

Figure B.20. Peak hour travel time for Project B westbound.

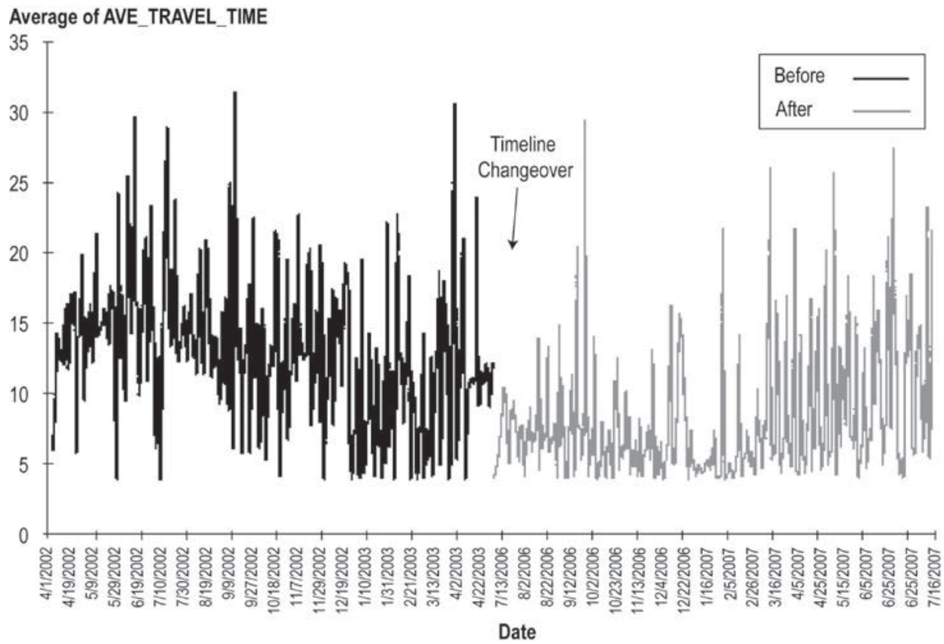

Figure B.21. Peak hour travel time for Project C.

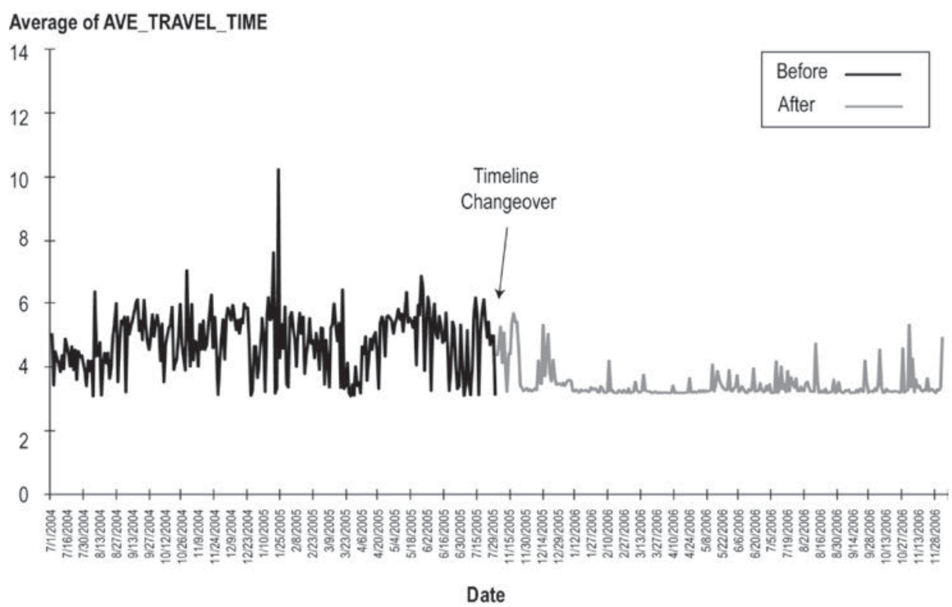

Figure B.22. Peak hour travel time for Project E.

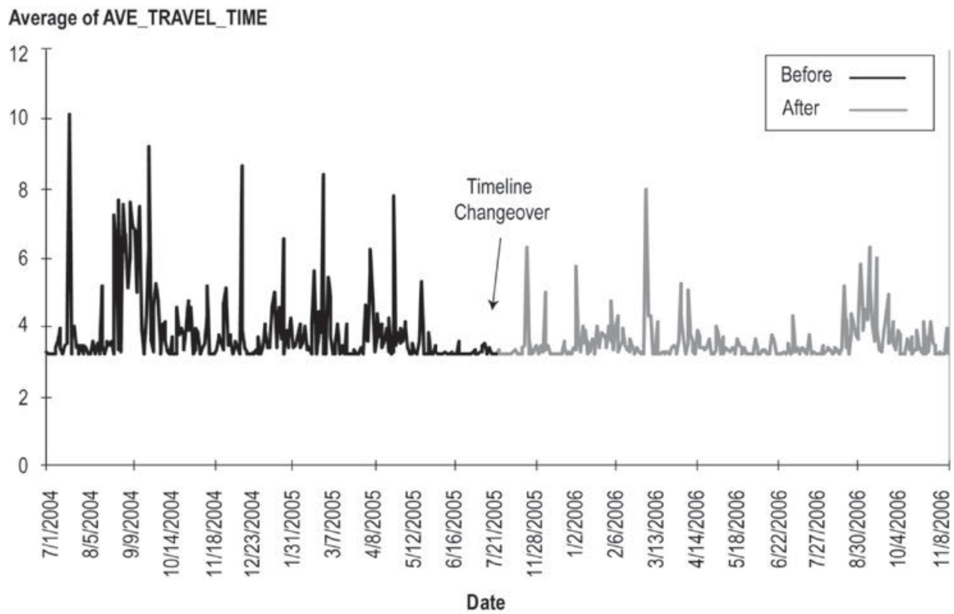

Figure B.23. Peak hour travel time for Project E2.

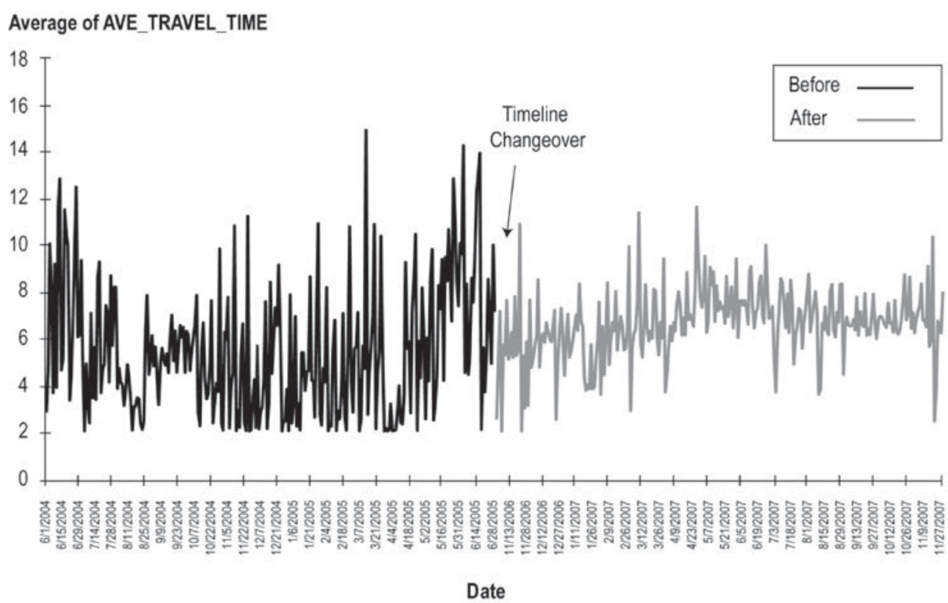

Figure B.24. Peak hour travel time for Project G.

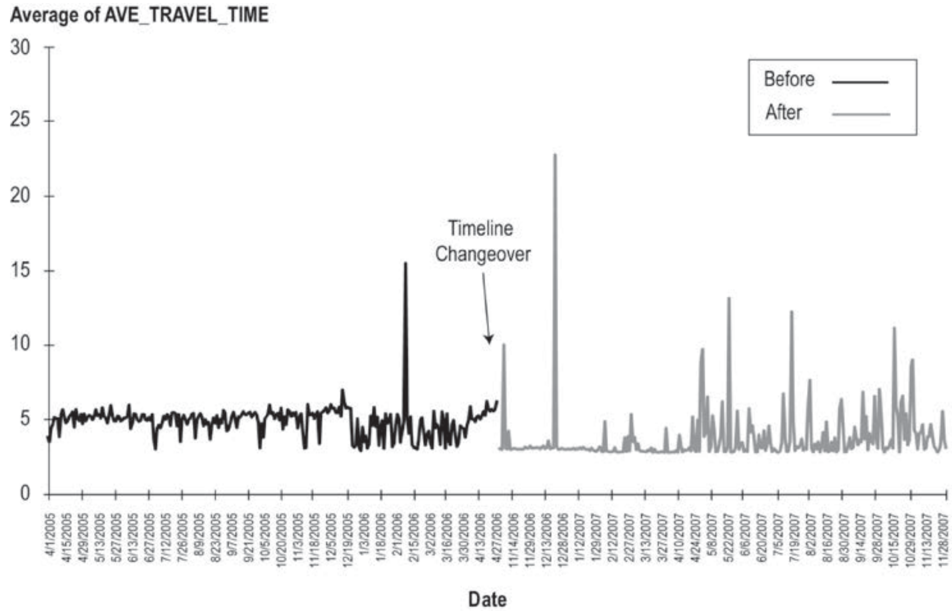

Figure B.25. Peak hour travel time for Project H.

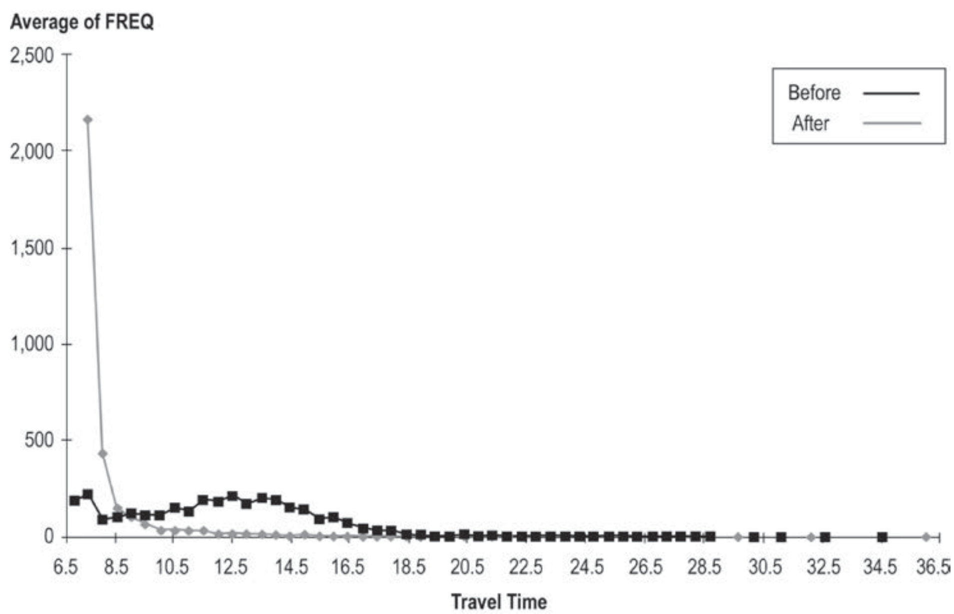

Figure B.26. Peak hour travel time frequency distribution for Project B eastbound.

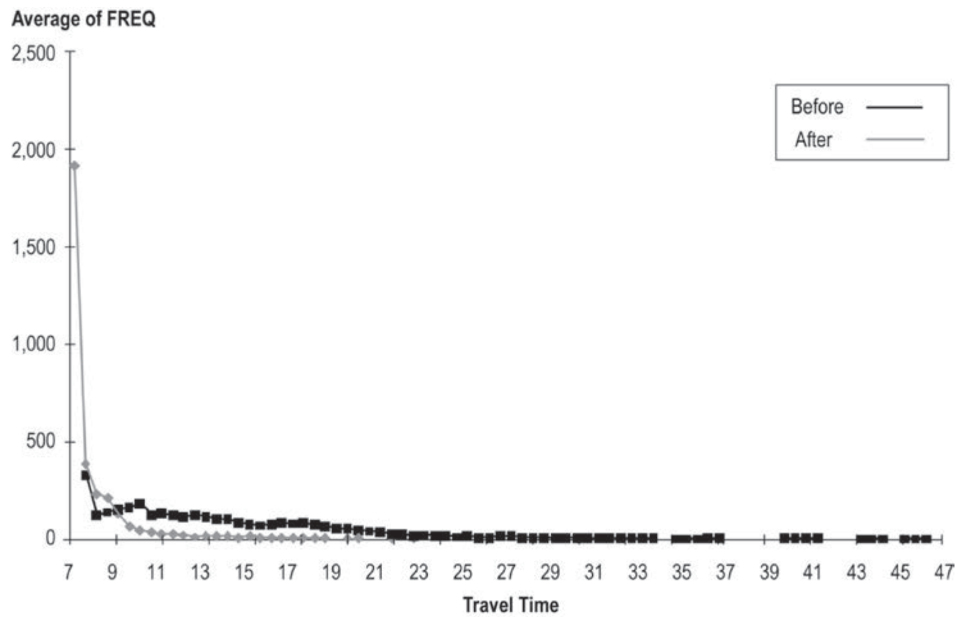

Figure B.27. Peak hour travel time frequency distribution for Project B westbound.

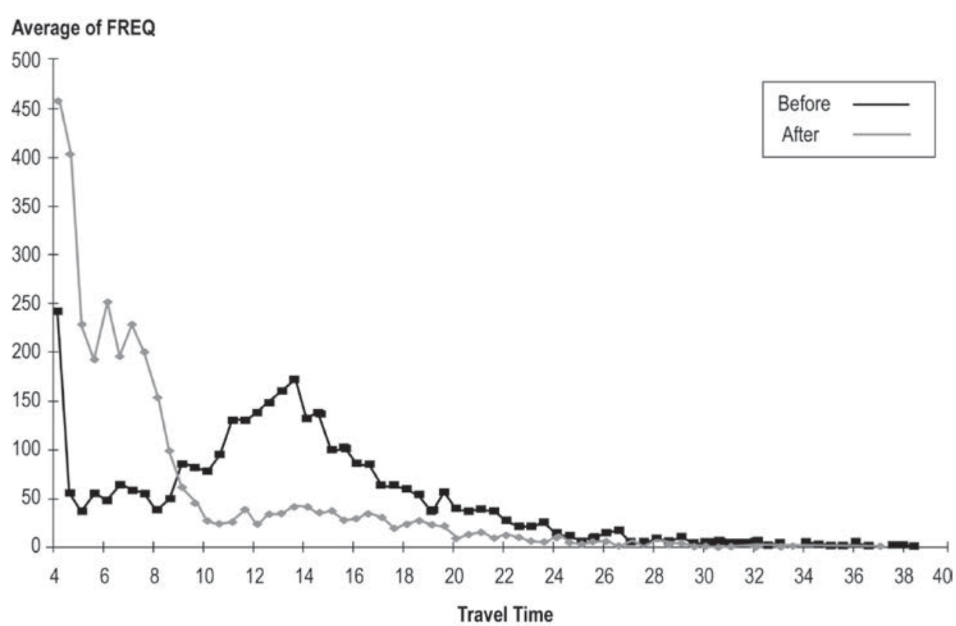

Figure B.28. Peak hour travel time frequency distribution for Project C.

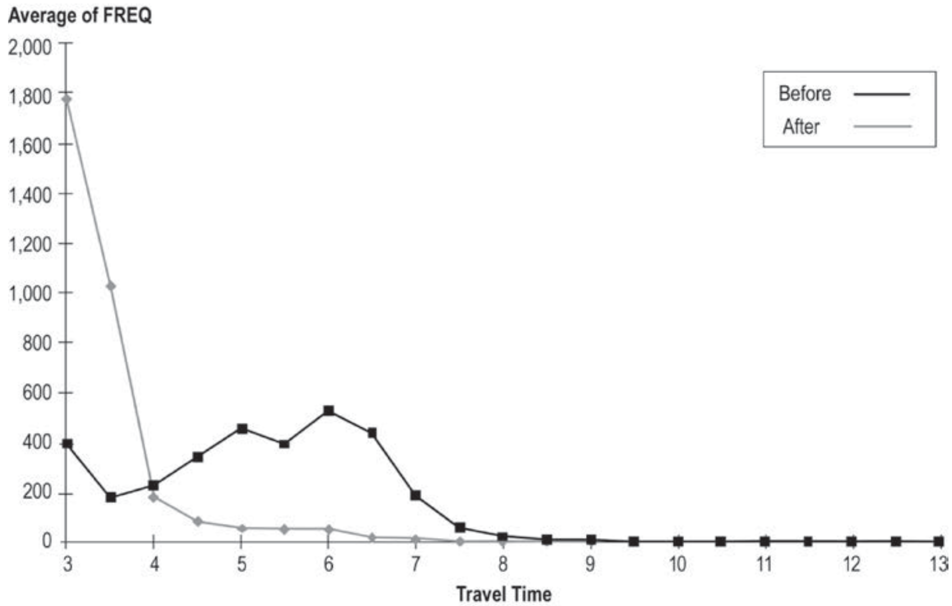

Figure B.29. Peak hour travel time frequency distribution for Project E.

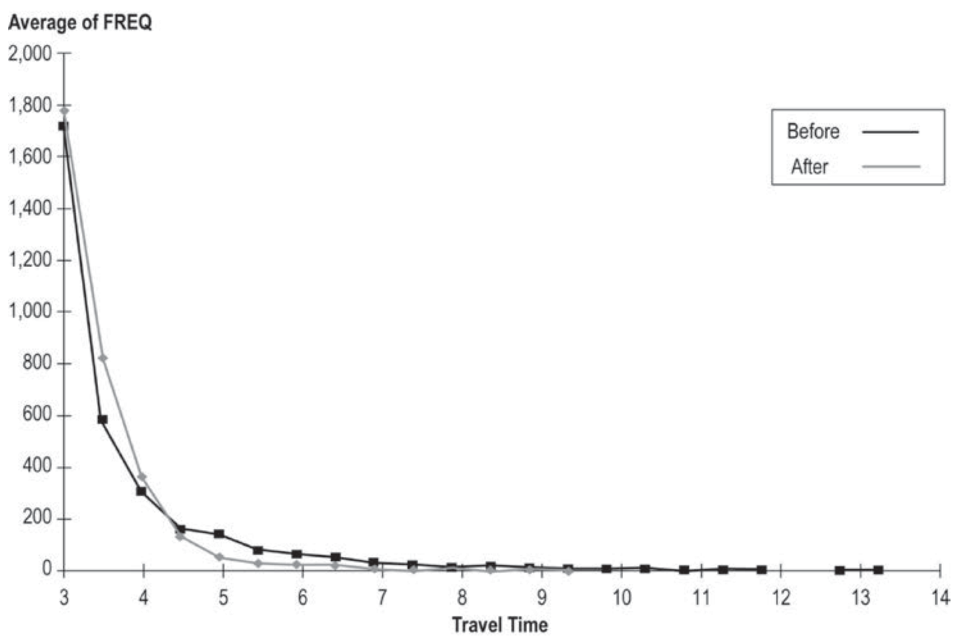

Figure B.30. Peak hour travel time frequency distribution for Project E2.

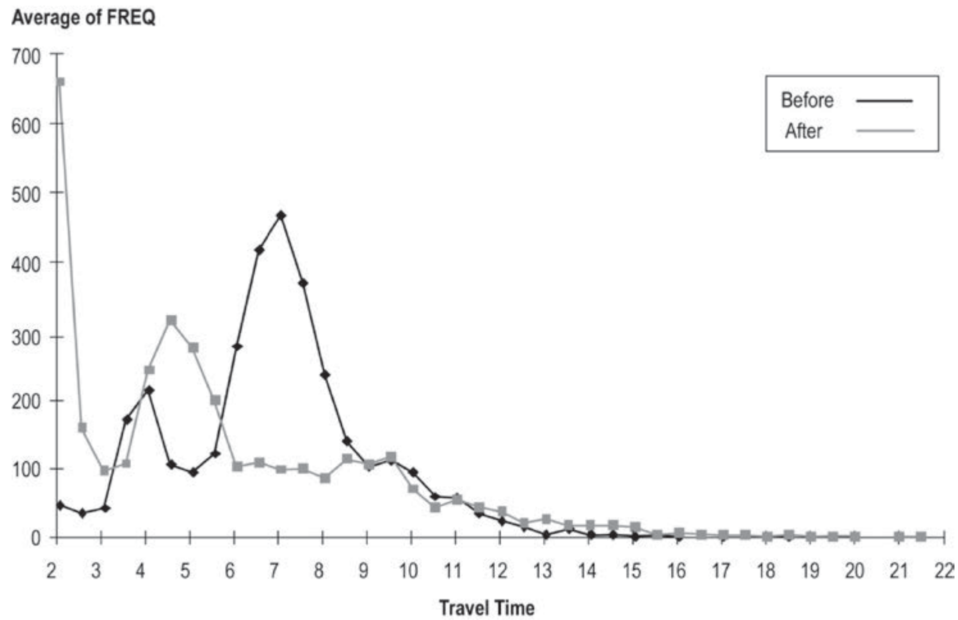

Figure B.31. Peak hour travel time frequency distribution for Project G.

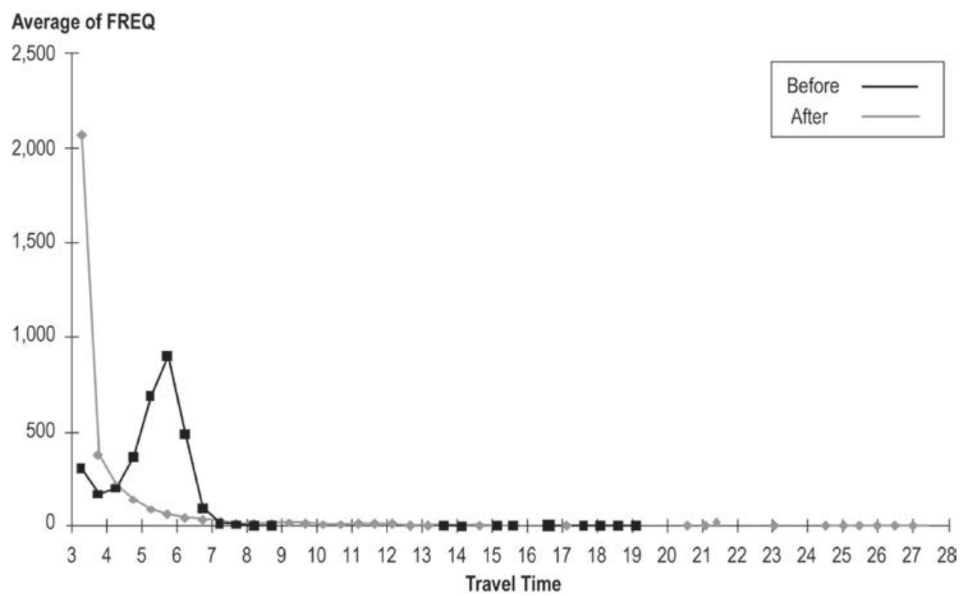

Figure B.32. Peak hour travel time frequency distribution for Project H.

Table B.23. Performance Measure Comparisons for Project B Eastbound

Time Period	Travel Time Index		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	1.74	1.09	0.44	0.37	2.51	1.49	0.84	144	3.08	2.11	0.23	0.91
Peak period	1.55	1.06	0.52	0.28	2.36	1.35	1.48	3,943	2.94	1.93	0.38	0.94
Counterpeak	1.23	1.01	0.63	0.02	2.00	1.03	22.73	3.13	2.55	1.20	0.79	0.99
Midday	1.09	1.01	0.12	0.05	1.22	1.06	2.08	18.89	1.80	1.15	0.96	1.00
Weekday	1.23	1.03	0.63	0.07	2.00	1.10	14.32	67.32	2.55	1.26	0.83	0.98

Table B.24. Performance Measure Comparisons for Project B Westbound

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	1.76	1.10	0.68	0.38	2.96	1.52	1.87	75.13	3.70	1.93	0.28	0.91
Peak period	1.86	1.12	0.65	0.36	3.07	1.52	1.55	15.56	3.71	1.90	0.25	0.89
Counterpeak	1.06	1.00	0.19	0.01	1.26	1.01	14.50	2.13	1.87	1.08	0.94	1.00
Midday	1.12	1.01	0.68	0.02	1.88	1.03	22.78	4.13	2.47	1.18	0.90	0.99
Weekday	1.28	1.04	0.97	0.17	2.52	1.22	70.60	2.14	3.31	1.41	0.83	0.98

Table B.25. Performance Measure Comparisons for Project C

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	3.15	2.08	0.76	1.33	5.53	4.85	0.87	4.60	6.64	6.00	0.10	0.34
Peak period	2.68	1.85	0.90	1.32	5.09	4.30	1.19	4.30	6.13	5.47	0.16	0.41
Counterpeak	1.51	1.39	0.58	0.76	2.39	2.45	1.87	9.82	3.32	3.22	0.43	0.66
Midday	1.29	1.10	0.59	0.40	2.04	1.53	44.10	4.06	2.70	1.98	0.66	0.93
Weekday	1.46	1.27	1.27	0.83	3.32	2.33	88.01	21.69	4.43	3.64	0.75	0.85

Table B.26. Performance Measure Comparisons for Project E

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	1.69	1.09	0.34	0.38	2.27	1.51	0.61	12.15	2.54	1.85	0.23	0.91
Peak period	1.70	1.11	0.34	0.44	2.28	1.59	0.56	12.69	2.51	1.90	0.23	0.90
Counterpeak	1.09	1.02	0.43	0.08	1.56	1.10	22.77	143.45	2.03	1.24	0.91	0.99
Midday	1.15	1.02	0.67	0.08	1.91	1.10	52.37	23.95	2.20	1.26	0.85	0.99
Weekday	1.18	1.04	0.70	0.12	2.01	1.16	78.39	43.23	2.27	1.37	0.86	0.98

Table B.27. Performance Measure Comparisons for Project E2

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	1.23	1.11	0.72	0.32	2.12	1.47	52.27	58.17	2.70	1.87	0.81	0.91
Peak period	1.19	1.09	0.72	0.32	2.04	1.43	851.50	7.14	2.59	1.82	0.85	0.92
Counterpeak	1.01	1.01	0.00	0.00	1.01	1.00	0.50	0.50	1.14	1.12	0.99	0.99
Midday	1.00	1.00	0.01	0.00	1.01	1.00	2.13	0.50	1.07	1.08	1.00	0.99
Weekday	1.04	1.02	0.14	0.08	1.18	1.10	7.13	3.13	1.52	1.27	0.98	0.99

Table B.28. Performance Measure Comparisons for Project G

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	2.64	3.27	1.09	0.56	5.52	5.09	1.83	0.94	6.57	5.72	0.25	0.03
Peak period	2.38	2.78	1.25	0.72	5.37	4.77	2.30	0.89	6.43	5.47	0.35	0.09
Counterpeak	1.10	1.14	0.57	0.11	1.73	1.26	51.23	1.29	2.34	1.43	0.95	0.98
Midday	1.21	1.50	1.03	0.82	2.45	2.73	33.09	3.04	3.28	3.70	0.89	0.53
Weekday	1.40	1.63	1.47	1.22	3.45	3.62	112.22	12.55	4.85	4.43	0.84	0.67

Table B.29. Performance Measure Comparisons for Project H

Time Period	TTI		Buffer Index		Planning Time Index		Skew Statistic		Misery Index		On-Time at 45 mph (%)	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Peak hour	1.77	1.37	0.24	0.89	2.20	2.58	0.42	10.47	2.54	4.10	0.15	0.75
Peak period	1.77	1.41	0.25	1.06	2.22	2.91	0.39	12.94	2.63	4.37	0.17	0.72
Counterpeak	1.76	1.26	0.38	0.55	2.43	1.95	0.62	9.66	0.29	2.35	0.29	0.80
Midday	1.09	1.06	0.13	0.09	1.23	1.16	3.03	4.75	1.72	1.23	0.96	0.99
Weekday	1.34	1.16	0.63	0.51	2.19	1.75	20.07	14.68	2.44	2.76	0.78	0.93

Table B.30. Crash Characteristics on Atlanta Highways Affected by TRIP Program, 2007 to 2008

Crash Type	Year	Number of Crashes	Average Incident Duration (min)	Lane Hours Lost	Lane Hours Lost Per Crash
Nonlarge-truck crashes	2007	3,823	48.5	2,909	0.761
	2008	4,057	47.0	2,656	0.655
	Difference (%)	+6.1	–3.1	–8.7	–14.0
Large-truck crashes	2007	417	88.9	852	2.043
	2008	420	77.4	778	1.852
	Difference (%)	+0.7	–12.9	–8.7	–9.3
All truck crashes	2007	4,240	52.5	3,761	0.887
	2008	4,477	49.8	3,433	0.767
	Difference (%)	+5.6	–5.1	–8.7	–13.6

Table B.31. Travel Time Data for Typical I-405 Trip Route During A.M. Peak Period

	A.M. Peak Period Travel Time (min)							A.M. Peak Period		
	Average	Median	80th Percentile	90th Percentile	95th Percentile	Skew	Frequency of Congestion (<35 mph)	Travel Time Index	Buffer Index	Planning Index
2005 (before construction)	31	30	37	40	44	0.50	65%	1.9	45%	2.8
2007 (during construction)	32	31	39	45	49	0.82	69%	2.0	52%	3.1
2008 (after construction)	27	26	32	37	41	1.53	39%	1.7	49%	2.5

Note: Travel times were based on a typical 16-mile southbound trip from Lynnwood to the Bellevue CBD that included the construction segment. Travel times were averaged over a 6:00 to 9:00 a.m. peak period. The time period each year was fixed (January to June, weekdays only) to minimize effects of seasonal variations.

is a significant suburban employment center that includes, most notably, Microsoft's headquarters. Before construction, there were three GP lanes and one inside high-occupancy vehicle (HOV) lane in the segment of interest. This project added a fourth GP lane, as well as on-ramp improvements.

Results

After the opening of the additional southbound GP lane in the Kirkland area north of Bellevue, congestion was reduced, and travel times decreased and became more reliable. Table B.31 summarizes the change in travel time statistics for a typical 16-mile freeway commute route to downtown Bellevue that includes the construction segment. The results show a drop in the average a.m. peak period travel time from 31 minutes (before construction start) to 27 minutes (after construction completion). Median trip time showed a similar reduction. In addition to a drop in average travel times, the overall reliability of travel on that freeway route improved; on days with outlier travel times at the 80th, 90th, and 95th percentile levels, the peak period travel times dropped at each of those levels.

The reduction in outlier travel times and the resulting improvement in travel time reliability were reflected in the overall likelihood of encountering a congested trip on that route on any given weekday (*congested trip* was defined as a trip with an overall trip speed of 35 mph or less); that likelihood dropped significantly, from 65% before construction to 39% after the additional GP lane was opened. The TTI and Planning Index also dropped, reflecting the changes in mobility and reliability, but the Buffer Index was largely unchanged.

Figure B.33 illustrates that the reduction in the frequency of congestion is significant throughout much of the a.m. peak period.

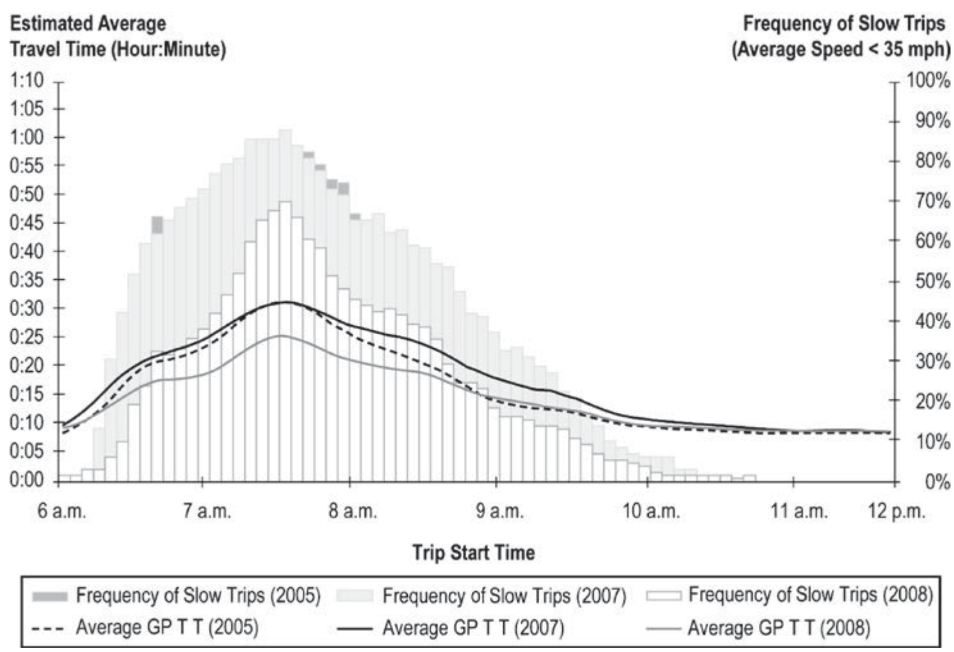

Figure B.33. Reductions in frequency of congestion and average travel time.

The congestion benefit from this project extended upstream from the construction segment for up to 6 miles along the corridor. A comparison of time–space diagrams of the average speed along the trip route before versus after the new lane was opened (Figure B.34) shows how the magnitude and duration of upstream congestion was reduced during the a.m. peak period after the addition of the GP lane between NE 124th and NE 85th (traffic is moving from bottom to top in the diagrams). Although congestion upstream from that segment has lessened, congestion persists just downstream from the construction location, indicating a possible bottleneck south of the construction segment where the additional lane stops. (In Stage 2 of this project, plans call for an extension of the Stage 1 GP lane an additional mile to the south.)

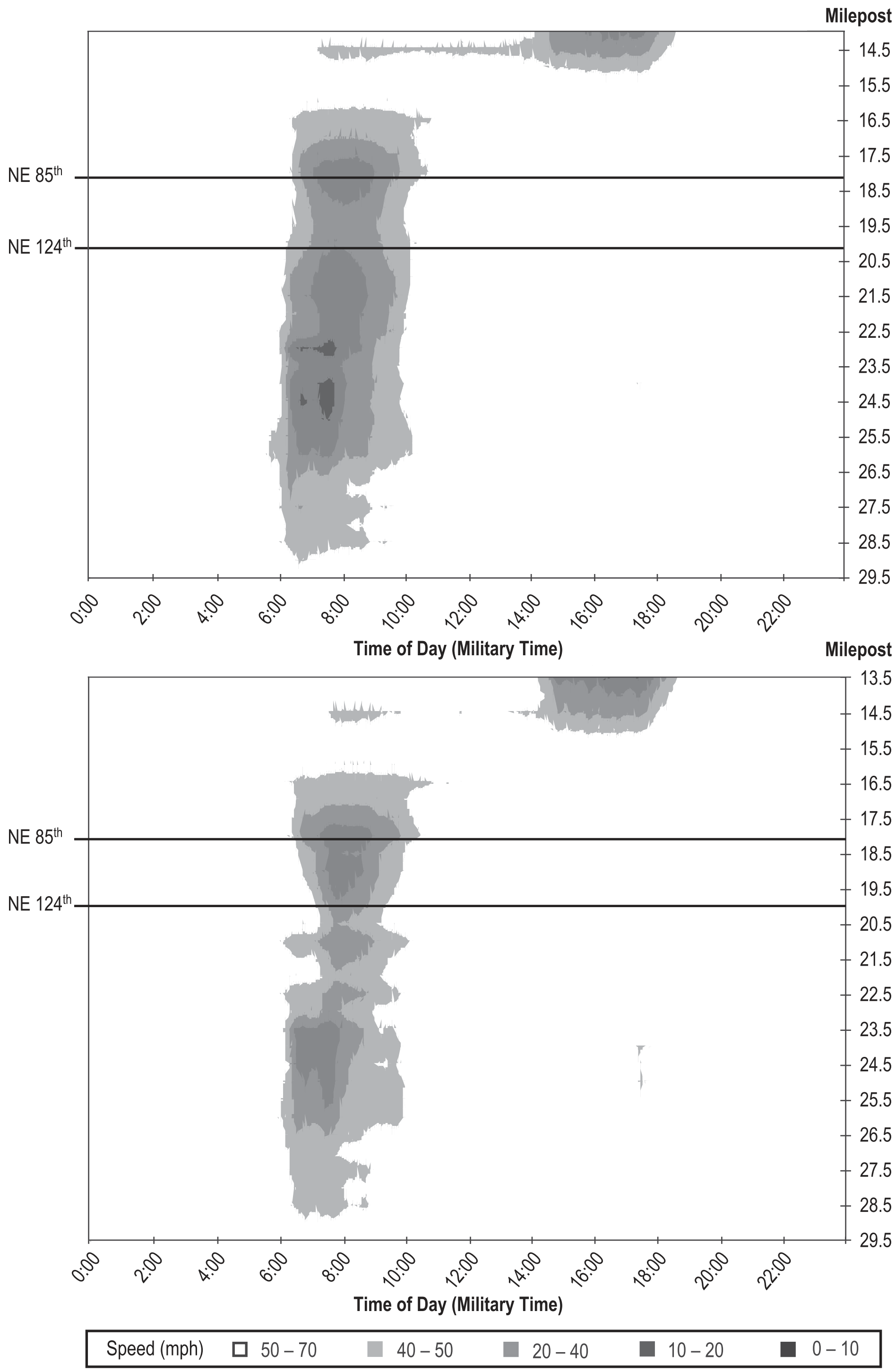

Figure B.34. Average speed in (top) 2007 and (bottom) 2008.

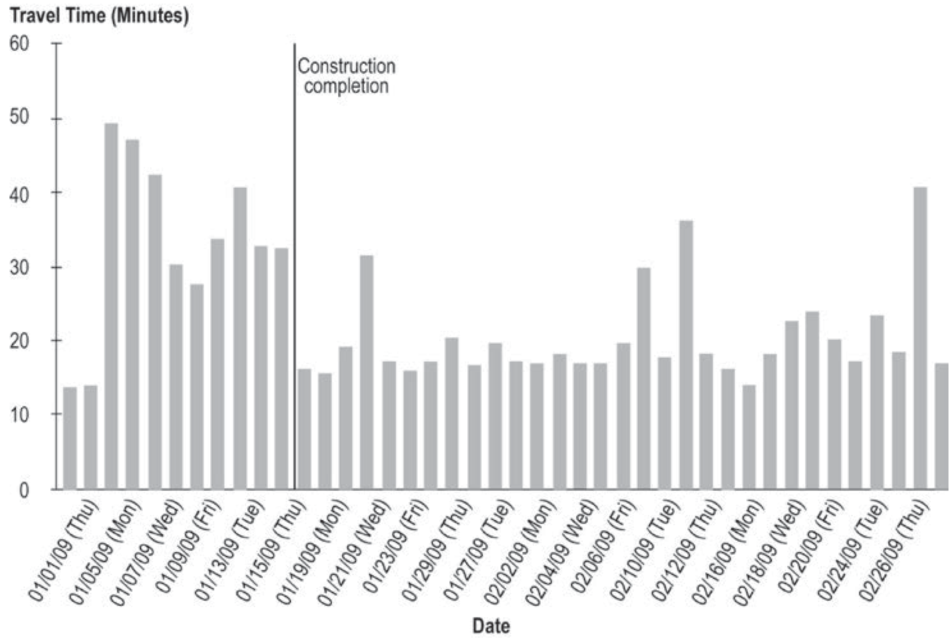

Figure B.35. Average a.m. peak period travel time by day.

I-405 Northbound in Bellevue, Washington

Background

The south segment of the I-405 South Bellevue Widening project expanded capacity at a bottleneck location on I-405 on the east side of Lake Washington by adding a new auxiliary GP lane. The project location was a 2-mile northbound urban freeway segment of I-405 that is part of a freeway commute route that experiences heavy volumes and congestion during the a.m. peak period as traffic approaches the central business district of Bellevue, a major suburban city, as well as a nearby interchange with I-90, a major east–west freeway that provides access to downtown Seattle (westbound) and eastern Washington (eastbound). Before construction, there were two GP lanes and one inside HOV lane in the segment of interest. This project added a third GP lane.

Results

The opening of the additional GP lane resulted in noticeably reduced travel times and higher travel time reliability, as well as reduced congestion. Figure B.35 illustrates the drop in average a.m. peak period travel times after the opening of the additional GP lane for a typical 13-mile northbound freeway commute route that included the construction segment.

Table B.32 summarizes the change in travel time statistics for the 13-mile northbound trip route. Average a.m. peak period travel time dropped significantly compared with the

Table B.32. Travel Time Data for Typical I-405 Trip Route During A.M. Peak Period

	A.M. Peak Period Travel Time (min)							A.M. Peak Period		
	Average	Median	80th Percentile	90th Percentile	95th Percentile	Skew	Frequency of Congestion (<35 mph)	Travel Time Index	Buffer Index	Planning Index
2007 (before construction)	35	35	40	43	45	–0.11	92%	2.6	31%	3.4
2008 (during construction)	32	31	40	44	46	0.41	85%	2.4	43%	3.4
2009 (after construction)	21	19	26	28	30	1.26	31%	1.5	44%	2.2

Note: Travel times were based on a typical 13-mile northbound trip from Tukwila to the Bellevue CBD that included the construction segment. Travel times were averaged over a 6:00 to 9:00 a.m. peak period. The time period each year was fixed (mid-January to mid-April, weekdays only) to minimize effects of seasonal variations.

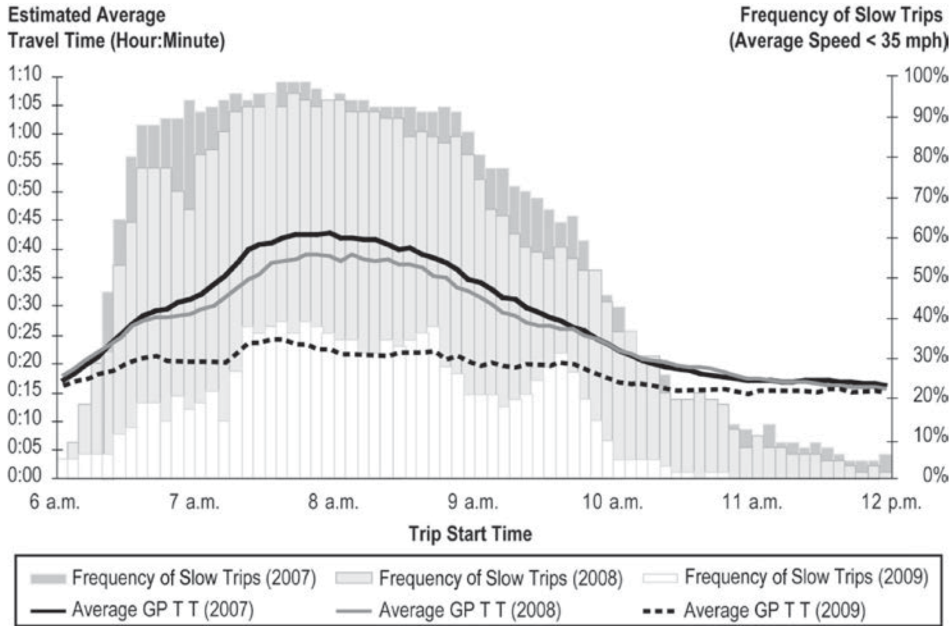

Figure B.36. Reductions in frequency of congestion and average travel time.

previous 2 years, down from 32 to 35 minutes to 21 minutes after the opening of the new lane. There was a similar reduction in median trip time.

In addition to a drop in average travel times, the overall reliability of travel on that freeway route was significantly enhanced. A review of days with outlier travel times at the 80th, 90th, and 95th percentiles showed that average peak period travel times dropped significantly at each of those levels. In fact, the new 95th percentile travel time dropped below the previous average travel time. The skew factor grew, but this was more a function of the significant drop in the central tendency of the travel time distribution rather than a higher frequency of outlier travel times.

Table B.32 also summarizes the change in the TTI, Buffer Index, and Planning Index values for the a.m. peak period. In this research TTI = (average a.m. peak period travel time)/(off-peak travel time at 60 mph); Buffer Index = (95th percentile a.m. peak period travel time – average a.m. peak period travel time)/(average travel time) * 100; and Planning Index = (95th percentile a.m. peak period travel time)/(off-peak travel time at 60 mph).

The TTI and Planning Index both dropped noticeably, reflecting the reduced average and 95th percentile trip times and the resulting higher travel time reliability. The Buffer Index was essentially unchanged, but the buffer percentage value was relative to a significantly smaller average travel time.

Travel time reliability also can be expressed in terms of the likelihood that a traveler will encounter heavy congestion. Table B.32 shows that the likelihood of having a heavily congested trip (overall trip speed 35 mph or less) on that route on any given weekday dropped sharply, from 85% to 92% in previous years to 31% after construction. Figure B.36 illustrates that the improvement in the likelihood of having a heavily congested trip is significant throughout the a.m. peak period, and continues during the shoulder of the peak period after 9:00 a.m.

Interchange of I-405 Southbound and SR 167 in Renton, Washington

Background

This project built a grade separation ramp connecting the southbound I-405 off-ramp with the southbound SR 167 on-ramp. The project location was an interchange of two major north–south roadways (I-405 and SR 167) in Renton, Washington, just south of Seattle. The interchange experiences heavy volumes and congestion during the p.m. peak period commute. The I-405/SR 167 interchange was one of the worst traffic bottlenecks in the region. This interchange, initially designed as a cloverleaf interchange, became a large bottleneck with increasing traffic volumes and merging conflicts. In the previous lane configuration, traffic using the collector–distributor lane to exit from southbound I-405 to southbound SR 167 was forced to weave with traffic entering the collector–distributor from northbound SR 167. These merging conflicts created increased congestion on both southbound I-405 and northbound SR 167. The new grade separation ramp eliminated the weaving movements by providing a separate elevated lane for the I-405 southbound off-ramp to SR 167.

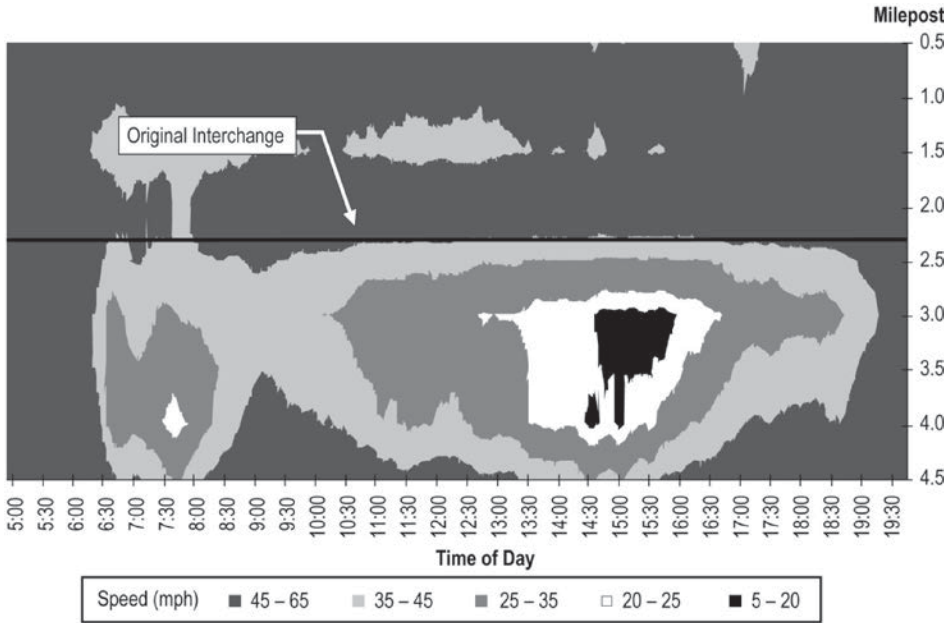

Figure B.37. Time–space speed contours of original interchange configuration in 2002.

Results

Six months of weekday data from before and after the completion of the ramp were analyzed. Study dates of July 1 to December 31, 2003, were selected and compared with the same 6-month period of the previous year (July 1 to December 31, 2002) in an effort to minimize the effects of seasonal variation.

Figures B.37 and B.38 display before-and-after speed contours centered near the interchange location; southbound traffic is moving from bottom to top in each figure. The new ramp significantly reduced the bottleneck at the interchange.

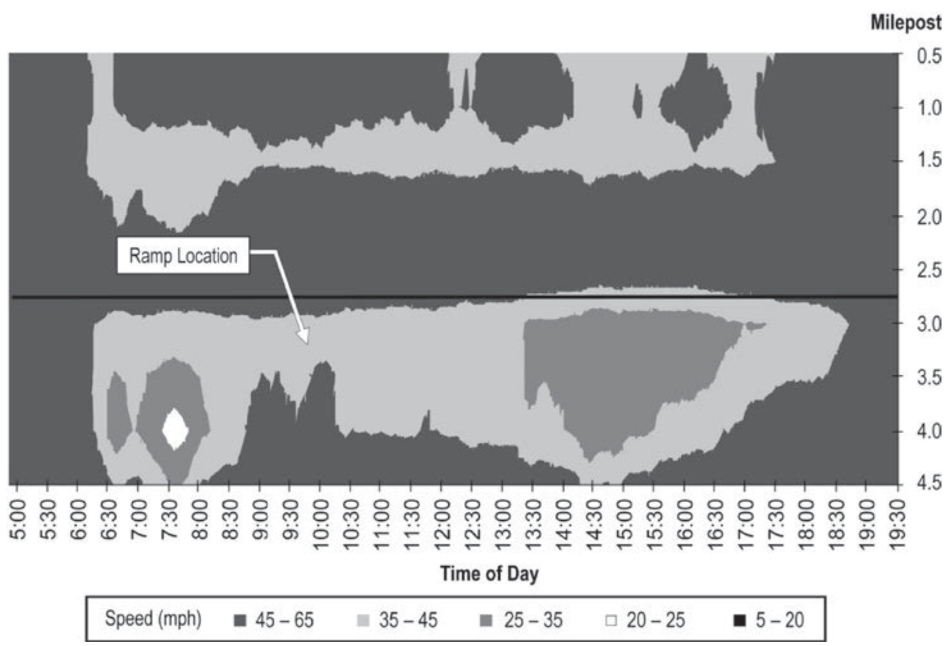

Figure B.38. Time–space speed contours of interchange after installation of grade separation ramp.

Table B.33. Speed Data for Trip Segment During P.M. Peak Period

	P.M. Peak Period Speed (mph)					Frequency of Congestion (<35 mph)
	Average	Median	80th Percentile	90th Percentile	95th Percentile	
2002	29	30	24	21	20	67%
2003	37	38	31	28	26	36%
Change (%)	25	26	32	28	31	–31%

Note: Speeds are based on the 4.59-mile trip from SR 900 to I-5 and were averaged over a 3:00 to 7:00 p.m. peak period. The time period each year was fixed (July 1 to December 31, weekdays only) to minimize effects of seasonal variations.

In 2002, average speeds approaching the interchange stayed below 35 mph for the entire afternoon and evening (10:30 a.m. to 6:30 p.m.) and dropped below 25 mph for approximately 3 hours (1:30 p.m. to 4:30 p.m.). After the off-ramp was separated, average speeds in 2003 never dropped below 25 mph. In addition, the duration of congestion was reduced by more than one-half; average speeds do not fall below 35 mph until 1:30 p.m., and only stay at that level until 5:00 p.m.

Table B.33 summarizes the change in p.m. peak period speed statistics for the 4.59-mile trip displayed in the contours in Figures B.37 and B.38. The route extends on I-405 from SR 900 to I-5. The results show an 8-mph increase (from 29 to 37 mph) in the average a.m. peak period speed compared with the previous year. The same increase was recorded for the median speed.

The overall reliability of travel on that freeway segment also improved. A review of days with outlier average peak period speeds at the 80th, 90th, and 95th percentiles showed that speeds went up by approximately 6 to 7 mph at each of those levels. Furthermore, the likelihood of encountering a congested trip (overall trip speed of 35 mph or less) on the segment on any given day dropped sharply, from 67% to 36%.

Figure B.39 illustrates that the improvement in congestion was significant throughout the afternoon. The figure represents travel times and frequency of congestion on an extended I-405 segment that includes the interchange area. The 11-mile

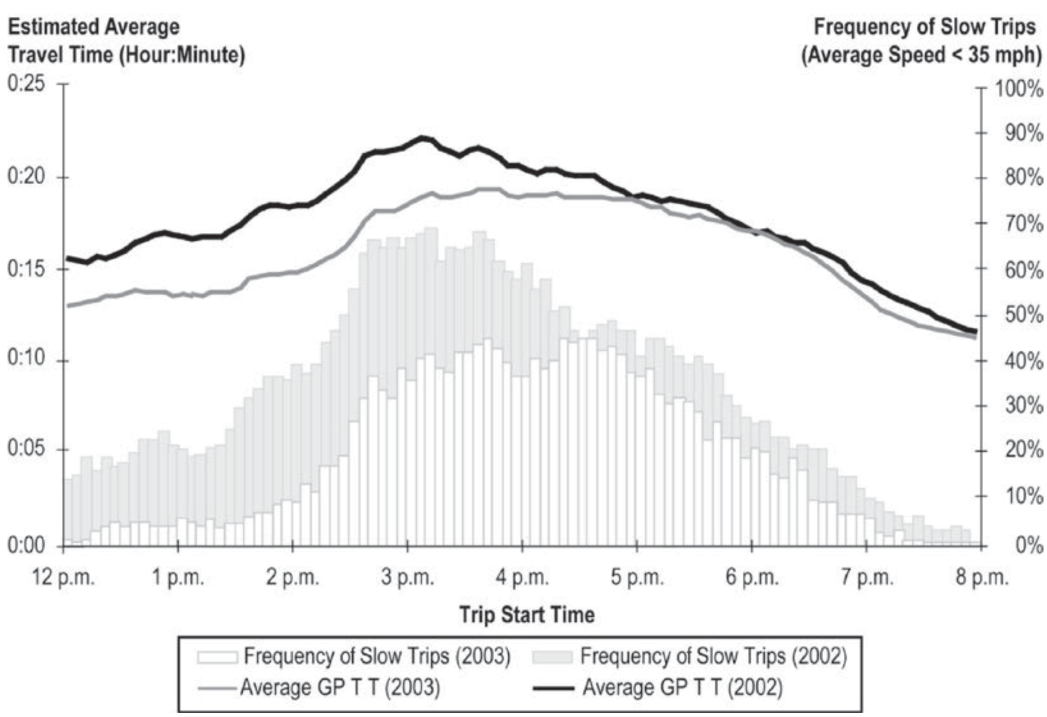

Figure B.39. Reductions in frequency of congestion and average travel time.

Table B.34. Mobility and Reliability Measures for 11.08-Mile Trip from I-90 to I-5

	P.M. Peak Period (3:00 to 7:00 p.m.) Travel Time (min)		
	Average	95th Percentile	Free Flow
2002 (old ramp configuration)	18.9	26.0	11.08
2003 (after installation of grade separation ramp)	17.8	22.5	11.08

Table B.36. Mobility and Reliability Measures for 4.59-Mile Trip Near Ramp

	P.M. Peak Period (3:00 to 7:00 p.m.)		
	TTI	Buffer Index	Planning Index
2002 (old ramp configuration)	2.04	48%	3.01
2003 (after installation of grade separation ramp)	1.63	41%	2.31

trip extends from the major interchange at I-90 to the interchange at I-5. The travel time curves show that travel time improvements as a result of the new ramp were not restricted to the peak period. Travel times during the off-peak early afternoon were approximately 3 minutes faster after the ramp installation. In addition, the frequency of congestion histograms shows that the onset of congestion on the segment was delayed until later in the afternoon.

Table B.34 displays travel time statistics for the p.m. peak period for the trip from I-90 to I-5. Mobility and reliability measures in Table B.35 were calculated based on the average, 95th percentile, and free-flow (trip time based on 60 mph) travel times. TTI compares the average travel time during the peak period to the free-flow travel time. The construction of the ramp resulted in increased mobility and a reduction in TTI. The Buffer Index and Planning Index, which measure the reliability of a trip, showed reliability improvements after the construction of the ramp. The Buffer Index measures the amount of extra time a traveler should budget to ensure an on-time arrival 95% of the time. In 2002, a traveler would have needed to budget an extra 7 minutes; with the new ramp, the traveler needed to budget less than 5 minutes extra. These improvements were more pronounced when focused specifically on the segment most affected by the ramp. Table B.36 displays the mobility and reliability indices for the 4.59-mile segment near the ramp. TTI for the shorter segment dropped from 2.04 to 1.63, meaning that in 2002, average travel times were over 100% longer than free-flow speeds, but in 2003, they were only 60% longer.

Table B.35. Mobility and Reliability Measures for 11.08-Mile Trip from I-90 to I-5

	P.M. Peak Period (3:00 to 7:00 p.m.)		
	TTI	Buffer Index	Planning Index
2002 (old ramp configuration)	1.71	37%	2.35
2003 (after installation of grade separation ramp)	1.61	26%	2.03

The grade separation ramp also significantly improved mainline throughput near the interchange. The bottleneck restricted the flow of vehicles through the segment. Table B.37 illustrates the freeway volumes just upstream of the interchange. Freeway volumes increased significantly throughout the p.m. and by 16% to 19% during the most congested period of the evening commute (3:00 to 5:00 p.m.).

Current State

In the 6 years since the ramp was completed, traffic conditions throughout the I-405 corridor have steadily declined. Figure B.40 shows the average speeds at the I-405/SR 167 interchange using data from July 1 to December 31, 2008. Peak period speeds are approaching conditions similar to those before the ramp installation. Speeds drop below 25 mph for approximately 2 hours (versus 2 hours in 2002). However, off-peak speeds are still improved from the preramp conditions. In 2002, off-peak speeds dropped below 35 mph by 10:30 a.m. In 2008, speeds did not begin dropping below 35 mph until about 1:15 p.m.

Table B.37. I-405 Volumes Near I-405/SR 167 Interchange

I-405 Southbound Throughput (vehicles/hour)			
Time Period	2002	2003	Change (%)
12:00 to 1:00 p.m.	3,057	3,529	15
1:00 to 2:00 p.m.	3,015	3,538	17
2:00 to 3:00 p.m.	2,952	3,466	17
3:00 to 4:00 p.m.	2,752	3,271	19
4:00 to 5:00 p.m.	2,743	3,187	16
5:00 to 6:00 p.m.	2,804	3,220	15
6:00 to 7:00 p.m.	2,869	3,236	13

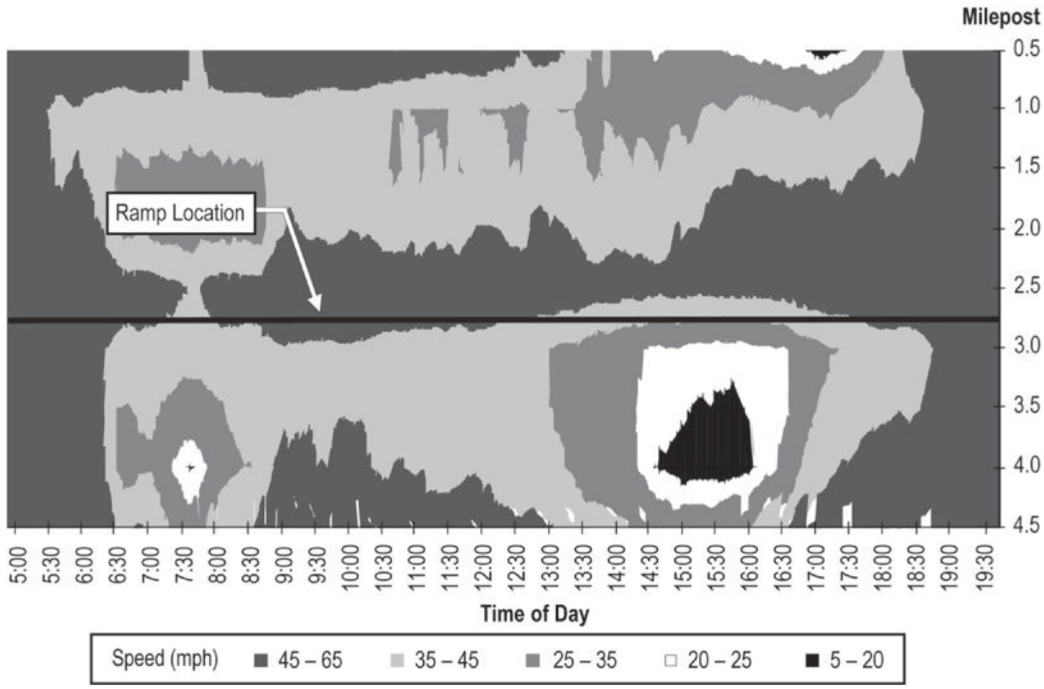

Figure B.40. Time–space speed contours in 2008 at I-405/SR 167 interchange.

Washington State DOT (WSDOT) has a current project to add a new interchange upstream of the grade separation ramp. This interchange is expected to improve access to downtown Renton and relieve some of the traffic demand at the I-405/SR 167 interchange.

Effect of Ramp Metering in Seattle, Washington

SR 520 Eastbound

Background

The SR 520 Ramp Metering project managed congestion on the mainline by using ramp metering to control the frequency of vehicles entering the roadway on two on-ramps to SR 520 eastbound.

SR 520 is one of two east–west roadways across Lake Washington, which forms the eastern boundary of Seattle. The roadway is heavily used by commuters in both directions. The traditional eastbound evening commute from downtown Seattle to the more suburban east side of Lake Washington via the SR 520 Evergreen Point Floating Bridge has been managed by ramp meters on the on-ramps at Montlake and Lake Washington Boulevards (just before reaching the bridge) since 1986. Over the years, traffic conditions in what had traditionally been the reverse commute direction (i.e., eastbound in the morning) worsened. This congestion was in part due to the growth of Bellevue, the major suburban city on the east side of the lake, as well as business development on the east side (e.g., Microsoft). In August 2001, WSDOT began to use the ramp meters to try to alleviate heavy eastbound morning congestion.

Results

Six months of weekday data from before and after the initiation of morning ramp metering were analyzed. Study dates of January 1 to June 28, 2002, were compared with the same 6-month period of the previous year (January 1 to June 29, 2001) in an effort to minimize the effects of seasonal variation.

Table B.38 summarizes the change in speed statistics for the 4-mile eastbound section from I-5 to just east of the Evergreen Point Floating Bridge. The results show an average 4 mph (from 32 to 36 mph) increase in the average a.m. peak period speed compared with the previous year. The same increase was recorded for the median speed.

The overall reliability of travel on that freeway segment also improved. A review of days with outlier average peak period speed at the 80th, 90th, and 95th percentiles showed that speeds went up by approximately 4 mph at each of those levels.

The speed benefits from the ramp metering extended through the project segment. Figure B.41 shows before-and-after speed contours of the segment affected by ramp metering. In 2001, average speeds near the ramps stayed below 25 mph for over 1.5 hours. After ramp metering was initiated,

Table B.38. Speed Data for Trip Segment During A.M. Peak Period

	A.M. Peak Period Speed (mph)					Skew	Frequency of Congestion (<35 mph)
	Average	Median	80th Percentile	90th Percentile	95th Percentile		
2001	32	32	27	26	24	–0.20	63%
2002	36	36	31	29	28	0.98	45%
Change (%)	12%	14%	16%	15%	13%		–18%

Note: Speeds were based on the approximately 4-mile trip from I-5 to just east of the Evergreen Point Floating Bridge and were averaged over a 6:00 to 9:00 a.m. peak period. The time period each year was fixed (January 1 to June 30, weekdays only) to minimize the effects of seasonal variations.

average speeds in 2002 only dropped below 25 mph for a third of that time (approximately 30 minutes). In 2001, speeds dropped below 25 mph by 7:30 a.m.; in 2002, the onset of congestion was delayed by about 15 minutes. In addition to delaying the onset, the lowest average speeds did not drop below 20 mph in 2002; in contrast, during 2001 they dropped below 20 mph for about 20 minutes during the peak congestion period.

The main goal of ramp metering is to reduce the congestion on the mainline. Table B.38 shows that the likelihood of encountering a congested trip (overall trip speed of 35 mph or less) on the sample route on any given day dropped from 63% to 45% after the implementation of ramp metering. Figure B.42 illustrates that the improvement in congestion was significant throughout the a.m. peak period, and it demonstrates that ramp metering delayed the onset of congestion for the segment.

Ramp metering also improved the mainline throughput of the segment. Table B.39 illustrates the freeway volumes near the Montlake Boulevard on-ramp. Freeway volumes increased by 13% to 15% during the most congested period of the morning commute (7:00 to 9:00 a.m.).

Table B.40 displays travel time statistics for a typical commute through the area affected by ramp meters, the 14.8-mile commute from Seattle to Redmond. Mobility and reliability measures were calculated based on average, 95th percentile, and free-flow (trip time based on 60 mph) travel times. TTI compares the average travel time during the peak period to

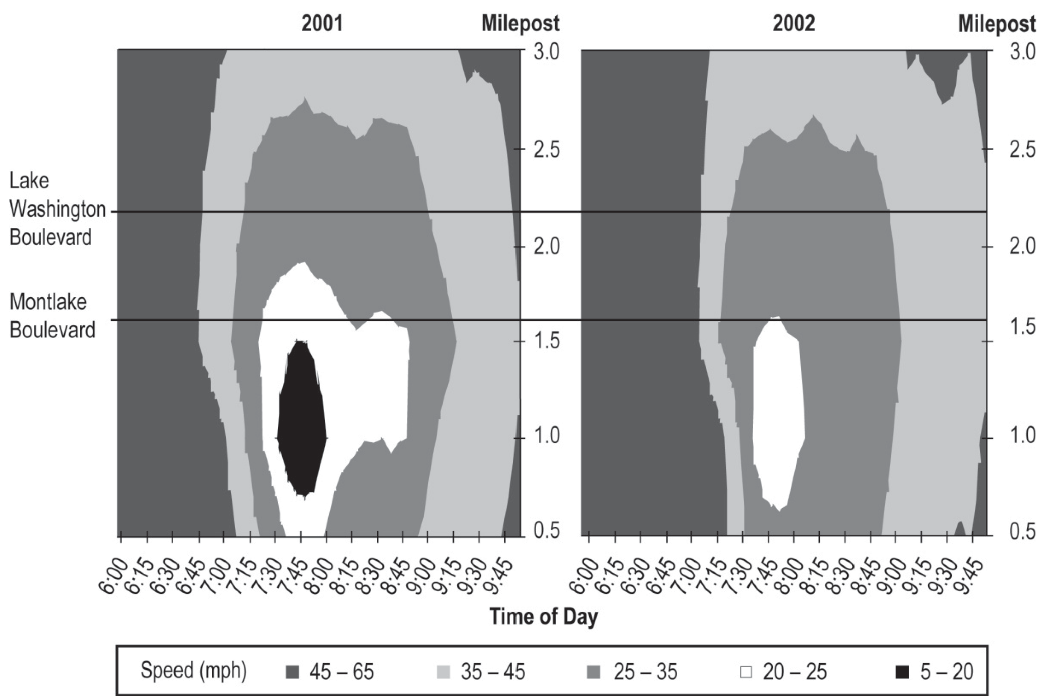

Figure B.41. Time–space speed contours.

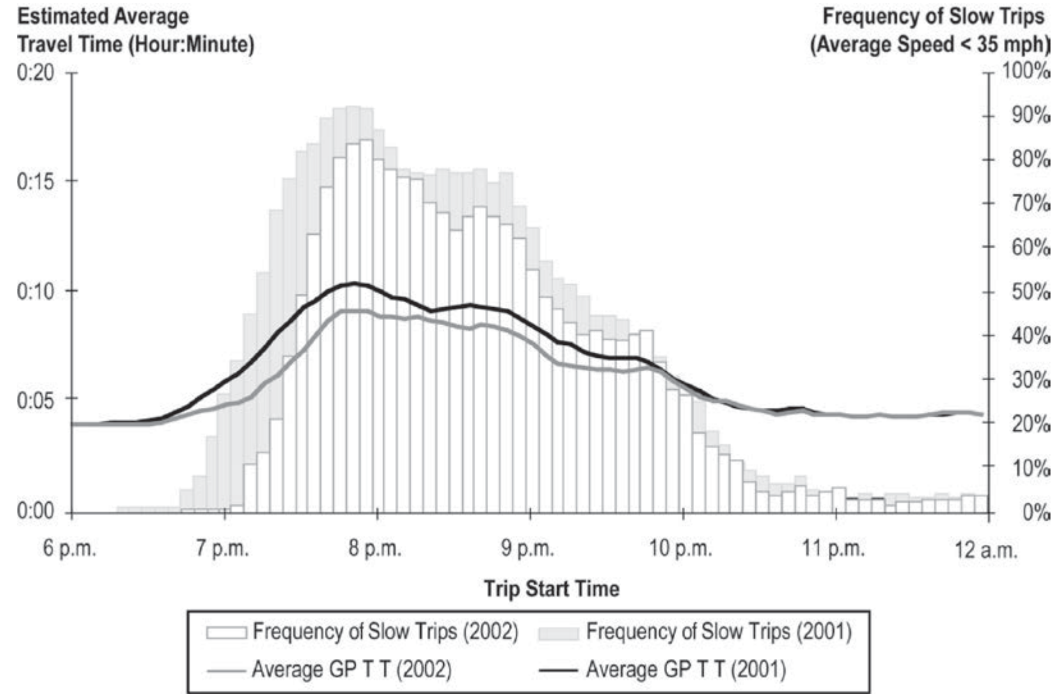

Figure B.42. Reductions in frequency of congestion and average travel time.

the free-flow travel time. The Buffer Index and Planning Index both measure the reliability of a trip based on the amount of extra time a traveler should budget to ensure an on-time arrival 95% of the time. These indices only showed small mobility and reliability improvements after the addition of ramp metering (Table B.41). The travel time improvements produced by the metered ramps may have been dampened by the rest of the trip, since the portion of the Seattle-to-Redmond route that is east of Lake Washington usually operates at near free-flow speeds. The travel time improvements were more pronounced when focused specifically on the segment most affected by the metering. Table B.42 displays the mobility and reliability indices for the 4-mile segment near the ramp. TTI for the shorter segment dropped

Table B.39. SR 520 Eastbound Throughput at Montlake Boulevard (vehicles/hour)

Time Period	January to June 2001	January to June 2002	Change (%)
6:00 to 7:00 a.m.	2,261	2,042	–10
7:00 to 8:00 a.m.	2,329	2,639	13
8:00 to 9:00 a.m.	2,128	2,454	15
9:00 to 10:00 a.m.	2,209	2,424	10

Table B.40. Travel Time Statistics for A.M. Commute from Seattle to Redmond

	A.M. Peak Period (6:00 to 9:00 a.m.) Travel Time (min)		
	Average	95th Percentile	Free Flow
2001 (before metering)	19.1	23.3	14.8
2002 (after metering)	18.6	22.2	14.8

Table B.41. Mobility and Reliability Measures for A.M. Commute from Seattle to Redmond

	A.M. Peak Period (6:00 to 9:00 a.m.)		
	Travel Time Index	Buffer Index	Planning Index
2001 (before metering)	1.29	22%	1.57
2002 (after metering)	1.25	20%	1.50

Table B.42. Mobility and Reliability Measures for 4-Mile Segment near the Ramps

	A.M. Peak Period (6:00 to 9:00 a.m.)		
	Travel Time Index	Buffer Index	Planning Index
2001 (before metering)	1.87	32%	2.46
2002 (after metering)	1.66	31%	2.17

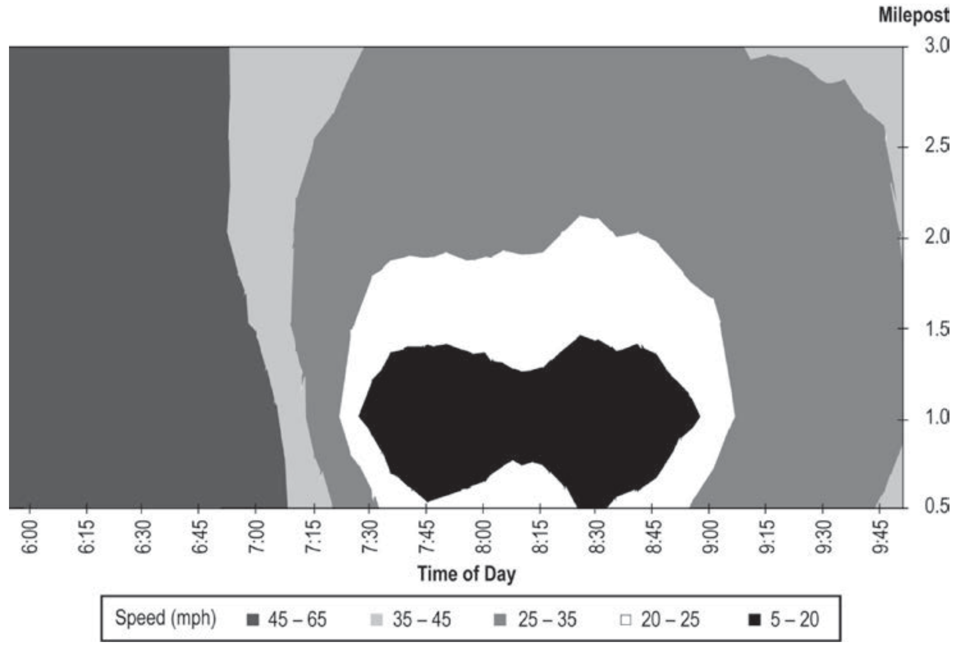

Figure B.43. Time–space speed contours in 2008 on SR 520 segment affected by ramp metering.

from 1.87 to 1.66; that is, in 2001 travel times were over 87% longer than travel times at free-flow speeds, but in 2002, they were only 66% longer.

Current State

In the 7 years since the ramp metering was initiated, traffic conditions on SR 520 have steadily declined. Figure B.43 shows the average speeds in the segment affected by ramp metering using data from January 1 to June 30, 2008. Peak period speeds are now slower than speeds seen in 2001 before metering. Speeds remain below 35 mph from 7:15 to 10:00 a.m. and drop below 20 mph for almost 1.5 hours (versus 20 minutes in 2001). In addition, throughput volumes are lower in 2008 than those seen immediately after starting ramp metering (2,589 vehicles/hour from 7:00 to 8:00 a.m.; 2,308 vehicles/hour from 8:00 to 9:00 a.m.), although they are not as low as the premetering levels.

WSDOT is in the beginning stages of a new project to replace the SR 520 Evergreen Point Floating Bridge. A continuous HOV lane and rebuilt on- and off-ramps are planned to improve mobility and reliability on the roadway.

APPENDIX C

Computation of Influence Variables, Seattle Analysis: Mechanisms for Determining When an Incident Affects Travel Time and Travel Time Reliability

As a bystander, it is fairly easy to watch traffic flow around the location of an incident and identify the delay associated with that incident as the queue that forms at that location. As long as that queue remains in place, even if it moves up- or downstream as a result of shock waves and other physical phenomena, all the delay can be associated with the observed incident. Even if that section of roadway might normally have a queue for a portion of the time the incident queue exists, all delay can be consider incident delay, which can then be compared in severity with the delay normally present for that roadway section. The difference in those conditions can be considered to have been caused by the incident.

When examine at a broader corridor level, however, the queues that form as a result of incidents can create different side effects that change the travel time experienced by motorists in the corridor. In some cases, the incident queue reduces downstream traffic volumes, allowing traffic to flow more smoothly. In other cases, the release of a queue that has formed behind a major accident can create a traffic volume wave when that accident scene is removed, and that wave can create one or more secondary queues downstream of the accident location. This condition is illustrated in Figure C.1, which shows (in black) the downstream movement of congestion caused when a pulse of vehicles flows downstream after having been released from a major accident scene. These secondary queues also are incident caused even though they are located at points removed from the location of the actual incident.

Visually, these effects can be identified on a case-by-case basis, so long as sufficient data are present. Mathematically, for very large data sets, and when only summary statistics (e.g., corridor travel time, vehicle miles traveled, or vehicle hours traveled) are available, this task becomes much more difficult. Part of the mathematical problem is that incident-caused delay can last considerably longer than the incident itself and can extend to geographic regions far removed from the incident location itself. In Figure C.1, for example, the actual incident lasted from 5:30 to 7:00 a.m. and occurred at a location just east of where traffic detection starts in the corridor, essentially to the left and above the black congestion blob in the figure. Figure C.1 does not show what happened during the incident; rather it shows the lingering effects of a severe incident after it has been cleared. An additional difficulty is that the geographic and temporal extent of the incident-caused delay is a function of the background traffic conditions within which the incident occurs. Compounding this difficulty is how travel times, which occur over extended times and spaces, differ from incidents, which occur in narrow temporal and geographic spaces.

The problem of associating an incident with a trip travel time is best explained with an example. Assume that the corridor being studied is 10 miles long (extending from Milepost 0 to Milepost 10), and the free-flow speed is 60 mph. Under free-flow conditions a car traverses the corridor in 10 minutes. An accident occurs at Milepost 6 at 8:00 a.m. and lasts 3 minutes, until 8:03 a.m. A car traveling the length of the corridor starting at Milepost 0 at 8:00 will be affected by this incident, even though the incident has been cleared before the car's arrival at the scene, because the car starting its trip at 8:00 a.m. must travel through the queue formed by the accident. But importantly, a car starting on that same trip at 7:55 (5 minutes before the accident takes place) also will be affected by the incident, because even at free-flow speeds, that car is only at Milepost 5 at 8:00 a.m. when the accident occurs. However, if that same accident occurs at Milepost 1, instead of Milepost 6 (both inside the study corridor) the 7:55 trip will not be affected, but the 8 a.m. trip will be.

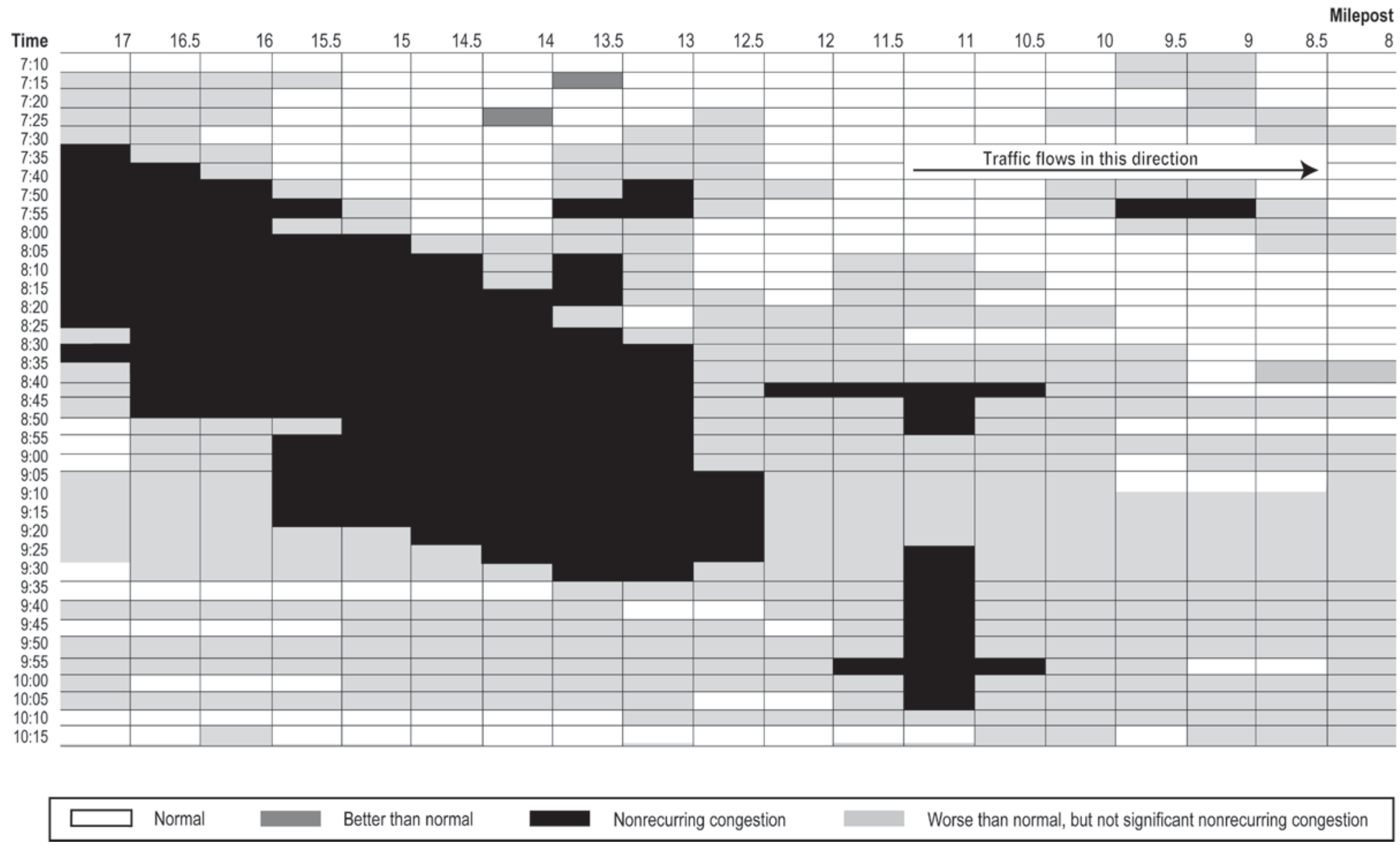

Figure C.1. Extra congestion caused by release of traffic delayed behind a major accident scene on westbound I-90.

The other difficulty with associating incidents and specific trips is understanding the duration of the congestion that forms as a result of that incident. In the above example, the queue formed (or disruption caused) by the 8:00 a.m. accident may last anywhere from zero additional minutes to several hours. If the 8:00 a.m. accident occurs in the middle of the a.m. commute period, the queue associated with that accident may last a full hour before traffic volumes reduce enough to allow the queue to dissipate. But if traffic volumes are light that morning, the queue may dissipate immediately. Thus a trip starting at 8:30 a.m. on this same corridor may or may not be influenced by the 8:00 a.m. accident, depending on the background traffic conditions occurring on the corridor and the nature of the accident itself.

Thus, without a detailed and complex data set and analysis algorithm for identifying time- and day-specific speeds, along with that same level of detail for when and where incidents occur within a corridor, it is impossible to directly associate any given trip with a given incident. This level of detail was not available to the study team for this analysis.

Consequently, no simple algorithm was identified that could identify which travel time (or vehicle miles traveled or vehicle hours traveled) measures for a given corridor were directly influenced by a given incident. As a substitute, this project developed three methods for defining the extent to which delay or trip travel time is influenced by any given incident. Each method has strengths and weaknesses. Taken together they are reasonably explanatory for how incidents affect travel time and travel time reliability. The three measures selected are defined as follows:

- **Active influence** assumes that any trip that starts into the corridor during a time period that contains an active incident is affected by that incident. Since travel time data were available on a 5-minute basis for L03, this method of association worked as follows: if an incident occurred from 8:04 to 8:08 a.m., trips with start times of 8:00 and 8:05 a.m. were associated with this incident. No other trips were considered to be influenced by this incident.

  This measure is the most restrictive of the methods used to associate incidents with travel times. All trips assumed to be influenced by an incident in this method are known to be influenced by incident-caused queues (if any form), but the method will miss some of the earliest trips influenced by the incident, and it will miss later trips that are influenced by the residual queue left after the incident has been cleared.
- **Time extended influence** assumes all incidents happen in the center of the study segment; this method extends the influence period earlier in time equal to the time it takes to drive half the corridor at free-flow speed. In addition, it assumes that influence extends an additional 20 minutes after any given incident ends. Using the 8:04 to 8:08 a.m. accident from the active influence example above, this method assumes that the incident's influence extends from trips starting at 7:59 a.m. to those ending at 8:28; that is, the 7:55 a.m. trip is the first affected, and the 8:25 a.m. trip is the last affected. This is an extension of three 5-minute time periods after the last period in which the incident was actually active. This technique makes the 20-minute extension (which is the origin of the 5+20 name in the data spreadsheet) appear to be a 5+15 time-period extension.

  Although the time extended methodology will miss a few incident-influenced trips when incidents occur at the far-upstream portion of the study corridor segment, it will capture the majority of the trips that are influenced by the formation of the incident-caused queue. It also will capture a significant portion of trips that are affected by residual queues. If those queues are nonexistent or short lived, it will overestimate the influence of a given incident. However, since the intent of this analysis is to capture the effect of incidents on trip reliability, overestimating the number of fast trips that have incident influence is less important than making sure that all very slow trips are associated with their causes. Thus this bias is assumed to be acceptable.
- **Queuing extended influence** assumes that once an incident occurs, any travel time increase on the corridor is at least partly associated with the (potential) queue that forms as a result of that incident. This method assumes that any increase in travel time that occurs while an incident is active is associated with that incident.

  The queue extended influence approach selects the fastest corridor travel time experienced before and during the incident. All subsequent travel times are assumed to be influenced by that incident until corridor travel times return to that fastest time. Once a measured travel time faster than the reference travel time is observed after the time extension has ended, the influence of that disruption has ended.

  The time extended influence definition is used to define the time periods from which the reference (fastest) travel time is selected. Note that the queue extension approach was originally tested using the 5+20–minute version of the time extension approach. It was then recomputed with new variables, including a more simple time extension definition of a one-time period before the disruption and a one-time period after the disruption has been cleared. These queue extension variables use the term 5+5 in their variable definition to reflect the 5 minutes before and the 5 minutes after the recorded incident time.

  In off-peak (low-volume and/or low-capacity) conditions, the queue extension approach is an excellent measure of incident effects. If the incident occurs at the beginning of peak period conditions, the queue extension approach is likely to associate all of the peak period congestion with the incident. Although this may overstate the extent of any given incident's congestion-causing influence, it is difficult to separate out the lasting influence of the incident on bottleneck formation, even when detailed statistics are available. Queuing extended influence is thus assumed to be a reasonable liberal measure of the effects of incidents on the travel times experienced by motorists.

None of these measures is perfect. Taken together, however, they are descriptive of the degree to which congestion and delay are related to incident occurrences.

By tracking all travel times influenced by a disruption, it is possible to identify the wide range of impacts a single disruption causes. The extra delay a trip experiences as a result of any given disruption changes depending on the time (relative to the formation of the queue) that a given trip arrives at the queue caused by the disruption. That queue grows from nothing to its largest extent, and then shrinks back to nothing. If the trip being monitored arrives at the beginning or end of the queue formation, the added delay experienced is modest. If it arrives at the height of the queue, its delay is the maximum experienced.

The methodologies described above associate each 5-minute average travel time with an incident or nonincident condition. The result is that some of these measured travel times experience the shoulders of the incident queues, and some experience the maximum queue. The result is an ability to monitor the entire spectrum of delays associated with each incident. It is therefore possible to explore the different travel times associated with any given incident, and if desired, select the maximum travel time associated with that incident. The trip with the largest travel time is assumed to be the trip made most unreliable as a result of that particular incident.

In general, the findings presented in the body of this report concentrate on using the queue extended (5+5) measure of influence. The Washington State Transportation Center project team at the University of Washington considers the queue extended measure as the best measure of incident influence; it also is the measure of maximum influence.

APPENDIX D

Seattle Analysis: Variable Definitions

This appendix describes the variables that are present in the data sets developed as part of the analysis of congestion causes performed by the University of Washington's Washington State Transportation Center (TRAC-UW). This work was performed as part of the SHRP 2 L03 project.

As noted in the main report, raw data were obtained from a variety of sources. Time, date, and location information (state route and mile post) were used to combine the various data items. Data were stored in a flat file record format, where each record in a file represents all data present for a specific five-minute interval in the year 2006 for a given direction for a given study segment. Consequently, each file contains 105,120 records of data. Because a separate file is used for each direction for each study corridor, there are 42 of these summary files produced for the SHRP 2 L03 project.

The primary data storage and analysis system was Microsoft Excel. (This effort is compatible with the 2007 version of Microsoft Office or any version thereafter, because the number of records present in each file exceeds the allowable limit for earlier versions of Excel.) For a wide variety of analyses, these records also were read into various statistical packages (SPSS, SAS, and R), which allowed efficient computation of statistical tests.

While a more capable database management system would be far more useful in the long term, the use of Excel allowed far easier development, testing, and analysis of derived statistics. Many of the statistics present in the analysis database are dependent on one or more data items from one or more prior time periods on that roadway segment. In Excel it was relatively easy to create these variables, test the variables, and visually examine how the variables reacted to changing traffic conditions (e.g., high/low volume and high/low speeds). It also was possible to easily find and examine how new test variables changed over time, given multiple different secondary inputs. It also is easy to identify specific anomalies (e.g., time periods with large amounts of congestion, but no traffic disruptions noted by a newly computed test variable, and track the performance of that computation over time). This process allowed the research team to identify specific computational techniques that did not work consistently. It also produced a better analysis database.

Note that the actual Excel computational formulas are not all included in these final datasets. Including all of the computations causes Excel to exceed the number of computations allowed in a single file. This causes unstable behavior within Excel. Consequently, once a computational variable was determined to work as intended, the data resulting from that latest series of computations was converted from an active Excel formula (i.e., recomputed each time variables were recomputed within Excel) to a constant. This was normally accomplished by simply saving the dataset as a CSV file and reimporting those values into a new Excel file. In other cases, especially cases where very complex, logical processes were necessary to compute new row values, a separate computational spreadsheet was used to produce one or more new columns of data. These were then cut-and-pasted into the primary analysis spreadsheets.

The following variables can be found in the final data sets developed and used in the L03 project by TRAC-UW (see Table D.1). In some datasets, specific variables were not computed. When this occurs, the term empty is included in the variable name column, indicating that this variable does not exist for the spreadsheet being examined.

Queue Extended Influence

Mathematically, the queue extended influence method assumes that any increase in travel time that occurs while an incident is active is associated with that incident. That is, if travel times increase over the travel time experienced at any time during an incident, that longer travel time is caused (at least in part) by the incident, even if other events are occurring in the corridor. An incident is defined as being active in two ways: 1) the incident is actually recorded as taking place within that specific five-minute period; and 2) a trip that entered

Table D.1. Data Items Used in the Seattle Congestion-by-Source Analysis

Column	Variable Name	Definition
A	link_name	Roadway and Direction.
B	direction	East, West, North, or South.
C	Date	Date (M/D/Yr).
D	Time	0:00 to 23:55 in 5-minute increments.
E	Decimal Time	Time expressed as a decimal.
F	Hour	The hour of the day.
G	Day of Week	Numeric day with 1 = Sunday to 7 = Saturday.
H	Month	Numeric month with 1 = January to 12 = December.
I	Day	Numeric day from 1 to 31 of each month.
J	[route]_[segment]_TT[dir]	Travel Time [direction] on [route], [segment] section.
K	avg_occupancy	Average Occupancy from Operation Archive.
L	avg_vht	Average VHT from Operation Archive.
M	avg_volume	Do not use, not a good value.
N	Accident Severity	Severity of Accident (1 = PDO, 2 = injury, 3 = fatal).
O	Accident	Accident Variable, equal 1 when an accident occurred.
P	Accident Severity (Calc)	The total number of 5-minute time periods during which a queue, influenced by a given accident lasts. (Value exists only for the first 5-minute period during which the accident occurs.)
Q	Max_closure_length	Maximum duration closure of lane(s) from Operation Archive.
R	Closure Severity	The total number of 5-minute time periods during which a queue, influenced by a given lane closure lasts. (Value exists only for the first 5-minute period during which the closure occurs.)
S	Max_incident_length	Maximum duration of incident from Operation Archive.
T	Incident Severity	The total number of 5-minute time periods during which a queue, influenced by a given incident lasts. (Value exists only for the first 5-minute period during which the incident occurs.)
U	Accident Rubbernecking	Has a value of 1 whenever there is an accident on the other side of the road.
V	Incident Rubbernecking	Has a value of 1 whenever there is an incident on the other side of the road.
W	Delay Variable	Computed Vehicle delay (Actual Travel Time—Free Flow Travel Time) * Maximum Section Volume.
X	IF Variable	Variable describing event effects present during that 5-minute time period: 0. No cause of congested noted in available variables; 1. ONLY Acc Queue Extended is present; 2. ONLY Inc Queue Extended is present; 3. ONLY Precipitation hour is present (it has rained in the past hour); 4. BOTH Acc Queue Extended and Inc Queue Extended are present; 5. BOTH Acc Queue Extended and Precipitation hour are present; 6. BOTH Inc Queue Extended and Precipitation hour are present; and 7. All three variables are present. Note: This variable is based on the 5+15 queue extended methodology[a]
Y	Max_occupancy	Maximum Occupancy from Operation Archive.
Z	Max_speed	Maximum Speed from Operation Archive.
AA	Max_volume	Maximum Volume from Operation Archive.
AB	Min_speed	Minimum Speed from Operation Archive.
AC	Min_volume	Minimum Volume from Operation Archive.

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Table D.1. Data Items Used in the Seattle Congestion-by-Source Analysis (continued)

Column	Variable Name	Definition
AD	Sum_vht	Sum of the VHT from Operation Archive.
AE	Sum_vmt	Sum of the VMT from Operation Archive.
AF	Accident –5+20	Associated with Accident variable (Column O)—time periods back 5 minutes and ahead 15 minutes from an accident (the variable is slightly misnamed).
AG	Acc Queue Extended[a]	Associated with Accident variable (Column O)—time periods extended from accident time period according to queue extended method (see end note).
AH	Inc –5+20	Associated with Max_incident_length variable (Column Q).
AI	Inc Queue Extended	Associated with Max_incident_length variable (Column Q).
AJ	Closure –5+20	Associated with Max_closure_length variable (Column P).
AK	Closure Queue Extended	Associated with Max_closure_length variable (Column P).
AL	Acc + Closure –5+20	Associated with the combination of Accident and Max_closure_length variables (Column O and P).
AM	Acc + Closure Queue Extended	Associated with the combination of Accident and Max_closure_length variables (Column O and P).
AN	Acc + Inc –5+20	Associated with the combination of Accident and Max_incident_length variables (Column O and Q).
AO	Acc + Inc Queue Extended	Associated with the combination of Accident and Max_incident_length variables (Column O and Q).
AP	Acc + Inc + AccRub –5+20	Associated with the combination of Accident, Max_incident_length and Accident Rubbernecking variables (Column O, Q, and R).
AQ	Acc + Inc + AccRub Queue Extended[a]	Associated with the combination of Accident, Max_incident_length and Accident Rubbernecking variables (Column O, Q, and R).
AR	Acc. + Inc. + Rub –5+20	Associated with the combination of Accident, Max_incident_length, Accident Rubbernecking and Incident Rubbernecking variables (Column O, Q, R, and S).
AS	Acc. + Inc. + Rub Queue Extended	Associated with the combination of Accident, Max_incident_length, Accident Rubbernecking and Incident Rubbernecking variables (Column O, Q, R, and S).
AT	Space Mean Speed	Average Speed derived from Travel Time and Segment Length.
AU	Rounded Speed 5.0	Rounded Average Speed (Column AT) to the nearest 5.0 mph.
AV	Rounded Speed 2.5	Rounded Average Speed (Column AT) to the nearest 2.5 mph.
AW	Rounded Speed 2.0	Rounded Average Speed (Column AT) to the nearest 2.0 mph.
AX	Regime	The condition of the road segment (minimum speed observed and maximum volume observed) (1 = lots of capacity left, 2 = less than one lane of capacity, 3 = minimal capacity left, speed slowed slightly, 4 = congestion present, 5 = recovery underway).
AY	Holiday	Has a value of 1 on the following days: Jan 2, Feb 20, May 29, July 3, July 4, Sep 4, Nov 10, Nov 23, Nov 24, Dec 25, Dec 26.
AZ	Rain	1 if NOAA Weather Type of Rain(RA), Mist(BR), Drizzle(DZ), T-storm(TS), or Haze(HZ) for the most recent time period reported (0 otherwise).
BA	Heavy_Rain	2 if Rain as defined above with NOAA hourly precipitation > 0.125 inches (0 otherwise).
BB	Wind	3 if NOAA Wind speed greater than 19 mph (0 otherwise).
BC	Snow	4 if NOAA Weather Type of Snow(SN), Freezing(FZ), Sm Hail(GS), Hail(GR), Ice Pellet(PL) or Squall(SQ) for the most recent time period reported (0 otherwise).
BD	Fog	5 if NOAA Weather Type of Fog(FG) OR NOAA Visibility < 0.25 (0 otherwise).
BE	Wind-Speed	Wind speed (in knots) directly from NOAA data for the most recent time period reported.
BF	Wind-Gusts	Wind speed for gusting winds (in knots) directly from NOAA data for the most recent time period reported.

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Table D.1. Data Items Used in the Seattle Congestion-by-Source Analysis (continued)

Column	Variable Name	Definition
BG	Precip_hour	Hourly precipitation (in inches and hundredths) from the most recent reported hourly NOAA data.
BH	Precip_2hours	Sum of last 2 hours of precipitation.
BI	Precip_4hours	Sum of last 4 hours of precipitation.
BJ	Precip_8hours	Sum of last 8 hours of precipitation.
BK	Hours_since_rain	Number of hours since last reported precipitation of any amount.
BL	R2-R4_5 min	Tells us that there was a change from Regime 2 to Regime 4 within the last 5 minutes.
BM	R2-R4_10 min	Tells us that there was a change from Regime 2 to Regime 4 within the last 10 minutes.
BN	R2-R4_15 min	Tells us that there was a change from Regime 2 to Regime 4 within the last 15 minutes.
BO	R3-R4_5 min	Tells us that there was a change from Regime 3 to Regime 4 within the last 5 minutes.
BP	R3-R4_10 min	Tells us that there was a change from Regime 3 to Regime 4 within the last 10 minutes.
BQ	R3-R4_15 min	Tells us that there was a change from Regime 3 to Regime 4 within the last 15 minutes.
BR	Number_of_2ndary_events_Accidents	Uses the Severity (duration) variable and then looks to see how many accidents and incidents occur within the duration (time the queue is present) of the accident in question.
BS	Numb_Sec_Rubnking_Accidents	Uses the Severity (duration) variable and then looks to see how many accident and incident rubbernecking events occur within the duration (time the queue is present) of the accident in question.
BT	Number_of_2ndary_events_Closures	Uses the Severity (duration) variable and then looks to see how many accidents and incidents occur within the duration (time the queue is present) of the closure in question.
BU	Numb_Sec_Rubnking_Closures	Uses the Severity (duration) variable and then looks to see how many accident and incident rubbernecking events occur within the duration (time the queue is present) of the closure in question.
BV	Number_of_2ndary_events_Incidents	Uses the Severity (duration) variable and then looks to see how many accidents and incidents occur within the duration (time the queue is present) of the incident in question.
BW	Numb_Sec_Rubnking_Incidents	Uses the Severity (duration) variable and then looks to see how many accident and incident rubbernecking events occur within the duration (time the queue is present) of the incident in question.
BX	5+5 Queue Extended Crash	The queue extended variable (1 = influence is present) using the 5-minute follow on period as the basis for computation crashes only.
BY	5+5 Queue Extended Incident	The queue extended variable (1 = influence is present) using the 5-minute follow on period as the basis for computation incidents only.
BZ	5+5 Queue Extended Closure	The queue extended variable (1 = influence is present) using the 5-minute follow on period as the basis for computation closures only.
CA	5+5 Queue Extended Rubbernecking	The queue extended variable (1 = influence is present) using the 5-minute follow on period as the basis for computation either rubbernecking variable is active.
CB	5+5 Queue Extended Incident or Accident	The queue extended variable (1 = influence is present) using the 5-minute follow on period as the basis for computation if an incident or accident has occurred.
CC	Mainline IF Variable 5+5	Sets a value 1-8 (see column X definition for what each value means) indicating what influences are present to cause congestion. Examines only WITHIN segment variables—and does NOT include construction effects. This version of the "IF" variable is based on the 5+5 Queue Extended computations and the variables in columns BX through CB.

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Table D.1. Data Items Used in the Seattle Congestion-by-Source Analysis (continued)

Column	Variable Name	Definition
CD	Construction variable	1. Construction. 2. All lanes closed. 3. 520 weekend closures. 4. Construction happens in two locations at one time in the same segment.
CE	IF 5+5 Construction Included	Variable describing event effects present during that 5-minute time period. Uses the 5+5 Queue Extended variables as input AND includes notifications of construction traffic management activities. 0. No cause of congested noted in available variables; 1. ONLY Inc Queue Extended is present; 2. ONLY Acc Queue Extended is present; 3. ONLY Precipitation hour is present (it has rained in the past hour); 4. BOTH Acc Queue Extended and Inc Queue Extended are present; 5. BOTH Inc Queue Extended and Precipitation hour are present; 6. BOTH Acc Queue Extended and Precipitation hour are present; 7. All three variables are present; 8. Ramp congestion, but no cause for ramp congestion is known; 9. Construction activity going on; 10. Construction activity plus ramp congestion; 11. Construction activity plus an incident queue extended; 12. Construction activity plus an accident queue extended; 13. Construction activity plus rain; 14. Construction activity plus an accident and incident queues extended; 15. Construction activity plus an incident queue extended and rain; 16. Construction activity plus an accident queue extended and rain; and 17. Construction activity plus an accident and incident queues extended and rain.
CF	Delays caused by ramps/downstream queues (1st location)	A nonzero value is present when loop detectors at a ramp have lane occupancy greater than 35%. (This is used as a measure that queues have formed on the ramp and are likely to cause congestion on the connecting roadway.) Uses the same variable definitions as in column CE. The name in the header row changes from dataset to dataset to describe the specific ramp and/or downstream segment. There are three columns allocated for these external to the road segment variables CF, CG, and CH.
CG	Delays caused by ramps/downstream queues (2nd location)	See CF definition.
CH	Delays caused by ramps/downstream queues (3rd location)	See CF definition.
CI	IF—Single Cause (5+5)	Combines the causes defined in the variables in CE, CF, CG, and CH. The effects are cumulative. So that a “1” on the mainline and a “2” on a connecting ramp means this variable would become a “4” (both accident and incident effects).
CJ	Rounded	Converts the Time variable to half hour increments (0 for 0:00 through 0:25, 0.5 for 0:30 through 0:55, 1 for 1:00 through 1:25) to allow easy aggregation of results on a half hour basis.
CK	Crash versus Volume	Is a three category variable. The variable is set to 0 when no known disruption is affecting roadway performance. It is set to the value “1” when a crash is affecting roadway performance. It is set to a “2” when some other (noncrash) is influencing roadway performance. (The value is “1” when a crash influences performance, even if other factors also influence that performance.)
CL	Incident versus Volume	Is similar to the Crash versus Volume variable, except that the value “1” is used to indicate that an incident reported by WSDOT’s incident response team is influencing roadway performance. A “2” indicates some disruption other than something reported by WITS is influencing roadway performance.
CM	Queue Duration Incidents	The number of 5-minute time periods during which the roadway is influenced (traffic is slower than the fastest travel time observed during an incident) for a defined incident. One value exists for each incident for which there is a valid travel time. That value is placed in the row that corresponds to the first occurrence of the incident.

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Table D.1. Data Items Used in the Seattle Congestion-by-Source Analysis (continued)

Column	Variable Name	Definition
CN	Queue Duration Crashes	The number of 5-minute time periods during which the roadway is influenced (traffic is slower than the fastest travel time observed during a crash) for a defined crash. One value exists for each crash for which there is a valid travel time. That value is placed in the row that corresponds to the first occurrence of the crash.
CO	Queue Duration Closures	The number of 5-minute time periods during which the roadway is influenced (traffic is slower than the fastest travel time observed during an incident) for a defined incident involving a lane closure. One value exists for each closure for which there is a valid travel time. That value is placed in the row that corresponds to the first occurrence of the closure.
CP	Queue Duration Incidents and Crashes	The number of 5-minute time periods during which the roadway is influenced (traffic is slower than the fastest travel time observed during an incident) for any defined incident or crash. One value exists for each incident or crash for which there is a valid travel time. That value is placed in the row that corresponds to the first occurrence of each incident or crash.
CQ	Rubbernecking Influence Duration 5+5	The number of 5-minute time periods during which the roadway is influenced (traffic is slower than the fastest travel time observed during a rubbernecking event) for a defined rubbernecking event. One value exists for each rubbernecking event for which there is a valid travel time. That value is placed in the row that corresponds to the first incidence of the rubbernecking event.
CR	When Congestion Ends a.m.[b]	This variable places a “1” in the first row which defines a noncongested condition during the A.M. peak period. “Not Congested” is defined as being four consecutive rows where travel times are faster than 1.05 times travel at the speed limit (i.e., faster than 57.15 mph.) For the a.m. time period, this event cannot take place prior to 7:00 a.m. It can occur any time AFTER 7:00 a.m. The row selected is the FIRST row in which the four consecutive rule is observed. Congestion due to a late occurring incident may cause congestion after this occurrence. This congestion is ignored by this variable.
CS	Incident Effected a.m.—4:00 a.m. Start	If ANY incident occurs after 4:00 a.m. on a given day, this variable is set to “1” at the time the first incident occurs. It remains set to “1” for the rest of the day.
CT	Crash Effected a.m.—4:00 a.m. Start	If ANY crash occurs after 4:00 a.m. on a given day, this variable is set to “1” at the time the first crash occurs. It remains set to “1” for the rest of the day.
CU	Selection a.m.	The section variable is set to “1” if the day is a Tuesday, Wednesday, or Thursday, AND it is not a designated holiday AND the “When Congestion Ends a.m.” variable is set to “1”.
CV	Effected Inc versus Crash versus Nothing a.m.	This categorical variable is set to “0” unless: a crash has occurred (value = 1) or an incident has occurred (value = 2). When both an incident and crash have occurred, the value is set to “1”.
CW	When Congestion Ends p.m.	This variable places a “1” in the first row which defines a “noncongested” condition during the P.M. peak period. “Not Congested” is defined as being four consecutive rows where travel times are faster than 1.05 times the travel time at the speed limit (i.e., faster than 57.15 mph.) For the P.M. time period, this event cannot take place prior to 4:00 p.m. It can occur any time AFTER 4:00 p.m. The row selected is the FIRST row in which the four consecutive rule is observed. Congestion due to a late occurring incident may cause congestion after this occurrence. This congestion is ignored by this variable.
CX	Incident Effected p.m.—4:00 p.m. Start	If ANY incident occurs after 3:00 p.m. on a given day, this variable is set to “1” at the time the first incident occurs. It remains set to “1” for the rest of the day.
CY	Crash Effected p.m.—4:00 p.m. Start	If ANY crash occurs after 3:00 p.m. on a given day, this variable is set to “1” at the time the first crash occurs. It remains set to “1” for the rest of the day.
CZ	Selection p.m.	The section variable is set to “1” if the day is a Tuesday, Wednesday, or Thursday, AND it is not a designated holiday AND the “When Congestion Ends p.m.” variable is set to “1”.
DA	Effected Inc versus Crash versus Nothing p.m.	This categorical variable is set to “0” unless: a crash has occurred (value = 1) or an incident has occurred (value = 2). When both an incident and crash have occurred, the value is set to “1”.

[a] Queue Extended Influence assumes that once an incident has occurred, any travel time increase along the corridor is associated with the (potential) queue that forms as a result of that incident, and thus all travel in the corridor is affected by that incident until the queue has fully dissipated.

[b] A discussion concerning the “When Congestion Ends” variable—Considerable testing went into the selection of the time period at which congestion was described as ending.

the test section in the time period immediately prior to that incident occurring or immediately after that incident stopped occurring.

These time periods are indicated as 5+5 in the variable names in the study spreadsheet. They account for the fact that a trip starting at 7:00 but requiring 10 minutes to traverse a section, may be adversely affected by an incident which occurs during the 7:05 time period. Conversely, the queue caused an incident occurring and cleared in the 7:05 time period, might not grow to the point where the loop sensors used in this analysis notice that queue until the 7:10 time period. These additional 10 minutes were referenced internally as the time extended incident period. The queue extended incident period uses these measures of extended duration within which to find the base travel time against which continued queuing is measured. (See two paragraphs below for the definition of how this process works.)

The initial test of the time extension variable was 5 minutes prior and 15 minutes after an incident, PLUS the (minimum) 5-minute period containing the incident. This initial set of analyses was called 5+20. The variables created and used in these initial computations are still present in the data set and are stored in columns AF through AS. The 15-minute extension was determined to be too lenient. That is, it was unclear that the delays beginning 15 minutes after the incidents had been cleared were related to the incident. This led to the adoption of the 5+5 rule. The 5+20 variables were not used in any of the published analyses, but have been left in the analysis data set to allow future analysis should they be of interest.

The queue extended computation begins by determining the fastest corridor travel time experienced in the 5-minute period before the disruption occurs through 5 minutes after that disruption is reported to have ended. All subsequent travel periods are assumed to be influenced by that disruption until corridor travel times return to (are equal to or faster than) the fastest time observed during the "5+5" time period (5 minutes prior to the incident through 5 minutes after the disruption). By changing the definition of disruption and reapplying these basic rules, the influence of any combination of disruptions can be indicated. This approach does mean that for the analytical purposes of this project—the influence of any disruption lasts at least 15 minutes.

In off-peak conditions (where low volume exists—or in other words there is considerable unused roadway capacity), this approach is an excellent measure of incident effects. If the incident occurs at the beginning of peak period conditions, the approach is likely to associate all of the peak-period congestion with the incident. This is assumed to be acceptable based on the concept that the incident condition combined with the growing peak-period traffic volume will cause congestion to form earlier than would otherwise have occurred on that particular peak period, and the increased congestion will cause travel times to remain elevated later into the tail end of the peak period. While this is a liberal measure of the congestion caused by a given incident, and may overstate the extent of any given incident's congestion causing influence, it does replicate the "lasting influence" that an incident can have on roadway performance. An example of how the Queue Extended Influence Area works and why it is used is as follows.

On Thursday, February 23, 2006 at 2:30 p.m., on SR 520 westbound headed into the city of Seattle, traffic is flowing slightly better than normal (travel time = 494 seconds versus an annual mean travel time of 549 seconds for the 2:30 p.m. time period.) A lane closing incident, which takes 17 minutes to clear, occurs. During that incident, travel times through the corridor slow to 738 seconds. After the incident is cleared, congestion begins to clear out, but does not return to its pre-incident condition, before increasing traffic volumes associated with the start of the p.m. peak period cause travel times to again degrade. (That is, the queue formed by the incident has yet to fully clear and thus P.M.-peak-period congestion occurs earlier than normal, because the incident caused queue has reduced the roadway's capacity, making it unable to serve the volumes associated with the beginning of the P.M. peak shoulder period.) Travel times in the P.M. peak are thus slower than normal throughout the peak period, and do not return to preincident conditions until well after the P.M. peak period ends. (Maximum travel time on this day in the traditional P.M. peak is 1,787 seconds at 6:05 p.m.) Before the P.M. peak ends, a two-car, injury collision occurs (at 6:50 p.m.) within the roadway analysis segment. Travel speeds (already bad) degrade considerably after the accident (reaching 2,960 seconds, or an average speed of 8.5 mph for the 7 mph road segment), and don't return to preaccident conditions (still much slower than the original preincident conditions) until 8:05 p.m. However, once again, before the queue can fully dissipate, a second injury accident occurs at 8:35 p.m. Travel times again climb, despite the lower traffic volumes experienced at 8:30 in the evening, peaking this time at just over 1,900 seconds. Only after this accident and its resulting queue is cleared, do travel times finally return to a point faster than that found at 2:35 p.m., just prior to the first incident. This occurs at 10:10 p.m. Further contributing to congestion on this day are two other factors, 1) a higher travel demand than normal caused by a University of Washington's men's basketball game (the team was ranked 17th in the country at the time) which occurred that evening at the University basketball arena located at the western end of this analysis corridor (the game was a 10,000 person sell out event, and started at 7:30 p.m.); and 2) the fact that it rained off and on that afternoon and evening. (The 6:50 p.m. accident notes rain and wet pavement conditions, while the 8:35 p.m. accident notes dry pavement and overcast conditions.)

The reality of this day is that a variety of events helped cause the congestion experienced by travelers. However, the instigating event appears to have been the original lane-blocking incident. Without that event and the extended queues it creates, it is possible that neither rear-end accident would have occurred. (Although it is impossible to directly tie the rear-end collisions with a specific queue length.) On the other-hand, delays would have been considerably smaller without the two accidents and without the added travel demand caused by the basketball game. Similarly, the rain may very well also have contributed to the cause of congestion on the corridor as well as the occurrence of both of the accidents, as well as to the time it took for the roadway to recover from all three events. Consequently, we believe that the queue extended influence variable works as defined—it indicates that a given event is likely to have influenced—but not totally caused—the level of congestion experienced on the roadway.

The queue extended approach successfully tracks the existence of that queue to that instigating event. What remains is to determine how to describe the relative importance of that event versus the contributions of the other causal factors.

When Congestion Ends

The project team was concerned that variations in speed both over time and over the length of the study section might give false indications that free flow travel had returned to the study section, when what was really being measured was a temporary improvement in conditions caused by random fluctuations in traffic density. Consequently, it was decided that the determination of when congestion abated must include both the facts that speeds were free flow throughout the study section and that they remained so for long enough to ensure that the observation was not just a temporary change in conditions. After testing the variation of travel times at the end of the peak periods on multiple study sections, it was determined that 20 minutes of consecutive travel times below a set value ensured that flow remained in a fluid state. However, while 20 minutes of fluid flow are required, the "end point" for congestion is indicated as the first of those 20-minute periods. The selection of the speed at which congestion ended was set based on the available data. The analysis data set had three measures of "speed"—maximum speed in the segment, minimum speed in the segment, and travel time through the segment. Travel time was selected as the variable of choice for two reasons: 1) on longer test sections, it more effectively replicates the travel conditions experienced by motorists—when compared to maximum and minimum speed values selected from different locations within that segment, but within a single time slice; and 2) travel time effectively accounts for the importance of different speed measurements along the length of the segment, while minimum and maximum values can shift from one location to another from one time slice to another. Thus use of travel time moderates the importance of any one slow speed measurement, while the 20-minute requirement ensures that fluctuations in the observed travel times do not artificially cause the procedures to end congestion too quickly.

Tests were made using 5%, 10%, and 20% increases in travel times, corresponding to average segment speeds of 57, 54, and 48 mph. Each of these travel time increases can be achieved in a variety of ways, ranging from modest slowing throughout the section, to a more substantial slowing at any one speed measurement location with a section. Tests of these speeds indicated that on most corridors, the slower travel times were frequently met during the middle of the traditional peak periods. As a result, they were assumed to be too lenient a travel time measure. (That is, one location of moderate congestion—speeds below 40 mph—could occur while travel times remained fast enough to meet the 10% increase criteria.) Thus, it was necessary to select the more stringent criteria of only a 5% increase in travel times. When combined with the 20-minute requirement, this gave results which matched local experts' general impressions in all cases except 11 corridors during the A.M. peak period. These corridors all experienced some level of routine vehicle slowing during the middle of the day, and thus frequently never reached "the end of congestion" as defined by the 5% and 20-minute rules until after the P.M. peak had ended. As a result, for those 11 routes, for the A.M. peak, either the 10 or 20% rules were applied in order to ensure that congestion "ends" prior to noon on days when no-incident occurs. The lowest percentage increase which ended mean travel time prior to noon for days in which no incident occurred was selected for each of these 11 corridors. (That is, if the mean "congestion end" time point for nondisrupted days occurred prior to noon based on a 10% increase in travel time that value was used. The 20% value was only used if the 10% value forced congestion to end after noon.)

APPENDIX E

Summary of Weather Data Tests: Seattle Analysis

Weather varies by time and locations for which there are no actual data sources. Consequently, the weather data used for these analyses were obtained from publicly available records collected from the National Oceanic and Atmospheric Administration (NOAA) weather station at SeaTac International Airport. Data are reported once per hour by NOAA, unless weather is severe or changes dramatically, in which case it may be reported more frequently. The analytic database created for this study tracked the major statistics reported by NOAA, including the following:

- Visibility
  - Up to 10 miles;
- Temperature
  - Dry bulb;
- Wind speed
  - Average speed, and
  - Gust speed (highest gust speed that hour);
- Precipitation
  - Inches; and
- Weather type
  - Rain,
  - Mist,
  - Thunderstorm,
  - Drizzle,
  - Haze,
  - Snow,
  - Freezing,
  - Small hail,
  - Hail,
  - Ice pellets,
  - Squall, and
  - Fog.

The research team acknowledges that these data are limited because they are provided only once per hour and they do not cover microclimates over a large region. For example, it may be raining at SeaTac, south of Seattle, but not on the SR 520 bridge. However, the team chose the SeaTac station as the most reliable and consistent of regional weather data sources.

In addition, the data were too detailed for the basic analyses intended for this study. Consequently, the team performed extensive analyses to determine the types of summary weather statistics that would effectively indicate whether weather conditions contributed to congestion. The outcome of those tests, which are summarized below, was to define *bad weather* most commonly as any period in which any measurable precipitation had fallen at some time in the previous hour. Importantly, the use of this indicator discounted several weather effects, including wind, fog, snow, and rainfall intensity. The analysis of wind effects is given later in this appendix. However, because the original weather data are retained within the Washington State Transportation Center's L03 data sets, they were available for both the analyses described below and for future analyses, should other researchers desire to use them.

Attempts to Compute a Summary Weather Variable

The complexity of the various weather conditions led the project team to test various approaches to dealing with weather in the cause of congestion analyses. One of the initial efforts involved attempting to convert the various weather statistics available into a single, categorical weather variable that could be used as an indicator of bad weather.

Considerations When Developing a Composite Weather Variable

One of the initial concerns with using the SeaTac weather records was that those records only provide a good measure of weather conditions at the airport. The weather experienced simultaneously in other areas of the Seattle metropolitan region can be different. For example, a storm moving northward that affects SeaTac at 5:00 p.m. will have occurred in the southernmost roadway sections before 5:00 p.m. and in the northern part of the city some time after 5:00 p.m. These temporal and spatial shifts are particularly important when trying to examine the effects of heavy, but short-duration, rainfall events. Conventional regional weather station data simply do not provide the temporal and geographic resolution required to observe these effects, but because regional weather station data are routinely available around the country, using these data means the SHRP 2 analysis can be more readily replicated in other parts of the country.

Another aspect of the differences between site-specific weather events and those recorded at a weather station is that the example storm above may have dropped exactly 0.25 inches of rain at the airport, but it may have deposited only 0.1 inch south of the airport, and 0.5 inches in areas north of the airport. Therefore, although the rain data are a reasonable estimate of weather conditions, they cannot be used as a precise, highly accurate measure of the actual weather occurring on any given segment of roadway during a specific 5-minute interval.

In addition to the basic time and geographic problems noted above, the snow and rainfall intensity variables presented a second problem in that many of the effects of precipitation occur after the precipitation has fallen. This is especially true for snowfall, as the effects of the snow falling are not nearly as significant as the effects from snow accumulations on the ground, depending on the amount remaining on the roadway. Snow flurries have little effect on driving, but 4 inches of snow on the ground 2 hours after the snow has stopped falling has a major impact on roadway performance.

Another issue associated with snowfall in the Seattle area was caused by a combination of how rarely snow falls in the region and how travel times are computed. When snow falls (and sticks), Seattleites tend to avoid driving whenever possible. The region does not routinely use salt to deice roadways. As a result, most cities do not clear snow as effectively as those in regions of the country that routinely experience snowfall, and snow is frequently turned into sheet ice on the roadways by cars that do travel, making the area's hilly terrain dangerous. The result is that a large percentage of travelers simply avoid going out. Therefore, after snow falls, volume and lane occupancy are frequently low on the freeways, despite the relatively slow speed of those cars that are present. However, the loop detector system only sees low volumes and low occupancy values and may thus overestimate the speeds at which the vehicles are moving. Finally, for this study, the number of days on which snow fell or heavy thundershowers occurred during the analysis year was small.

Tests of a Single Composite Weather Variable

The initial attempt to compute this variable tried to create a four-category variable with the following definitions:

- 1 = good;
- 2 = mediocre (minor weather conditions exist);
- 3 = bad (moderate weather conditions exist); and
- 4 = very bad.

The detailed definitions of these conditions were as follows:

- 1 = everything else (dry, clear);
- 2 = at least one of these weather elements is present: rain, mist, thunderstorm, drizzle, or haze. This definition was meant to represent a situation in which the pavement is wet or may still be wet, meaning that spray may be an issue;
- 3 = at least one of these weather elements is present: wind speed >20 mph or precipitation >0.125 in.; and
- 4 = at least one of these weather elements is present: snow, freezing, small hail, hail, ice pellets, squall, visibility <0.25 mile, or minor weather conditions with a temperature <33°F.

For the initial test, the weather value was reset to one at midnight of each day, and remained at that value until weather conditions occurred that set the weather statistic to a higher value (i.e., weather became worse than previously indicated). The weather value would then be set to that higher number, and would remain there until weather conditions worsened, or the end of the day was reached.

One major limitation with this approach was that it did not allow conditions to improve as the day progressed. For example, it is well known that wet roadways dry off as the day progresses if additional rain does not fall. Consequently, a second iteration in the testing of a categorical weather variable attempted to gradually reset the weather variable. A literature search identified various drying factors for roadways, but they required far more detailed geometric and temperature information than that which was available to the project team. A variety of time-based drying adjustments were tested. The final version of this categorical variable based the value of that variable on the worst condition measured during the previous 2 hours. The project team also tested 1-, 4-, 6-, and 8-hour periods.

In the end, this approach was abandoned. The primary issue was that a 4 rating frequently did not produce travel conditions that were worse than those produced by a 3 rating because a snowy hour as defined by NOAA did not affect travel time as much as a windy or heavy rain hour did. Similarly, a windy or heavy rain hour was often not worse than a rainy hour. For example, the mean travel time for p.m. peak travel times on the SR 520 Seattle westbound analysis segment when the past 2 hours was set to 4 (severe = snowy) was 612 seconds, but the mean travel time for the same time period was 676 seconds when the variable was set to 3. Similarly, on the SR 520 Redmond westbound test segment, the mean travel time for Condition 4 (snowy) was 350 seconds, but the mean travel time for Condition 3 was 408 seconds, and Condition 2 was 416 seconds.

Further tests showed that determining which variables had the most impact on roadway performance and should be used to determine the various degrees of bad weather in a categorical weather variable was a task beyond the ability of the research team, within the greater context of analyzing the causes of congestion. It was consequently decided to concentrate on the major types of weather conditions independently.

The main weather variables carried forward to the next set of analyses were

- **Rain** = 1 if NOAA weather type of rain (RA), mist (BR), drizzle (DZ), thunderstorm (TS), or haze (HZ) was reported for the most recent time period (0 otherwise);
- **Heavy_Rain** = 2 if rain as defined above with NOAA hourly precipitation was >0.125 inches (0 otherwise);
- **Wind** = 3 if NOAA wind speed greater than 19 mph (0 otherwise);
- **Snow** = 4 if NOAA weather type of snow (SN), freezing (FZ), small hail (GS), hail (GR), ice pellet (PL) or squall (SQ) was reported for the most recent time period (0 otherwise);
- **Fog** = 5 if NOAA weather type of fog (FG) or NOAA visibility <0.25 mile (0 otherwise);
- **Wind Speed** = Wind speed (in knots) directly from NOAA data for the most recent time period reported;
- **Wind Gusts** = Wind speed for gusting winds (in knots) directly from NOAA data for the most recent time period reported;
- **Precip_hour** = Hourly precipitation (in inches and hundredths) from the most recent reported hourly NOAA data;
- **Precip_2hours** = Sum of past 2 hours of precipitation;
- **Precip_4hours** = Sum of past 4 hours of precipitation;
- **Precip_8hours** = Sum of past 8 hours of precipitation; and
- **Hours_since_rain** = Number of hours since last reported precipitation of any amount.

All of these variables are available in the final analysis data sets.

Analysis of Different Rain Variables

Because of the frequent rain in Seattle, the team hypothesized that rain was likely a significant contributing source of congestion in the region. Consequently, considerable effort was placed on examining the effects of rain and determining which measure of rain worked most effectively.

One of the most illustrative analyses examined the effects of rain on the formation of congestion as measured using different definitions of rain. The analysis computed the probability that a given test section of roadway was operating in each regime for each time slice of a day. (See Appendices C and D and the Chapter 5 section "Computed Variables Used for Tracking the Influence of Disruptions on Travel Times and Delays" for a definition of the regime variable.) These probabilities were computed for days when rain occurred within the past hour and were then compared with probabilities on days when the same roadway was dry at that same time of day. The mean, median, 80th percentile, and 95th percentile travel times and speeds for each corridor and time period also could be computed for wet and dry conditions. The following analysis uses the SR 520 roadway sections as the illustrative example of these findings; summary results are included.

As Tables E.1 and E.2 show, the percentage of travel time that occurs in Regimes 1 and 2 is not affected by rain. In corridors and times when the population would be traveling in ideal conditions (60 mph and Regime 1 or 2), rain does not appear to affect the speed of travel at all. For example, on SR 520 Seattle westbound between 5:00 and 6:00 a.m., with no rain the percentage of travel time in combined Regimes 1 and 2 is almost 100% regardless of the weather condition. This effect is seen across all four corridors of SR 520 for both Regimes 1 and 2.

However, when conditions approach roadway capacity, the effects of rain become apparent. Rain causes a significant decrease in the percentage of time a roadway spends in Regime 3 (near-capacity volumes with free-flowing speeds) and a commensurate increase in Regime 4 (congested) travel. For example, if no rain falls between 7:00 and 8:00 a.m., then 21% of the time westbound SR 520 operates in Regime 3; however, if it has rained in the past hour, only 5% of the time. Similarly, if there is no bad weather between 4:00 and 5:00 p.m. on Seattle SR 520 eastbound, the probability of traveling in Regime 3 is 30.49%, and Regime 4 is 62.73%. Once it begins raining, the probability of traveling in Regime 4 jumps to 80.53%, and Regime 3 moves to around 13.94%.

Because speeds vary slightly in Regime 3 (they can range between 42 and 58 mph), a drop in average speed is seen within this regime. Figure E.1, shows how mean speed is at its slowest in this regime when rain has fallen recently. Figure E.1 also shows how this change in speed is partly dependent on how long it has been since it rained. The variable used in this figure is an inclusive variable that is set to *rain* if any rain has fallen in the past 1, 2, 4, or 8 hours. As the time period during which rain has fallen is increased (i.e., moves further away from when it might have last rained), it can be seen that the speeds gradually increase and return to what they were before the rain began. This same time effect, which is illustrated in

Table E.1. Percentage of Travel Time Occurring in Specific Regimes Given Different Weather Conditions (A.M. Peak)

	SR 520 Seattle WB 5:00 to 6:00 a.m.				SR 520 Seattle WB 7:00 to 8:00 a.m.		
	No Bad Weather	Precip 1 Hour	Precip 2 Hour		No Bad Weather	Precip 1 Hour	Precip 2 Hour
N	2,656.000	409.00	528.000	*N*	2,724.00	339.00	477.00
Regime 1	63.10%	61.12%	62.69%	Regime 1	0.29%	0.00%	0.00%
Regime 2	36.71%	37.90%	36.55%	Regime 2	1.06%	0.00%	0.00%
Regime 3	0.00%	0.00%	0.00%	Regime 3	20.96%	4.72%	7.34%
Regime 4	0.15%	0.98%	0.76%	Regime 4	73.64%	93.81%	91.61%
Regime 5	0.04%	0.00%	0.00%	Regime 5	4.04%	1.47%	1.05%
	SR 520 Seattle EB 5:00 to 6:00 a.m.				SR 520 Seattle EB 7:00 to 8:00 a.m.		
	No Bad Weather	Precip 1 Hour	Precip 2 Hour		No Bad Weather	Precip 1 Hour	Precip 2 Hour
N	2,536.00	409.00	528.000	*N*	2,556.00	318.00	459.00
Regime 1	77.21%	82.40%	81.82%	Regime 1	0.04%	0.00%	0.00%
Regime 2	22.67%	17.60%	18.18%	Regime 2	0.82%	0.00%	0.00%
Regime 3	0.00%	0.00%	0.00%	Regime 3	8.49%	1.89%	3.49%
Regime 4	0.08%	0.00%	0.00%	Regime 4	89.63%	98.11%	96.51%
Regime 5	0.04%	0.00%	0.00%	Regime 5	1.02%	0.00%	0.00%
	SR 520 Redmond WB 5:00 to 6:00 a.m.				SR 520 Redmond WB 7:00 to 8:00 a.m.		
	No Bad Weather	Precip 1 Hour	Precip 2 Hour		No Bad Weather	Precip 1 Hour	Precip 2 Hour
N	2,643.00	409.00	538.000	*N*	2,711.00	339.00	487.00
Regime 1	68.63%	67.48%	68.96%	Regime 1	0.44%	0.00%	0.00%
Regime 2	31.37%	32.52%	31.04%	Regime 2	2.73%	0.59%	0.62%
Regime 3	0.00%	0.00%	0.00%	Regime 3	92.48%	72.27%	78.64%
Regime 4	0.00%	0.00%	0.00%	Regime 4	4.02%	27.14%	20.74%
Regime 5	0.00%	0.00%	0.00%	Regime 5	0.33%	0.00%	0.00%
	SR 520 Redmond EB 5:00 to 6:00 a.m.				SR 520 Redmond EB 7:00 to 8:00 a.m.		
	No Bad Weather	Precip 1 Hour	Precip 2 Hour		No Bad Weather	Precip 1 Hour	Precip 2 Hour
N	2,643.00	409.00	528.000	*N*	2,643.00	409.00	528.00
Regime 1	51.46%	52.32%	52.27%	Regime 1	60.00%	60.00%	60.00%
Regime 2	48.35%	46.45%	46.78%	Regime 2	60.00%	60.00%	60.00%
Regime 3	0.00%	0.00%	0.00%	Regime 3	0.00%	0.00%	0.00%
Regime 4	0.00%	0.00%	0.00%	Regime 4	0.00%	0.00%	0.00%
Regime 5	0.19%	1.22%	0.95%	Regime 5	53.00%	49.00%	49.00%

Note: *N* = number of 5-minute periods included in each 1-hour period for each analysis; WB = westbound; EB = eastbound. Precip 1 Hour and Precip 2 Hour = sum of past 1 and 2 hours of precipitation, respectively.

Table E.2. Percentage of Travel Time Occurring in Specific Regimes Given Different Weather Conditions (P.M. Peak)

	SR 520 Seattle WB 4:00 to 5:00 p.m.				**SR 520 Seattle WB 7:00 to 8:00 p.m.**		
	No Bad Weather	**Precip 1 Hour**	**Precip 2 Hour**		**No Bad Weather**	**Precip 1 Hour**	**Precip 2 Hour**
N	2,675.000	429.00	514.000	*N*	2,636.00	393.00	521.00
Regime 1	0.00%	0.00%	0.00%	Regime 1	0.95%	0.00%	1.54%
Regime 2	0.11%	0.00%	0.00%	Regime 2	21.85%	13.49%	13.82%
Regime 3	1.79%	0.70%	0.58%	Regime 3	7.66%	1.53%	3.65%
Regime 4	97.72%	99.07%	99.22%	Regime 4	58.19%	73.79%	66.22%
Regime 5	0.37%	0.23%	0.19%	Regime 5	11.34%	11.20%	14.78%
	SR 520 Seattle EB 4:00 to 5:00 p.m.				**SR 520 Seattle EB 7:00 to 8:00 p.m.**		
	No Bad Weather	**Precip 1 Hour**	**Precip 2 Hour**		**No Bad Weather**	**Precip 1 Hour**	**Precip 2 Hour**
N	2,624.00	416.00	502.000	*N*	2,599.00	381.00	517.00
Regime 1	0.00%	0.00%	0.00%	Regime 1	1.23%	4.20%	4.45%
Regime 2	0.50%	0.00%	0.00%	Regime 2	76.49%	70.87%	69.63%
Regime 3	30.49%	13.94%	14.34%	Regime 3	1.19%	0.00%	0.19%
Regime 4	62.73%	80.53%	80.82%	Regime 4	9.08%	12.07%	0.00%
Regime 5	6.29%	5.53%	5.38%	Regime 5	12.00%	12.86%	0.58%
	SR 520 Redmond WB 4:00 to 5:00 p.m.				**SR 520 Redmond WB 7:00 to 8:00 p.m.**		
	No Bad Weather	**Precip 1 Hour**	**Precip 2 Hour**		**No Bad Weather**	**Precip 1 Hour**	**Precip 2 Hour**
N	2,690.00	429.00	525.000	*N*	2,645.00	393.00	537.00
Regime 1	0.19%	0.23%	0.19%	Regime 1	2.38%	3.31%	4.42%
Regime 2	61.12%	31.70%	35.81%	Regime 2	89.91%	84.48%	85.29%
Regime 3	6.88%	1.63%	2.10%	Regime 3	0.08%	0.00%	0.00%
Regime 4	31.60%	66.20%	61.71%	Regime 4	7.60%	11.45%	11.73%
Regime 5	0.22%	0.23%	0.19%	Regime 5	0.04%	0.76%	0.56%
	SR 520 Redmond EB 4:00 to 5:00 p.m.				**SR 520 Redmond EB 7:00 to 8:00 p.m.**		
	No Bad Weather	**Precip 1 Hour**	**Precip 2 Hour**		**No Bad Weather**	**Precip 1 Hour**	**Precip 2 Hour**
N	2,689.00	428.00	513.000	*N*	2,642.00	393.00	521.00
Regime 1	0.04%	0.00%	0.00%	Regime 1	1.51%	1.02%	0.19%
Regime 2	2.31%	1.40%	1.17%	Regime 2	78.73%	68.96%	73.13%
Regime 3	2.86%	1.64%	2.34%	Regime 3	0.00%	0.00%	0.00%
Regime 4	90.03%	90.65%	91.91%	Regime 4	14.72%	22.14%	18.81%
Regime 5	4.76%	6.31%	4.68%	Regime 5	5.03%	7.89%	7.87%

Note: *N* = number of 5-minute periods included in each 1-hour period for each analysis; WB = westbound; EB = eastbound. Precip 1 Hour and Precip 2 Hour = sum of past 1 and 2 hours of precipitation, respectively.

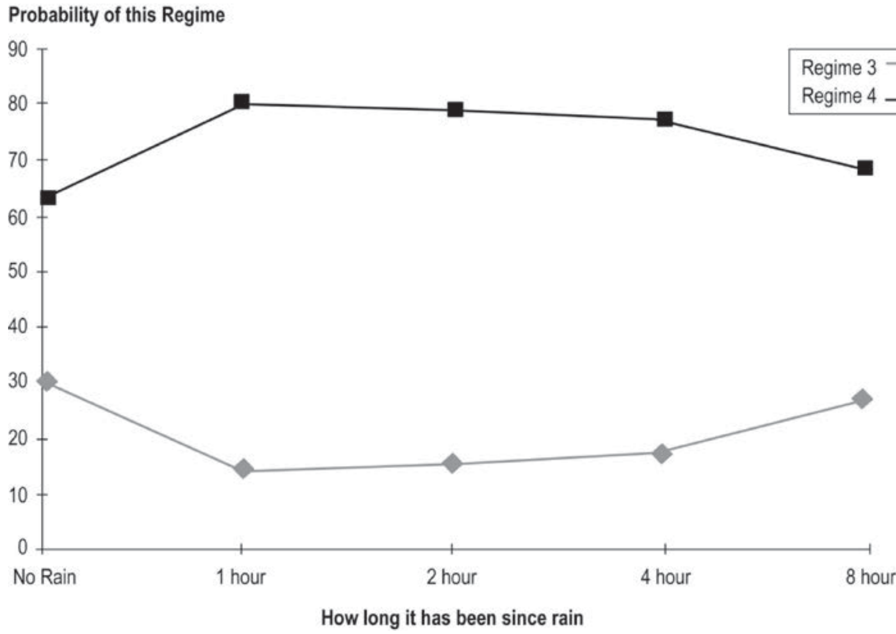

Figure E.1. Percentage of time spent in Regimes 3 and 4 (eastbound on SR 520, Seattle section).

Figure E.2, can be seen in the percentage shift from Regime 3 travel to Regime 4 travel.

Regime 4 sees a much sharper change in speed than Regime 3. In a normal Regime 4 condition, without rainfall, SR 520 Redmond eastbound between 4:00 and 5:00 p.m. has a mean speed of 38.82 mph. When precipitation has fallen in the past hour, however, the mean speed for Regime 4 drops to 35.60 mph.

One limitation with the above analyses is best explained with an example. Rain falls between 3:00 and 4:00 p.m. The time periods between 3:00 and 5:00 p.m. are assumed to be rain affected (within 1 hour of when measurable rain has fallen). Travel times occurring at 4:55 p.m. that day are rain affected, but travel times at 5:05 p.m. are considered dry trips. The limitation with this analysis is that the rain may have created a queue that affects the 5:05 dry trip. This possibility was

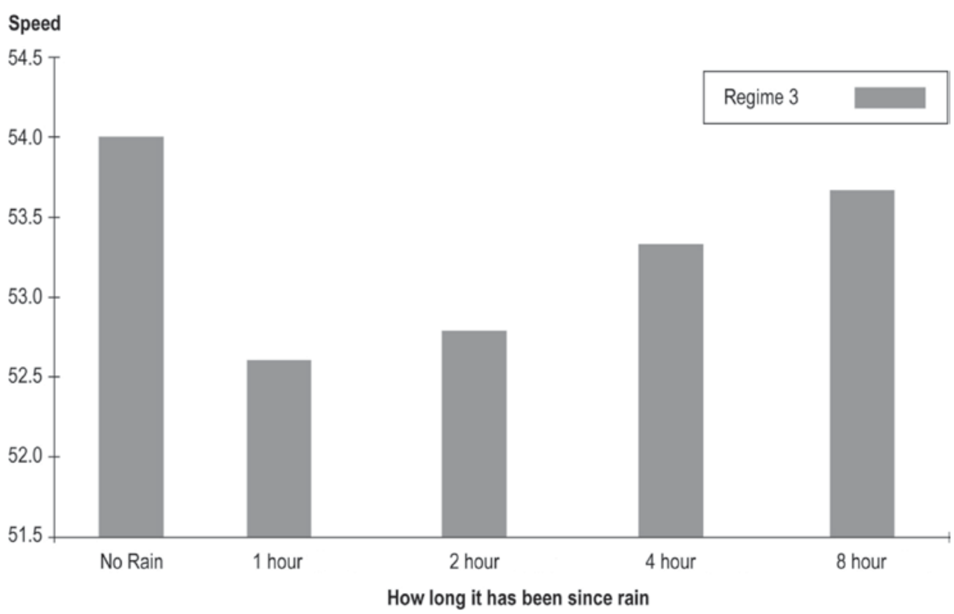

Figure E.2. Percentage of time spent in Regimes 3 and 4 (eastbound on SR 520, Seattle section).

ignored in the analysis results (discussed below), thus slightly underestimating the potential impacts of rain on travel time.

Analysis of Rain Effects on Accident Rates on SR 520

Comparing Accident Rates Under Rain and No-Rain Conditions

Although the above analysis shows that rain helps cause congestion under the correct volume conditions, the research team was also interested in whether rain increases the likelihood of crashes. A statistically rigorous analysis of this question was undertaken using the data for all four SR 520 test segments. The results of that analysis are as follows.

For the year 2006 there were 105,120 ($365 \times 24 \times 12$) consecutive 5-minute measurement intervals with a wide variety of recorded or deduced variables, including indicators for the presence of rain and the occurrence of accidents during each interval. Such data were available for four freeway segments of the Seattle–Redmond SR 520 corridor, designated here as Sea520WB, Sea520EB, Red520WB, and Red520EB.

For the following analysis the intervals were divided into those with rain (15,703) and those without rain (89,417). These counts were the same for all four segments, since the weather indicator came from a single location (SeaTac International Airport). Given the distance between SeaTac and the 520 corridor, the rain indicator may sometimes be in error (see discussion above concerning the team's decision to use NOAA weather observations from SeaTac); nevertheless, it was used to determine differences in accident occurrence rates during intervals with rain and intervals without rain. These measurement intervals were also classified by their accident indicator, which should be accurate for each of the four segments. The resulting cross-classifications are shown in Tables E.3 through E.6.

Since accidents are rare events, it is reasonable to treat their occurrence from time interval to time interval as independent events, with probability $p1$ when there is no rain and probability $p2$ when there is rain. The number X1 of accidents observed over the n1 = 89,417 no-rain intervals can be treated as having a binomial distribution with parameters n1 and $p1$. This distribution is well approximated by a Poisson distribution with mean $\lambda 1 = n1p1$. This distributional relation is expressed as X1 < Pois($\lambda 1 = n1p1$). Similarly, X2 < Pois($\lambda 2 = n2p2$), where X2 is the accident count over the n2 = 15,703 intervals with rain.

Estimates of $p1$ and $p2$ are easily obtained as $i = X_i/n_i$ for i =1, 2, respectively, with a resulting estimate of 1/2 for $p1/p2$. 100γ% confidence intervals for $p1/p2$ are obtained by the exact method (Clopper–Pearson):

$$xL = \left(1/qbeta\left[\left(1+gam\right)/2, X2+1, X1\right]-1\right) < n2/nl$$

where xL is the lower limit; and

$$xU = \left(1/qbeta\left[\left(1-gam\right)/2, X2+1, X1\right]-1\right) < n2/nl$$

where xU is the upper limit, gam = γ = 0.95, X1 = X1, X2 = X2, n1 = *n1,* n2 = *n2,* and qbeta denotes the beta distribution quantile function that is intrinsic to *R*.

Table E.3. Accident–Rain Cross-Classification for Sea520WB

	Rain		
Accident	**No**	**Yes**	**Total**
No	89,239	15,644	104,883
Yes	178	59	237
Total	89,417	15,703	105,120

Table E.4. Accident–Rain Cross-Classification for Sea520EB

	Rain		
Accident	**No**	**Yes**	**Total**
No	89,196	15,633	104,829
Yes	221	70	291
Total	89,417	15,703	105,120

Table E.5. Accident–Rain Cross-Classification for Red520WB

	Rain		
Accident	**No**	**Yes**	**Total**
No	89,358	15,686	105,044
Yes	59	17	76
Total	89,417	15,703	105,120

Table E.6. Accident–Rain Cross-Classification for Red520EB

	Rain		
Accident	**No**	**Yes**	**Total**
No	89,365	15,687	105,052
Yes	52	16	68
Total	89,417	15,703	105,120

Table E.7. Estimates and 95% Confidence Intervals for p1/p2

Segment	Estimate	Lower Bound	Upper Bound
Sea520WB	0.530	0.393	0.724
Sea520EB	0.554	0.422	0.736
Red520WB	0.609	0.350	1.115
Red520EB	0.571	0.321	1.071
520 Corridor	0.553	0.462	0.664

The resulting estimates and 95% confidence bounds for $p1/p2$ are shown in Table E.7 and graphically illustrated in Figure E.3. The estimates for $p1/p2$ are consistently around 0.53 to 0.61. The confidence intervals for the Sea520WB and Sea520EB segments do not contain the value 1, and the hypothesis $p1 = p2$ can be rejected in those situations at significance level $\alpha = 0.05$. For segments Red520WB and Red520EB these intervals do contain 1, and the same hypothesis cannot be rejected at that significance level. However, this weaker form of evidence in those two cases probably results from there being fewer accidents on those segments. The combined analysis rejects the hypothesis $p1 = p2$ quite strongly. Based on that analysis, it can be stated with 95% confidence that the true ratio $p1/p2$ is in the interval $[0.462, 0.664]$. This interval is the tightest of all intervals because of the combined number of involved accidents. This result indicates that the accident rate during rain is almost twice as high as during periods without rain. In both the table and figure, an aggregated analysis was performed for all four segments combined; analysis results for that case are labeled "520 Corridor."

Figures E.4 through E.7 show the derived travel times for each workday, averaged over each respective commute period, in relation to the highest accident severity recorded for that commute period. Accident severity = 0 means that there was no accident, 1 indicates a minor accident, and 2 indicates a major accident. The results are shown as box plots for morning and afternoon commute periods.

Some of the box plots in these figures suggest that accident severity may not affect the average travel time over the commute period very much; see, for example, the box plot for Sea520WB during the afternoon commute. To examine this issue the team performed the Anderson–Darling k-sample test, which tests whether k independent samples could arise from sampling the same population. Here the $k = 3$ populations concern average commute travel times when no accident occurs, when the most severe accident during that period has a severity level of either 1 or 2.

The Anderson–Darling k-sample test can be performed in R by installing the package adk (this needs to be done just once for each installation of R), then executing library (adk) for each new R session during which adk.test is needed, and then executing the command:

```
adk.test(x1, x2, x3)
```

where x1, x2, and x3 are the $k = 3$ samples to be compared.

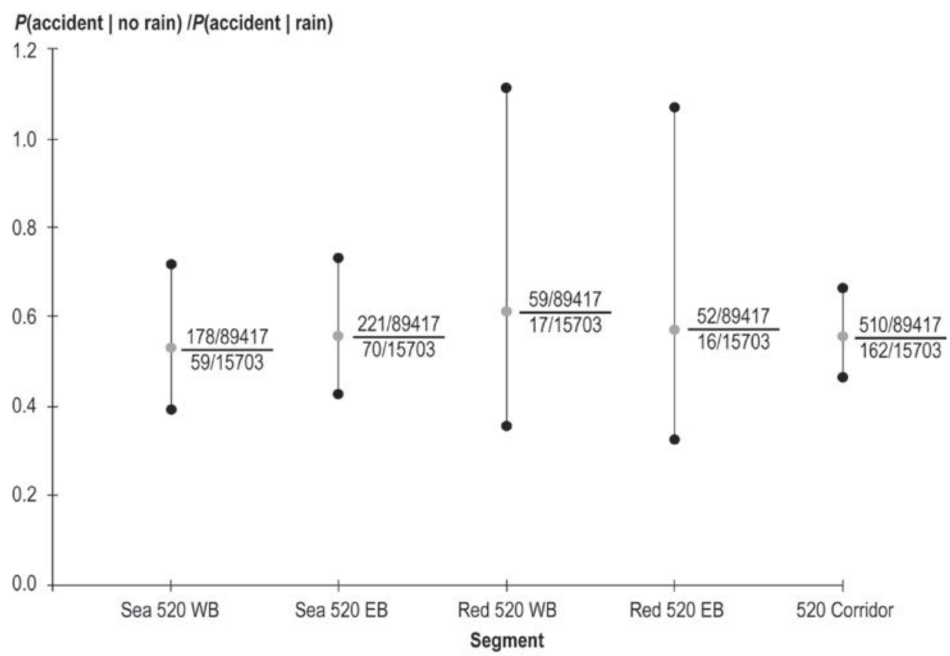

Figure E.3. Estimates and 95% confidence intervals for p1/p2*.*

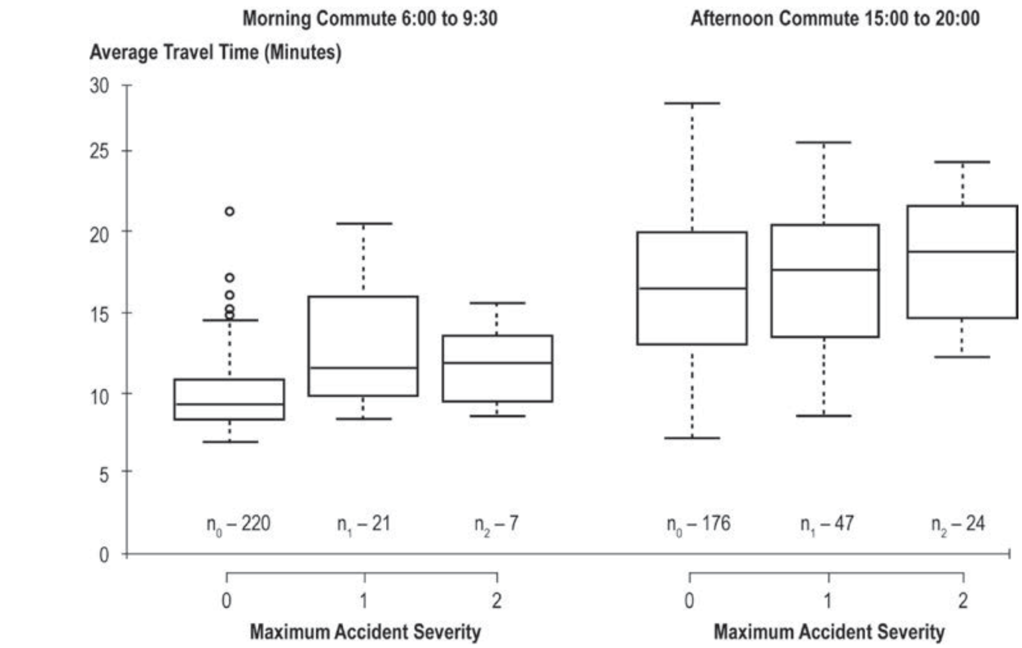

Figure E.4. Sea520WB travel times in relation to accident severity or no accident.

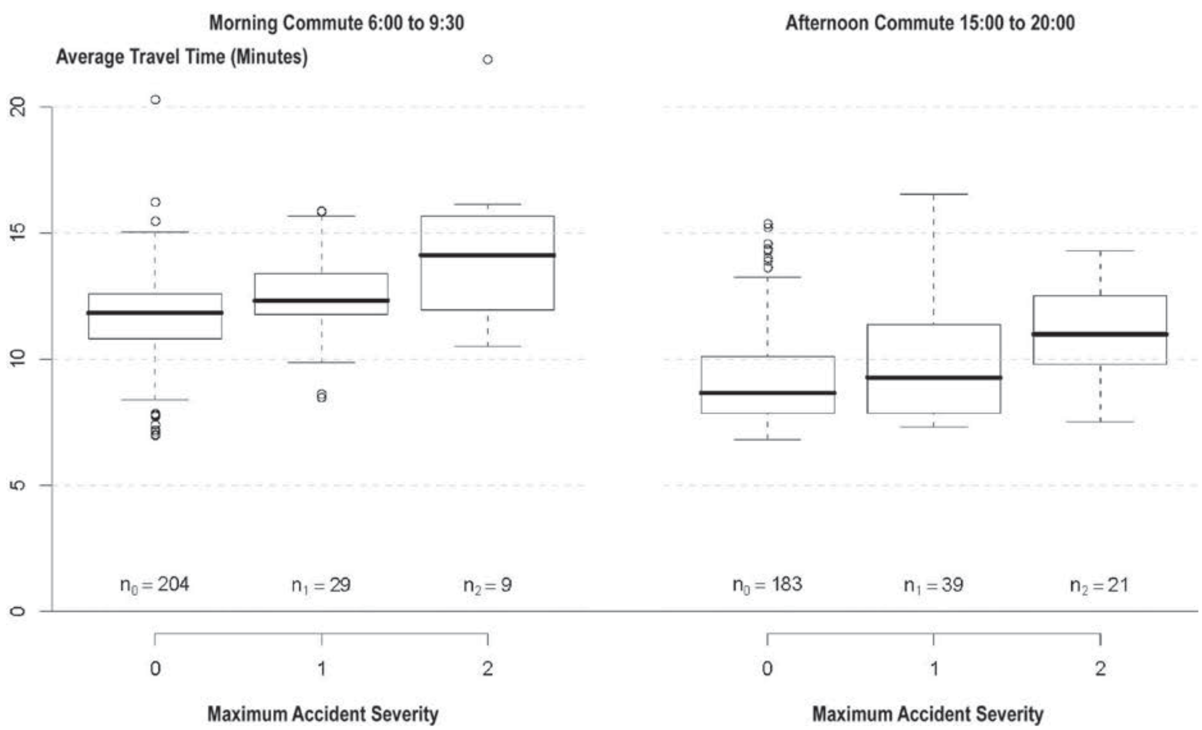

Figure E.5. Sea520EB travel times in relation to accident severity or no accident.

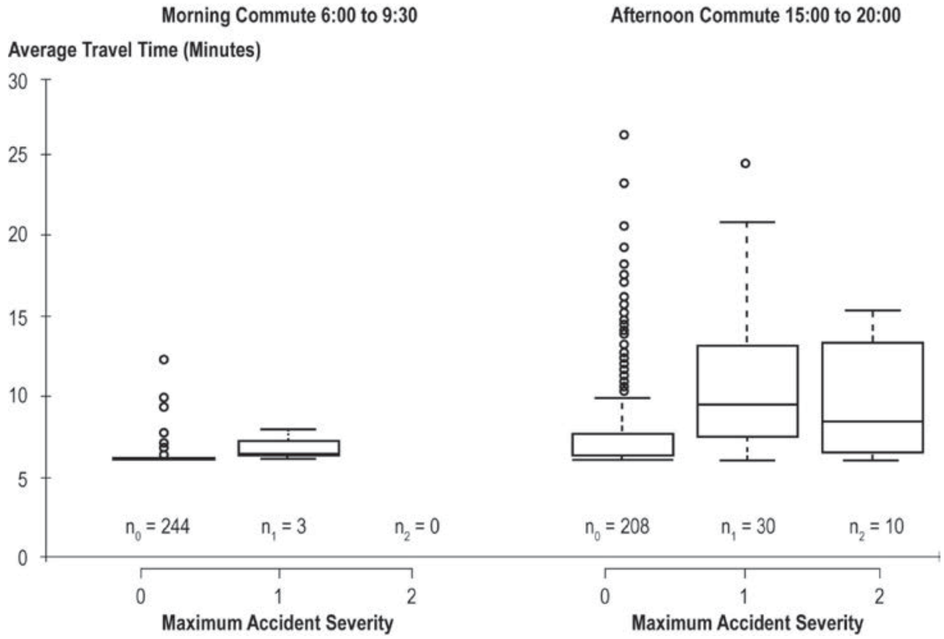

Figure E.6. Red520WB travel times in relation to accident severity or no accident.

The *p*-values for all eight comparisons (four segments, two commute periods each) are given in Table E.8. As suspected, there seems to be no significant difference in average travel time under the three accident scenarios during the afternoon commute for Sea520WB. There also seems to be no significant difference for the morning commute of Red520EB. However, that lack of significance is easily explained by the small number of accidents, three of Severity 1 and none of Severity 2.

Accidents After Significant Dry Periods

Another rain analysis explored the link between long dry periods and the accident rates during subsequent periods of rain. The idea was to determine where long periods of dry weather allow sufficient oil to soak into pavements, so that oil comes to the surface when it rains, making roadways unusually slick and increasing accident rates.

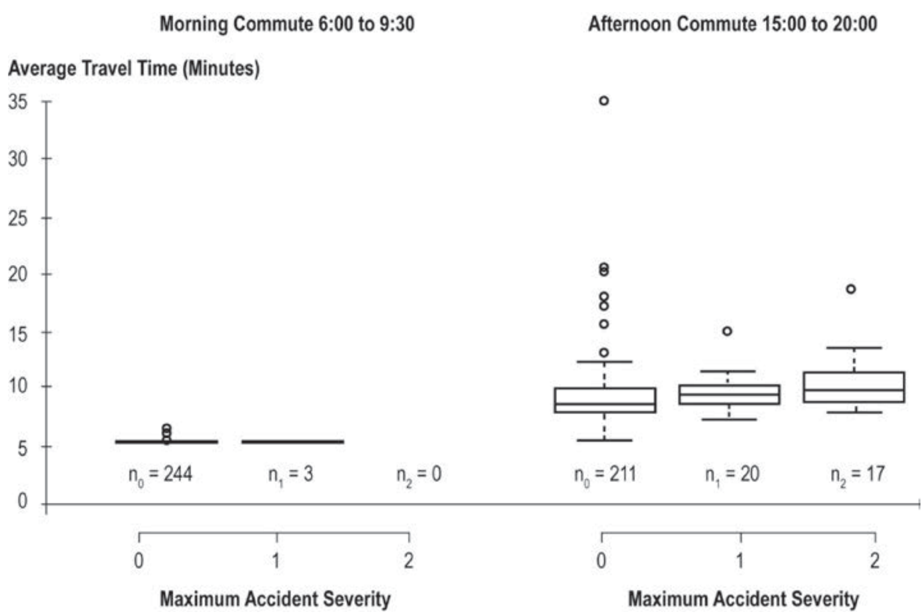

Figure E.7. Red520EB travel times in relation to accident severity or no accident.

Table E.8.* p*-Values for Anderson–Darling* k*-sample Test When Comparing Travel Times with No Accident with Accident Severity 1 and with Accident Severity 2 (1; 2, pp. 918–924)

	Commute	
	Morning	Afternoon
Segment	*p*-Value	
Sea520WB	4e-05	0.17753
Sea520EB	0.00053	0.00242
Red520WB	0.00959	0
Red520EB	0.56444	0.00555

The analysis examined whether accident rates are higher during the 6 hours after rainfall after it has been dry for 504 hours (3 weeks) or 336 hours (2 weeks).

Summary

There were five occurrences in 2006 when it was dry for >336 hours and then rained 0.01 inch or more and two occurrences in 2006 when it was dry for >504 hours and then rained 0.01 inch or more. They are as follows:

- Wednesday, August 9, 7:55–13:50: 639 hours rain free, then rain;
- Saturday, September 9, 1:50–7:45: 633 hours rain free, then rain;
- Tuesday, July 4, 4:55–10:50: 424 hours rain free, then rain;
- Tuesday and Wednesday, August 29–30, 18:15–00:40: 490 hours rain free, then rain; and
- Friday, October 6, 5:50–16:45: 349 hours rain free, then two independent rains.

Accident numbers were aggregated and nonparametric independent sample tests were run to compare accidents during these days and times with the numbers of accidents during these cases. A basic accident per hour number was developed to determine if the accident rate during these cases was higher than the yearly average. For example, all Wednesdays from 7:55 to 13:50 were compared with the August 9 case. This analysis was limited because it used 0 and 1, which excluded multiple accidents; thus, the findings were not relevant.

To deal with the multiaccident problem, a basic cross-tabs analysis was done to account for times with multiple accidents. This technique allowed a basic probability of an accident at the given times to be determined overall compared with the probability of an accident when it rained after an extended dry period. The results of the cross-tabs analysis suggested that accident rates were not significantly higher when it was dry and then rained compared with accident rates at similar times.

The probability of accidents during all days and all hours compared with the +336 hours of dry weather followed by rain cases was

- Probability of an accident anywhere: 0.082235; and
- Probability of an accident during the dry, then wet cases: 0.121429.

The probability of accidents during all days in the p.m. peak period (2:00 to 7:30 p.m.) only compared with the +336 hours of dry weather followed by rain cases was

- Probability of an accident anywhere: 0.1502; and
- Probability of an accident during the dry, then wet cases: 0.095238.

The probability of accidents during the weekday p.m. peak period compared with the +336 hours of dry weather followed by rain cases was

- Probability of an accident anywhere: 0.170639; and
- Probability of an accident during the dry, then wet cases: 0.095238.

The probability of accidents during all days and all hours compared with the +504 hours of dry weather followed by rain cases was

- Probability of an accident anywhere: 0.082235; and
- Probability of an accident during the dry, then wet cases: 0.090278.

Results and Recommended Further Analysis

The results above show that the probability of accidents during the 6 hours after rainfall subsequent to 336 hours or more of dry weather was slightly higher than the probability of accidents any day or time on major roadways in greater Seattle. However, the probability of accidents during these times was lower than the probability of accidents anywhere when looking only at p.m. peak times and p.m. peak weekdays. Without a clear result that states that accident rates are significantly higher during these times, the claim cannot be made that there is a higher likelihood of getting into accidents when it has been dry for a significant period of time and then rains.

Other analyses may include

- Adjusting the threshold for rain to include, for example, >0.02 inch instead of >0.01 inch;

- Adjusting the 6 hours of rain threshold to capture 8 or 10 hours after the rain begins to see if there are more accidents; and
- Developing a statistical test to determine whether the above findings are statistically relevant.

Analysis of Snowfall Effects

An analysis comparing roadway performance when snow was falling versus when snow was not falling and when no precipitation was falling resulted in counterintuitive findings that snow was not a significant contributing factor to roadway performance. Because this result was counterintuitive, a series of case studies was undertaken to examine traffic performance on those days that snow fell in the city.

The case study of delays on I-90 when snow fell illustrates the difficulties in determining the effects of weather on roadway performance. It also indicates why the selection of the variable snow falling in the initial analysis of the effects of snow on travel time produced poor results. In the case study, the largest roadway performance effects caused by snowfall did not occur while the snow was falling at the SeaTac weather station. Instead, they occurred as a result of the accumulation of snow on the roadway and the conversion of that snow into sheet ice on some roadway sections. The latter event occurred well after the snow had stopped falling at the weather station.

In addition, the analysis of that case study revealed that delays did not happen similarly on all roadway sections that evening (although the newspaper reported long delays on several corridors). In fact, the eastbound and westbound sections of I-90 (presumed to experience the same level of snowfall) experienced very different roadway performance (delay) conditions during and after the snow storm. While the westbound direction showed modest delays in the evening, with moderate delays occurring between 6:00 and 9:00 p.m., the eastbound section experienced an unusually heavy day of congestion before the snowfall, and then a major additional pulse of congestion starting at 8:00 p.m. that lasted well into the morning hours. Exacerbating the eastbound congestion was the traffic volume added because of a professional football game that occurred that night in downtown Seattle. The Seahawks played the Packers on Monday Night football, adding 65,000 fans, divided across multiple freeways, to the outbound traffic beginning at about 8:30 p.m.

The snowfall case study revealed many of the analytic problems associated with an analysis of the effects of bad weather. The most significant problem was finding a good definition, in analytic terms, of bad weather. The key regionwide weather variable used to indicate bad weather, the presence of measurable rainfall during the previous hour, was a poor choice for analyzing the effects of snowfall.

The proper variable for analysis of the effects of snow on travel time performance would have been snowfall accumulation on the roadway, but unfortunately the data necessary to estimate or compute this variable were not available for this project.

Analysis of Wind Effects

An analysis of the effects of wind on roadway performance indicated that on the two roadways (I-90 and SR 520) that cross Lake Washington on floating bridges, high winds (wind gusts above 19 mph) had an observable effect in moderate volume conditions. This effect was especially noticeable eastbound when the winds, generally from the south, caused waves to crash against the bridge, creating significant spray. However, wind appeared to have inconsistent effects on all other freeway corridors in the region. Some roadway sections were adversely affected by strong winds, while the performances of other segments were not.

The effects of wind on roadway performance were analyzed differently from the effects of rain. This is partly because other than the prolonged effect of any queues being formed, wind does not have a lasting effect similar to that of rain. Once wind stops, its direct effects stop. That is, wind does not have a lasting effect equivalent to spray from wet roadways caused by rain. The lack of this effect limited the project team's confidence in the use of the available NOAA wind data for specific roadway sections.

As a consequence, the team did not use the wind gust variable produced by NOAA because there was little confidence that this variable was effectively applicable to geographically removed locations. Similarly, the wind speed variable that was used was assumed to be only a reasonable surrogate for windy conditions, rather than a definitive statistic indicating the precise wind speed at which travel might be affected.

To test the effects of wind on travel times, the data set was divided into wind-affected and not-wind-affected groups on the basis of the wind speed variable present in each 5-minute time slice. The travel times for these two groups were compared within specific time intervals with both traditional *t*-tests, which assumed normally distributed travel times within those time periods, and nonparametric tests of the sample means. Tests were performed only for nonholiday Tuesdays, Wednesdays, and Thursdays (combined).

Sensitivity tests were performed with different values of the wind speed variable to determine the sensitivity of the analysis results to the breakpoint selected for identifying windy versus not-windy conditions. Figures E.8 through E.11 illustrate how travel times by direction across the two floating bridges were affected by various wind speeds. The graphs show mean travel times by time of day by wind speed for nonholiday Tuesdays through Thursdays.

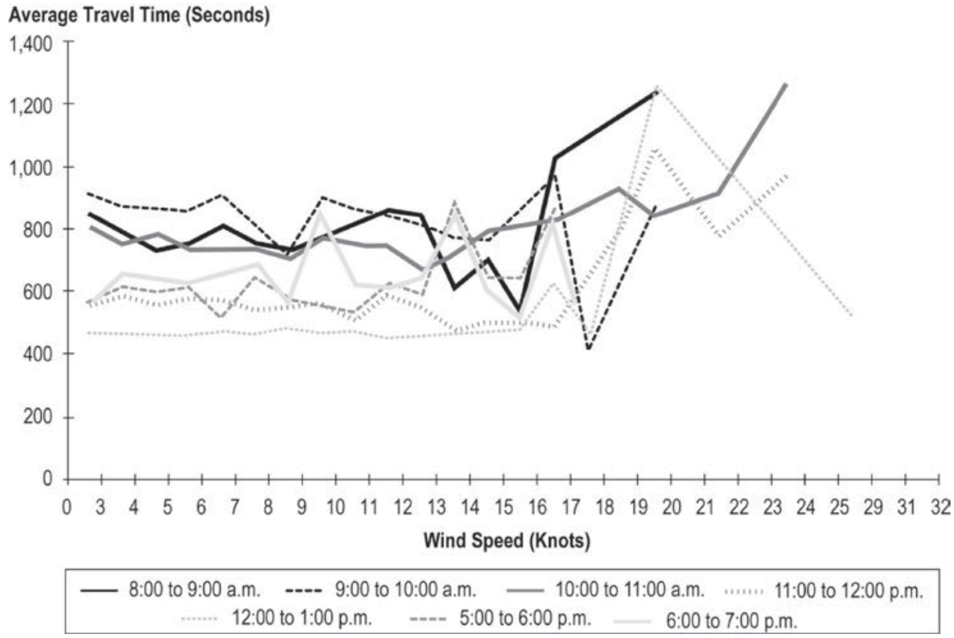

Figure E.8. SR 520 Seattle eastbound.

The analytic tests performed on the Seattle test corridors showed that travel times in all test corridors were not equally affected by wind. In fact, in many corridors, wind did not have any statistically significant effect on travel times. In other corridors, wind had a high impact on roadway performance. The authors believe that this is due in part to differences between actual wind speeds within the study corridor and those measured at the airport, and in part to the way that site-specific roadway geometry affects how drivers respond to wind. That is, travel times over the SR 520 floating bridge, which has narrow lanes, no shoulders, and physically moves when struck by wind-blown waves, are affected at much lower wind speeds than travel times on I-5 in the northern reaches of the metropolitan region, where lanes are wider, full-width shoulders

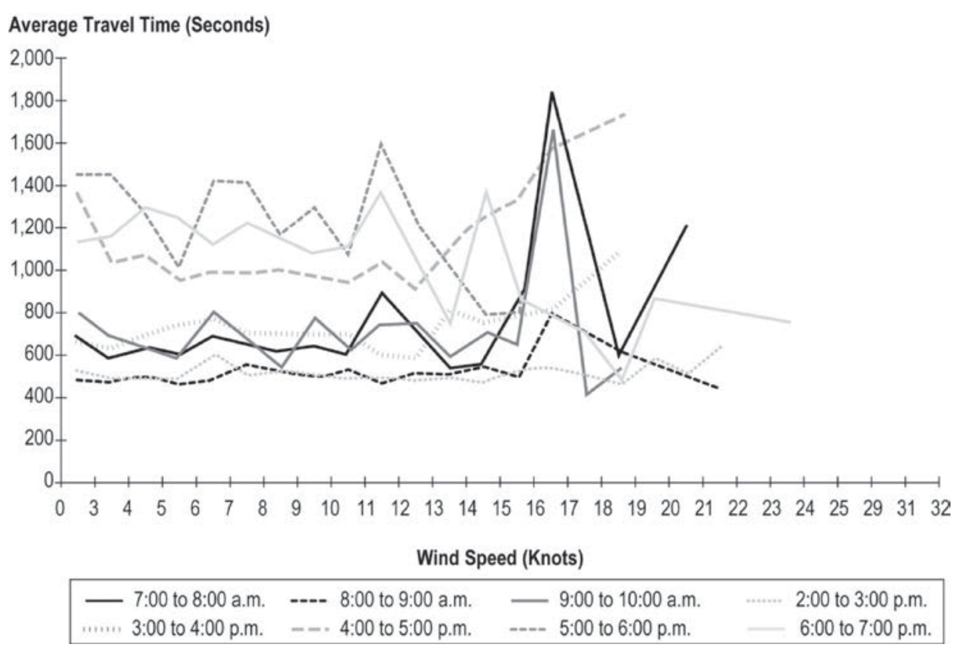

Figure E.9. SR 520 Seattle westbound.

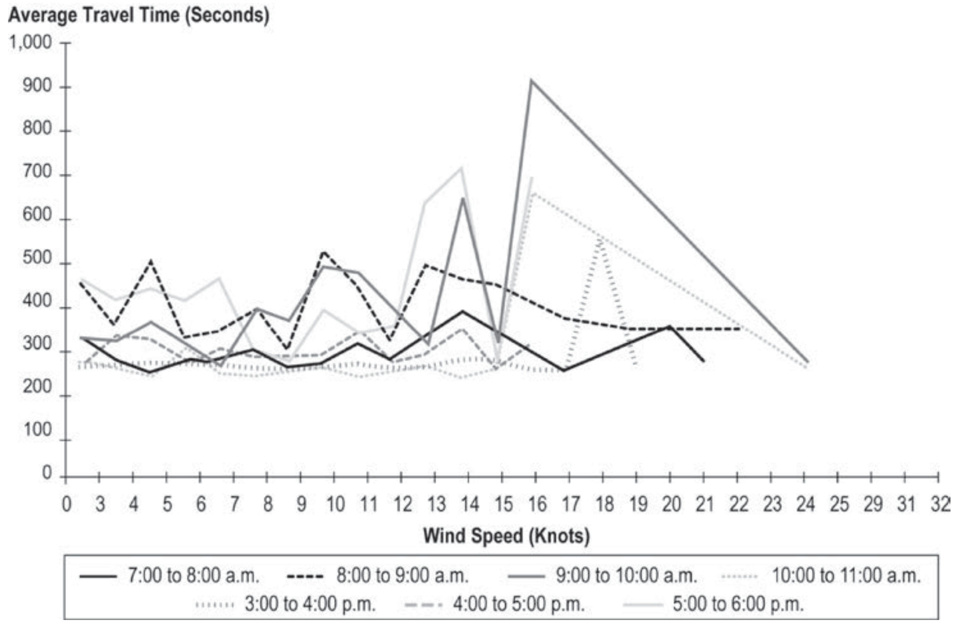

Figure E.10. I-90 Bridge eastbound.

exist, and wind does not cause the roadway to move. Table E.9 gives examples of how wind affects various corridors differently, even though the corridors are directly connected. Table E.9 also gives examples of the results of the sensitivity tests performed with different wind speeds to separate windy from not-windy conditions.

As Table E.9 shows, the SR 520 bridge is affected by relatively moderate winds (10 mph sustained wind speeds), mainly because the bridge is a 2-mile-long floating span. The roadway is two lanes in each direction with no shoulders. In even moderate wind, a driver crossing the bridge can feel the bridge sway. The wind also can create some spray, as wind-driven waves break against the bridge, causing drivers to slow down. Because the bridge operates near capacity 12 to 14 hours each weekday, these wind effects are sufficient to cause congestion.

The I-90 bridge, located nearby to the south, also is affected by wind, but to a lesser degree than the SR 520 bridge. This

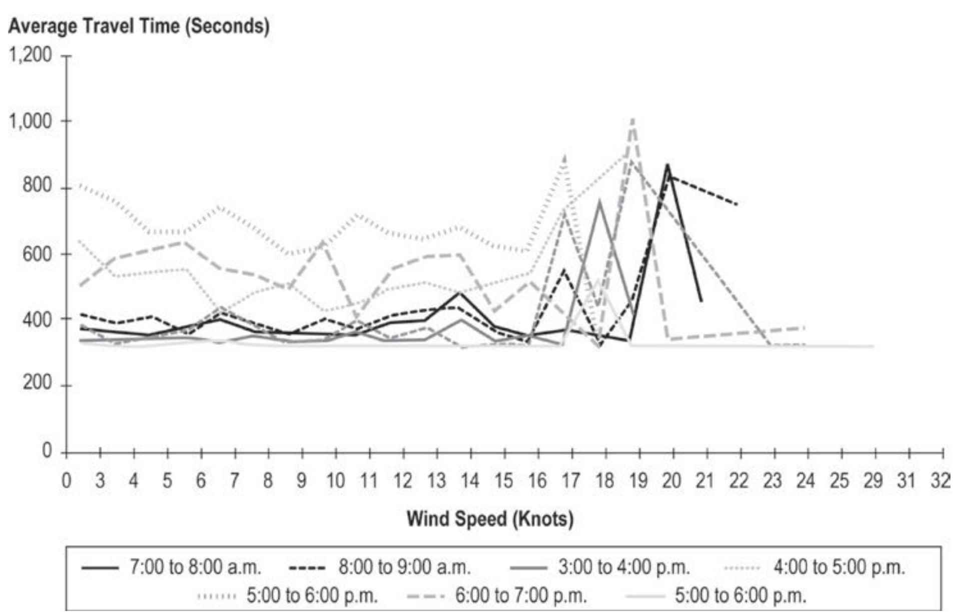

Figure E.11. I-90 Bridge westbound.

Table E.9. Example Effects of Wind on Travel Times by Corridor

Route	Mean Travel Time A.M. Peak (s)		Difference	Statistically Significant?	Mean Travel Time P.M. Peak (s)		Difference	Statistically Significant?
	With Wind[a]	Without Wind[b]			With Wind	Without Wind		
I-5 Everett southbound	190	207	–17	No	191	209	–18	No
I-5 North King southbound	759	690	68	Yes	400	422	–22	No
I-5 North Seattle southbound	751	606	145	Yes	926	686	239	Yes
I-5 South northbound	1,671	1,073	598	Yes	649	649	0	No
SR 520 Seattle westbound	1,020	638	382	Yes	1,548	1,052	495	Yes
I-90 Bridge eastbound	425	410	15	No	543	437	106	Yes
I-90 Seattle eastbound	198	169	29	Yes	151	115	36	Yes
SR 520 Seattle westbound, 10 mph wind speed	781	626	154	Yes	1,093	1,049	44	Yes
I-90 Bridge eastbound, 10 mph wind speed	434	407	27	No	431	441	–10	No
I-90 Seattle eastbound, 10 mph wind speed	174	169	5	No	107	118	–12	No

[a] Sustained wind speed >16 mph.
[b] Sustained wind speed ≤16 mph.

is most likely due to a combination of factors: the I-90 bridge is more modern, has full shoulders, and sits higher off the water (and therefore experiences less wind-driven spray). Interestingly, the evening commute across the I-90 bridge is affected by wind, but the morning commute is not, even though traffic volumes are similar in both periods. This difference is partly because the test section that included the I-90 bridge also included a large segment of nonbridge travel across Mercer Island. Back-ups on the bridge affecting eastbound traffic actually create some free-flow conditions on the island itself, decreasing the travel time impact of the wind. However, wind-caused back-ups significantly affect the upstream section of eastbound I-90 (the Seattle section also shown in Table E.9). This explains why the I-90 Seattle section is statistically affected by wind in the morning, even though it does not include the bridge itself. At more moderate wind speeds (e.g., 10 mph sustained winds), none of the I-90 segments showed a statistically significant change in expected travel time.

The I-5 segments included in Table E.9 indicate that wind affects some corridors in some peak periods, but not all corridors or all peak periods within all corridors. In general, high peak period volumes relative to their capacity make roadway segments more likely to be affected by high winds.

Other reasons that a roadway may be susceptible to winds are that the road segment is exposed to high levels of wind (e.g., the I-5 North Seattle segment crosses the Ship Canal Bridge, an exposed portion of road where wind is often felt) or that the segment is immediately upstream of another segment that is wind affected. For example, the I-5 North King segment is upstream of the I-5 North Seattle segment. The I-5 Everett segment is considerably farther north and does not experience spillback from North King or North Seattle segments, except in extreme cases.

Figure E.12 illustrates how wind affects the SR 520 bridge westbound, and Figure E.13 illustrates the I-90 eastbound bridge section. In both figures it can be seen that the primary effects of wind are in the peak periods when traffic volumes are highest. If the same graphics were presented with a higher wind speed, more impacts would be seen in the middle of the day, especially on SR 520.

In Figure E.13, wind appears to have a significant effect on expected travel times during the later portion of the a.m. peak period, but not on the earlier portion of the peak. This difference helps explain why the difference in mean travel times shown in Table E.9 is not statistically significant. In the end, sustained wind speeds of 16 mph were used as the primary split between windy and not-windy conditions. Adopting a different definition would marginally change the travel times associated with windy and not-windy conditions for some corridors, but would not change the ultimate conclusions of the study.

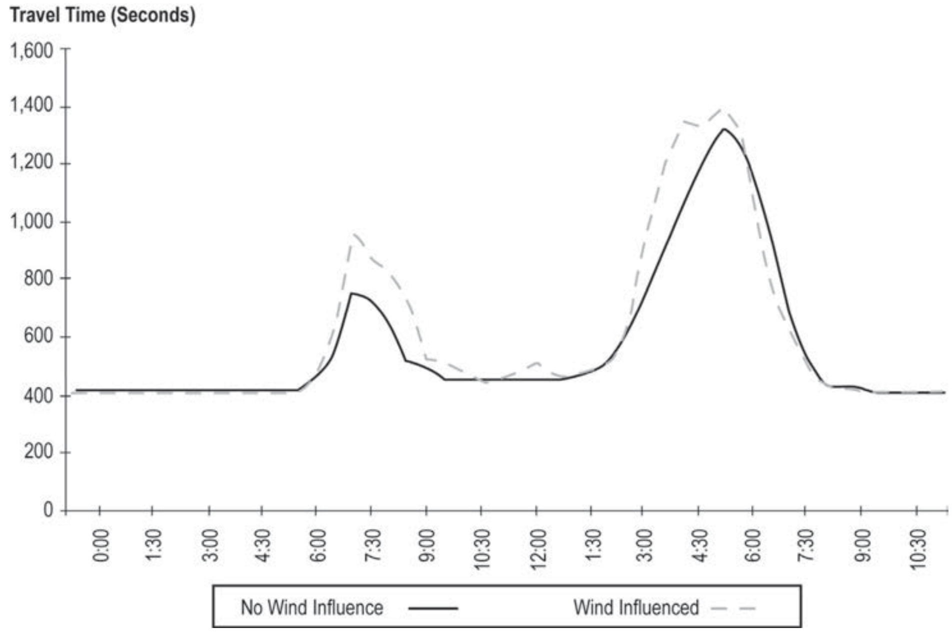

Figure E.12. Mean travel times by time of day in wind and no-wind conditions on SR 520 westbound (Bellevue toward Seattle).

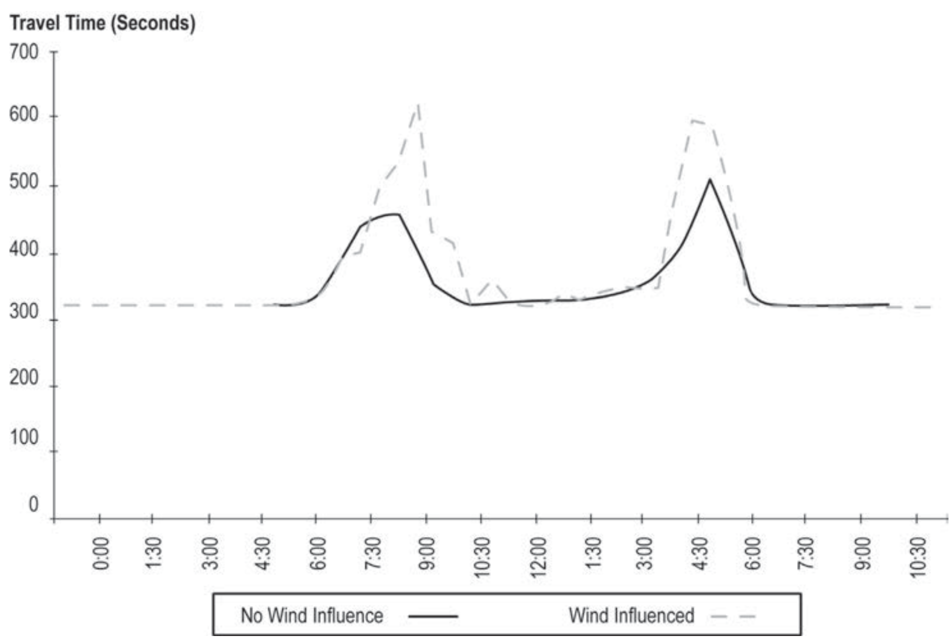

Figure E.13. Mean travel times by time of day in wind and no-wind conditions on I-90 bridge section eastbound (Seattle toward Bellevue).

Analysis of Fog Effects

The analysis of the effects of fog was problematic, as fog tends to be highly localized. Thus, while the airport may be very foggy (to the point that landings and take-offs are restricted for lack of visibility), at the same time I-5, passing within 2 miles of SeaTac, may have clear visibility. As a result, the fog variable that described conditions only at SeaTac airport was not useful in identifying specific fog-related delays.

References

1. Scholz, F. Confidence Bounds & Intervals for Parameters Relating to the Binomial, Negative Binomial, Poisson and Hypergeometric Distributions: With Applications to Rare Events. University of Washington, Seattle, 2008. www.stat.washington.edu/fritz/DATAFILES498B2008/ConfidenceBounds.pdf.
2. Scholz, F. W., and M. A. Stephens. *K*-Sample Anderson–Darling Tests. *Journal of the American Statistical Association,* Vol. 82, No. 399, 1987, pp. 918–924. www.jstor.org/discover/10.2307/2288805?uid=3739960&uid=2&uid=4&uid=3739256&sid=21101238038017.

APPENDIX F

Statistics Related to the End of Congestion: Seattle Analysis

Two sets of statistical comparisons were made regarding the end of congestion. One was made assuming a normal distribution. The other was made using the Anderson–Darling *K*-sample test, a nonparametric test that allows a comparison of two populations with skewed distributions (*1,* pp. 918–924). Tables F.1 through F.3 show the results for the a.m. and p.m. periods. The boldface numbers in the tables indicate statistically significant differences at the 95% confidence level, and italic numbers indicate statistically significant differences at the 90% confidence level. The results are generally very similar, with many of the observed differences easily attributable to how these two types of tests treat the importance of outliers given the total number of data points in the samples being tested.

Table F.1. **p-*Values for Comparing Ending Times of Congestion Under Disruptive Versus Nondisruptive Conditions***

	A.M. Peak Period			P.M. Peak Period		
Route	Crash Influenced	Incident Influenced	Either Crash or Incident Influenced	Crash Influenced	Incident Influenced	Either Crash or Incident Influenced
I-405 Bellevue northbound	**0.00**	**0.00**	**0.00**	**0.00**	0.40	**0.01**
I-405 Bellevue southbound	**0.00**	**0.00**	**0.00**	**0.03**	0.20	0.11
I-405 Eastgate northbound	**0.01**	0.21	**0.03**	**0.00**	0.47	**0.02**
I-405 Eastgate southbound	**0.01**	0.20	**0.01**	**0.03**	0.49	0.11
I-405 Kennydale northbound	**0.00**	0.16	**0.00**	**0.01**	0.25	**0.01**
I-405 Kennydale southbound	**0.00**	(*0.06*)	**0.00**	0.63	0.32	0.60
I-405 Kirkland northbound	0.68	**0.00**	**0.01**	(*0.07*)	0.62	**0.04**
I-405 Kirkland southbound	**0.02**	**0.01**	**0.03**	**0.00**	**0.00**	**0.00**
I-405 North northbound	**0.00**	**0.03**	**0.00**	**0.00**	0.55	**0.01**
I-405 North southbound	**0.00**	**0.00**	**0.00**	**0.00**	0.44	**0.01**
I-405 South northbound	**0.00**	**0.02**	**0.00**	0.11	0.34	0.24
I-405 South southbound	**0.01**	**0.01**	**0.00**	0.48	0.32	0.43
I-5 Everett northbound	**0.00**	0.61	**0.00**	**0.00**	**0.01**	**0.00**
I-5 Everett southbound	**0.00**	0.38	**0.00**	**0.00**	**0.00**	**0.00**
I-5 Lynnwood northbound	0.45	0.69	0.70	0.21	0.19	0.12

(continued on next page)

Table F.1. p-Values for Comparing Ending Times of Congestion Under Disruptive Versus Nondisruptive Conditions (continued)

Route	A.M. Peak Period			P.M. Peak Period		
	Crash Influenced	Incident Influenced	Either Crash or Incident Influenced	Crash Influenced	Incident Influenced	Either Crash or Incident Influenced
I-5 Lynnwood southbound	**0.01**	**0.01**	**0.01**	**0.00**	0.21	**0.00**
I-5 North King northbound	0.69	0.51	0.77	(*0.09*)	0.54	0.13
I-5 North King southbound	**0.03**	**0.02**	**0.04**	**0.00**	(*0.06*)	**0.00**
I-5 Seattle CBD northbound	0.55	0.51	**0.00**	0.42	0.54	**0.00**
I-5 Seattle CBD southbound	**0.00**	0.48	**0.00**	0.55	0.50	0.54
I-5 Seattle North northbound	0.55	0.51	**0.00**	0.42	0.54	**0.00**
I-5 Seattle North southbound	**0.00**	0.24	**0.00**	**0.01**	0.11	(*0.06*)
I-5 South northbound	(*0.08*)	0.49	0.30	**0.00**	NA	**0.00**
I-5 South southbound	**0.05**	**0.04**	(*0.05*)	0.15	0.40	0.25
I-5 Tukwila northbound	(*0.10*)	0.24	0.23	**0.00**	**0.00**	**0.00**
I-5 Tukwila southbound	**0.00**	0.55	**0.00**	**0.00**	**0.01**	**0.00**
I-90 Bellevue eastbound	0.69	0.69	0.85	**0.01**	0.16	**0.02**
I-90 Bellevue westbound	0.29	(*0.06*)	(*0.07*)	**0.00**	**0.00**	**0.00**
I-90 Bridge eastbound	**0.00**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**
I-90 Bridge westbound	**0.00**	**0.02**	**0.00**	**0.02**	**0.00**	**0.00**
I-90 Issaquah eastbound	0.69	0.69	0.85	0.66	0.29	0.60
I-90 Issaquah westbound	**0.00**	0.51	**0.00**	NA	NA	NA
I-90 Seattle eastbound	**0.00**	0.37	**0.00**	(*0.10*)	0.35	0.17
I-90 Seattle westbound	**0.00**	**0.05**	**0.00**	0.63	0.30	0.58
SR 167 Auburn northbound	0.17	0.41	0.31	0.41	0.46	0.53
SR 167 Auburn southbound	**0.00**	**0.00**	**0.00**	(*0.10*)	0.39	0.23
SR 167 Renton northbound	**0.00**	**0.00**	**0.00**	**0.00**	**0.04**	**0.00**
SR 167 Renton southbound	**0.00**	**0.00**	**0.00**	0.16	0.20	0.12
SR 520 Redmond eastbound	0.46	0.65	0.69	0.44	0.63	0.67
SR 520 Redmond westbound	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
SR 520 Seattle eastbound	**0.00**	**0.00**	**0.00**	**0.01**	0.25	**0.02**
SR 520 Seattle westbound	**0.00**	0.12	**0.00**	**0.05**	0.53	0.11

Note: CBD = central business district.

Table F.2. Comparison of Ending Times of Congestion for A.M. Peak Period

Route	Nonevent End of Congestion Time	Added Time if Incident Occurs	Added Time if Crash Occurs	*Z* Score for Incident Comparison	*Z* Score for Crash Comparison
I-405 Kennydale northbound[a]	11:47	0:34	1:33	1.265	**3.368**
I-405 North southbound	9:56	1:27	2:09	**2.209**	**3.101**
I-5 North King southbound[a]	11:06	0:48	1:29	**2.472**	**3.321**
I-5 Seattle CBD northbound	12:15	(0:42)	1:20	NA[b]	NA[b]
I-405 Kirkland southbound	10:16	0:56	1:14	**2.590**	**2.732**
SR 520 Seattle eastbound	11:54	6:02	6:53	**4.820**	**5.752**
I-5 Lynnwood southbound	10:06	1:57	1:39	**3.048**	**2.659**
I-5 South northbound	9:16	0:12	0:22	1.204	**2.344**
SR 167 Auburn northbound[a]	11:40	0:51	0:59	1.318	1.576
I-405 Eastgate northbound[a]	11:38	0:16	1:04	1.100	**2.368**
I-5 Seattle North southbound	9:38	1:10	4:58	**2.650**	**7.531**
I-405 Kennydale southbound[c]	9:08	1:19	1:23	*1.674*	**2.083**
I-405 South southbound[c]	12:46	3:12	2:17	**3.171**	**2.782**
SR 167 Renton northbound[c]	9:13	1:47	1:22	**2.765**	**2.513**
SR 520 Seattle westbound[a]	9:51	0:47	2:54	*1.694*	**3.412**
I-5 Tukwila northbound	10:06	0:14	0:32	1.103	*1.778*
I-90 Issaquah westbound	9:10	0:09	0:33	0.521	4.616
I-90 Bellevue westbound	9:26	0:13	(0:06)	1.607	–0.781
I-405 Bellevue northbound[a]	11:01	3:34	5:00	**5.252**	**7.928**
I-405 South northbound[c]	8:21	4:49	7:47	**2.478**	**10.562**
I-90 Seattle eastbound	8:45	0:05	1:05	0.317	**5.102**
I-90 Seattle westbound	7:35	0:42	1:52	1.238	**8.146**
I-90 Bridge eastbound	9:23	0:45	1:04	**3.806**	**5.876**
I-405 Bellevue southbound[a]	8:27	7:56	11:07	**8.517**	**27.434**
I-5 Everett southbound	7:08	0:06	1:06	**1.975**	**2.398**
I-90 Bridge westbound	8:04	0:26	1:30	**2.048**	**3.518**
I-5 Seattle CBD southbound	9:28	1:04	4:57	**2.387**	**8.190**
SR 167 Auburn southbound	8:58	7:29	9:59	**8.068**	**30.022**
I-405 Eastgate southbound	7:22	0:07	0:32	1.294	**5.227**

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Table F.2. Comparison of Ending Times of Congestion for A.M. Peak Period (continued)

Route	Nonevent End of Congestion Time	Added Time if Incident Occurs	Added Time if Crash Occurs	*Z* Score for Incident Comparison	*Z* Score for Crash Comparison
SR 167 Renton southbound	9:42	7:33	7:30	**7.033**	**4.957**
I-5 Tukwila southbound	7:08	0:05	7:51	0.719	1.026
SR 520 Redmond westbound	7:09	0:56	2:10	**2.266**	**2.888**
I-405 North northbound	7:56	0:12	1:47	*1.882*	1.562
I-5 Everett northbound	7:05	0:01	0:14	1.202	*1.928*
I-5 Lynnwood northbound	7:13	(0:01)	0:20	(0.403)	0.709
I-5 Seattle North northbound	7:07	0:04	(0:02)	1.332	NA[d]
I-90 Bellevue eastbound	7:05	(0:00)	(0:00)	(1.380)	NA[d]
I-5 South southbound	7:07	0:08	(0:00)	1.047	(0.204)
I-405 Kirkland northbound	7:05	0:05	(0:00)	*1.882*	(1.686)
SR 520 Redmond eastbound	7:05	(0:00)	(0:00)	(0.267)	**(2.015)**
I-90 Issaquah eastbound	7:05	(0:00)	(0:00)	(1.381)	NA[d]
I-5 North King northbound	7:05	(0:00)	(0:00)	(1.324)	(1.324)

[a] Uses a 10% travel time increase as the point at which congestion has abated rather than the 5% norm.
[b] Too few nondisrupted days occurred to compute a test statistic.
[c] Uses a 20% travel time increase as the point at which congestion has abated rather than the 5% norm.
[d] Too few crash days occurred to compute a test statistic.

Table F.3. Comparison of Ending Times of Congestion for P.M. Peak Period

	Nonevent End of Congestion Time	Added Time if Incident Occurs	Added Time if Crash Occurs	*Z* Score for Incident Comparison	*Z* Score for Crash Comparison
I-405 Bellevue northbound	18:09	0:07	0:27	1.264	**3.927**
I-405 Bellevue southbound	19:44	0:13	0:20	*1.943*	**2.629**
I-405 Eastgate northbound	16:24	0:05	0:47	0.351	**2.221**
I-405 Eastgate southbound	19:12	0:00	0:15	0.064	**2.377**
I-405 Kennydale northbound	18:05	0:17	0:23	**2.323**	**2.006**
I-405 Kennydale southbound	19:27	(0:01)	0:00	(0.195)	0.137
I-405 Kirkland northbound	19:03	0:01	0:11	0.246	**2.196**
I-405 Kirkland southbound	16:55	1:00	1:21	**4.686**	**4.849**
I-405 North northbound	19:18	(0:05)	0:14	(0.799)	**3.236**
I-405 North southbound	17:40	(0:11)	0:46	(0.919)	**3.611**
I-405 South northbound	20:41	0:21	0:17	0.940	*1.698*
I-405 South southbound	19:36	(0:03)	0:05	(0.336)	0.776
I-5 Everett northbound	17:08	0:28	0:58	2.174	**4.216**
I-5 Everett southbound	16:35	0:24	0:57	2.979	**4.441**
I-5 Lynnwood northbound	19:00	0:08	(0:07)	1.320	(1.082)
I-5 Lynnwood southbound	17:21	0:12	1:09	0.922	**7.154**
I-5 North King northbound	18:55	0:04	0:12	0.741	**2.092**
I-5 North King southbound	16:47	0:29	1:57	2.424	**6.575**
I-5 Seattle CBD northbound	18:53	(0:06)	0:13	(0.490)	1.020

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Table F.3. Comparison of Ending Times of Congestion for P.M. Peak Period (continued)

	Nonevent End of Congestion Time	Added Time if Incident Occurs	Added Time if Crash Occurs	*Z* Score for Incident Comparison	*Z* Score for Crash Comparison
I-5 Seattle CBD southbound	18:49	0:06	0:13	0.271	0.520
I-5 Seattle North northbound	18:34	0:05	0:07	0.726	1.093
I-5 Seattle North southbound	18:20	0:16	0:31	1.513	**2.481**
I-5 South northbound	16:05	0:00	0:45	0.000	*1.914*
I-5 South southbound	18:08	0:09	0:19	1.179	**2.168**
I-5 Tukwila northbound	16:23	0:23	1:56	**2.329**	**5.897**
I-5 Tukwila southbound	17:18	0:21	0:51	**2.083**	**4.972**
I-90 Bellevue eastbound	16:35	0:21	1:02	1.131	1.433
I-90 Bellevue westbound	16:13	1:21	2:10	**2.078**	**8.804**
I-90 Bridge eastbound	18:18	0:22	0:35	**3.196**	**4.751**
I-90 Bridge westbound	18:25	0:34	0:48	**2.921**	**4.299**
I-90 Issaquah eastbound	16:10	(0:05)	(0:05)	(2.858)	NA[a]
I-90 Issaquah westbound	16:05	0:00	0:00	0.000	0.000
I-90 Seattle eastbound	17:07	(1:02)	1:05	NA[b]	**6.457**
I-90 Seattle westbound	17:29	0:19	0:07	1.274	0.219
SR 167 Auburn northbound	17:31	(0:08)	(0:31)	(0.641)	NA[a]
SR 167 Auburn southbound	18:47	0:08	0:08	*1.799*	**2.716**
SR 167 Renton northbound	17:22	0:27	0:57	1.973	**4.550**
SR 167 Renton southbound	18:47	0:08	0:16	1.293	**2.853**
SR 520 Redmond eastbound	19:09	0:05	(0:07)	0.835	(0.841)
SR 520 Redmond westbound	16:51	1:24	1:53	**2.652**	**7.432**
SR 520 Seattle eastbound	18:52	0:11	0:22	*1.654*	**3.232**
SR 520 Seattle westbound	20:00	(0:01)	0:12	(0.206)	*1.727*

[a] Too few crash days occurred to compute a test statistic.
[b] Too few incident days occurred to compute a test statistic.

Reference

1. Scholz, F. W., and M. A. Stephens. *K*-Sample Anderson–Darling Tests. *Journal of the American Statistical Association*, Vol. 82, No. 399, 1987, pp. 918–924. www.jstor.org/discover/10.2307/2288805?uid=3739960&uid=2&uid=4&uid=3739256&sid=21101238038017.

APPENDIX G

Computation of Travel Time Metrics

Introduction

The key principle for constructing reliability metrics for use in Project L03 was that the metrics had to be based on the measurement of travel times over an appreciable amount of time and meaningful highway distances. Travel times are easily relatable to nontechnical audiences, and once measured they can be transformed into a wide variety of additional metrics. The Travel Time Index (TTI) was used as the primary congestion metric in Project L03 for various reliability estimation and prediction models.

Three reasons exist for this choice. First, because study sections vary in length, using raw travel times is misleading, and the travel times must be normalized for distance. As a unitless index, the TTI is normalized. Second, the TTI is already in widespread use in congestion performance monitoring. Third, the moments and derivative measures derived from the TTI turn out to be identical to those of the travel time distribution for a particular road section and time slice. An alternative metric to the TTI is the travel rate (the inverse of space mean speed, in minutes per mile).

For the statistical modeling, moments from the distribution of TTIs were used as the dependent variables (e.g., the 80th percentile TTI). As shown below, these can be easily converted to travel times, and these travel times can be used to create additional performance metrics (e.g., delay).

Calculation of Travel Time Index

The starting point for the research was to transform field data into travel time–based metrics. The first step in this process was to define highway sections over which travel time statistics would be calculated. The following principles were used in defining sections:

- Sections should be relatively homogenous in terms of traffic and geometric conditions. Multiple interchanges are allowed as long as they do not provide for major drops or additions in traffic volumes along the section;
- Sections should represent portions of trips taken by travelers. Typical distances for urban freeway sections are 3 to 6 miles; and
- Major bottlenecks, defined as major freeway-to-freeway interchanges, can be present at the downstream end of the section, but never in midsection.

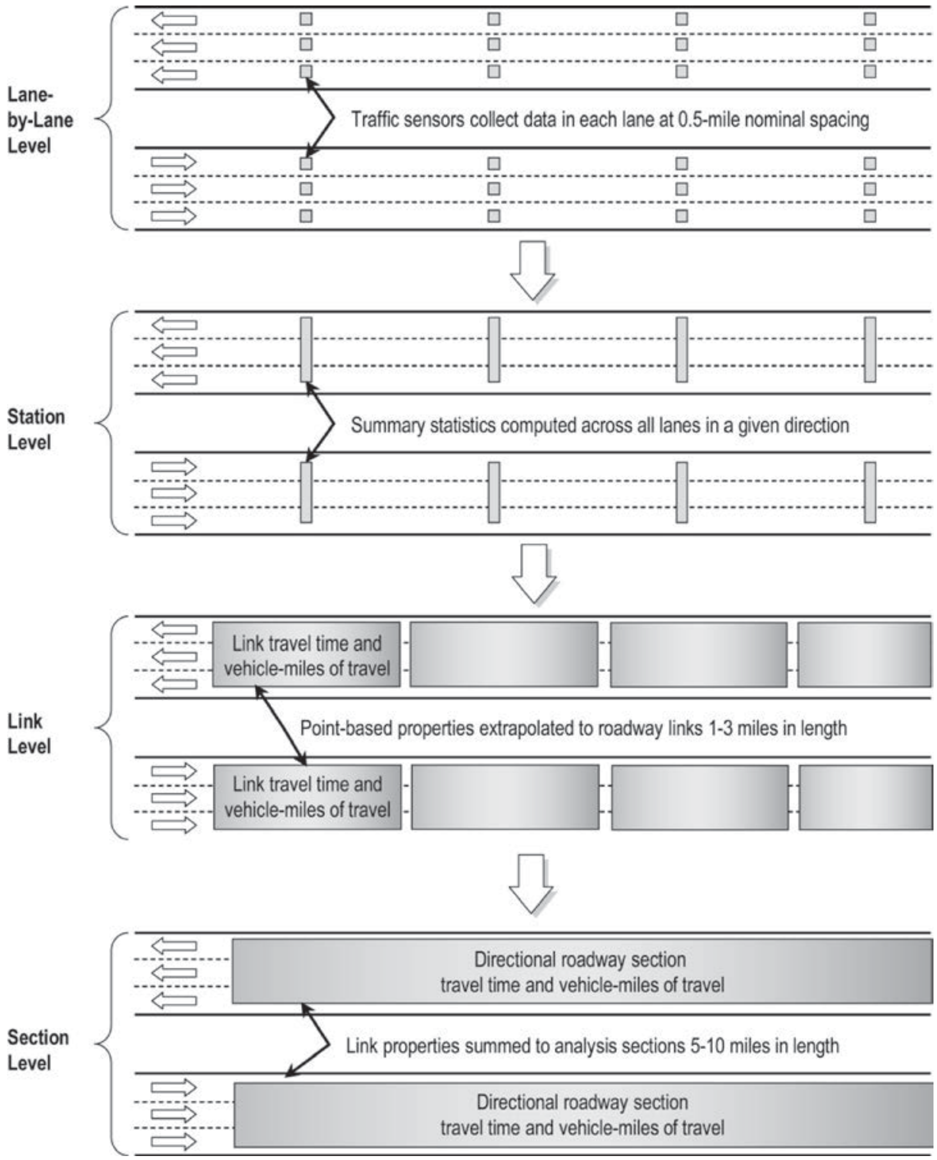
The majority of data that were available came from urban freeway surveillance systems, specifically, point detection of volumes and speeds from closely spaced equipment. These point measurements were converted to travel times over fixed highway distances with a method in widespread use by researchers and practitioners: it is assumed that the point speed measures the travel time over a distance half the distance to the nearest upstream and downstream detectors. This assumption works well if detector spacing is close (i.e., 0.5-mile spacing or less). Figure G.1 shows the process for computing section travel times from individual detectors; this was done at a 5-minute time interval level. For each detector zone, vehicle miles traveled (VMT) and vehicle hours traveled (VHT) were computed:

$$\text{VMT} = \text{VOLUME} * \text{DetectorZoneLength} \tag{G.1}$$

$$\text{VHT} = \text{VMT}/\left(\text{Min}\left(\text{FreeFlowSpeed}, \text{Speed}\right)\right) \tag{G.2}$$

When aggregating to the section level, at least half of the detectors had to report valid data for each of the 5-minute periods; otherwise the data were set to *missing*. If less than half of the detector data was missing, VMT and VHT were factored up based on the ratio of total section length to the sum of the lengths of the individual detector zones.

For every 5-minute interval in the year, total VMT and VHT were computed. From these, key performance measures were computed:



Source: Turner, S., R. Margiotta, and T. Lomax, *Monitoring Urban Freeways in 2003: Current Conditions and Trends from Archived Operations Data*. Report No. FHWA-HOP-05-018. December 2004. http://mobility.tamu.edu/mmp/FHWA-HOP-05-018/.

Figure G.1. Converting spot speeds to section travel times.

$$\text{SpaceMeanSpeed} = \text{VMT}/\text{VHT} \tag{G.3}$$

$$\text{TravelRate} = 1/\text{SpaceMeanSpeed} \tag{G.4}$$

$$\text{TTI} = \text{MAX}\left(1.0, \left[\text{TravelRate}/\left(1/\text{FreeFlowSpeed}\right)\right]\right) \tag{G.5}$$

Because the bases for the measures were total VMT and VHT, the process was self-weighting. For urban freeways, FreeFlowSpeed was fixed at 60 mph. Note that TTI was not allowed to be lower than 1.0; that is, speeds higher than 60 mph were set to 60 mph. This adjustment was made because the purpose of the study was to measure congestion, not high speeds. If speeds were not capped, the resulting statistics would be biased because of the credit given to high speeds. However, the original data have been preserved for future examination by researchers who may wish to remove this restriction.

The congestion metrics were computed for each 5-minute period in a day over the course of a year. For any given analysis time slice (e.g., peak hour, peak period), a TTI distribution and its moments were computed as the VMT-weighted average of all the 5-minute TTIs in that time slice for the entire year. The various moments of the TTI distributions (e.g., 95th percentile TTI) were then used in the statistical modeling.

Table G.1. Travel Time and TTI Distributions for A.M. Peak Hour, Selected Atlanta Study Sections

Section	Travel Time (min)					TTI			
	Free-Flow	10th Percentile	Median	Mean	95th Percentile	10th Percentile	Median	Mean	95th Percentile
1	5.510	5.510	5.523	5.562	5.629	1.000	1.002	1.009	1.022
2	5.840	5.846	7.601	7.805	10.727	1.001	1.302	1.337	1.837
3	4.970	5.091	7.548	7.580	10.996	1.024	1.519	1.525	2.213
4	4.550	4.560	5.081	5.411	7.342	1.002	1.117	1.189	1.614
5	6.860	6.883	10.113	10.013	13.152	1.003	1.474	1.460	1.917

Note: Section 1 is a radial freeway leading away from the I-285 Beltway; its peak is in the afternoon.

Converting Predicted TTI Percentiles to Other Metrics

TTI percentiles can be thought of as a ratio comparing the travel time for a given percentile with the travel time under free-flow conditions. For example, a 95th percentile TTI of 1.8 means that the 95th percentile travel time is 80% higher than the free-flow travel time. Therefore, the travel time associated with any percentile can be computed as

$$\text{TravelTime}_n = \text{TTI}_n * \text{TravelTime}_{\text{ff}} \tag{G.6}$$

where n is the percentile and $\text{TravelTime}_{\text{ff}}$ is the travel time under free-flow conditions.

Travel times can be combined with other data to compute other congestion-related metrics such as vehicle hours of delay:

$$\text{SpaceMeanSpeed} = \text{SectionLength}/\text{TravelTime} \tag{G.7}$$

$$\text{Delay} = \left(\left[\frac{\text{SectionLength}}{\text{SpaceMeanSpeed}}\right] - \left[\frac{\text{SectionLength}}{\text{FreeFlowSpeed}}\right]\right) * \text{Volume} \tag{G.8}$$

Percentiles for the various travel times can also be used to compute the Buffer Index and Skew Index:

$$\text{Buffer Index} = \frac{\left(\begin{array}{c}\text{95th percentile travel time}\\ -\text{ mean travel time}\end{array}\right)}{\text{mean travel time}} \tag{G.9}$$

$$\text{Skew Index} = \frac{\left(\begin{array}{c}\text{90th percentile travel time}\\ -\text{ median travel time}\end{array}\right)}{\left(\begin{array}{c}\text{median travel time}\\ -\text{ 10th percentile time}\end{array}\right)} \tag{G.10}$$

As an example, consider the data in Table G.1, which were derived from a few Atlanta study sections for 2007. Both the travel time and TTI distributions were developed by following the procedure discussed above. Applying Equation 6 for the 95th percentile for Section 2,

$$\begin{aligned}\text{95th percentile travel time} &= \text{95th percentile TTI} \\ &\quad * \text{ free-flow travel time} \\ &= 1.837 * 5.840 \\ &= 10.728\end{aligned}$$

which matches the actual 95th percentile travel time developed straight from the data (accounting for slight round-off error).

Note also that the Buffer and Skew Indices can be computed either from the travel times or TTIs. Again for Section 2, the Buffer Index using the TTI distribution is

$$(1.837 - 1.337)/1.337 = 0.374$$

And with the pure travel times is

$$(10.727 - 7.805)/7.805 = 0.374.$$

APPENDIX H

Revised Data-Poor Equations

The original equations that predicted the percentiles of the Travel Time Index (TTI) as a function of the mean TTI used a power function. This form fit the data extremely well when the mean TTI was less than 2.0. This is where the majority of the data points were distributed. However, especially for planning applications, mean TTIs well over 2.0 (i.e., average annual speeds less than 30 mph for the section) are possible. It was observed that the relationship flattened at the upper end of the data, and this flattening was more pronounced for the higher percentiles. Therefore, a natural log relationship was chosen as a more appropriate model form:

$$Y = 1 + a * \ln(x) \tag{H.1}$$

The original power (exponential) relationship for the standard deviation as a function of the mean was verified, but the coefficients were reestimated using an expanded data set.

The original functional form for the prediction of the percentage of trips on-time at different speed thresholds was also assumed to be a power fit, but further investigation revealed that a negative exponential form fit the on-time measures for 50 and 45 mph:

$$Y = \exp(a * [x - 1]) \tag{H.2}$$

A sigmoidal function fit the on-time measure for 30 mph extremely well:

$$Y = a + \frac{b - a}{1 + \exp(w * [x - x0])} \tag{H.3}$$

Note that MeanTTI in the predictive equations is the overall annual average TTI, which includes the effect of demand fluctuations and disruptions. If analysts only have an estimate of the recurring-only average TTI, it should be adjusted upward using the original L03 equation:

$$\text{MeanTTI} = 1.0274 * \text{RecurringMeanTTI}^{1.2204} \tag{H.4}$$

More work remains to be done to make this adjustment more sensitive to the effect of disruptions.

Revised section-level equations are as follows:

$$95\text{th percentile TTI} = 1 + 3.6700 * \ln(\text{MeanTTI}) \tag{H.5}$$

$$90\text{th percentile TTI} = 1 + 2.7809 * \ln(\text{MeanTTI}) \tag{H.6}$$

$$80\text{th percentile TTI} = 1 + 2.1406 * \ln(\text{MeanTTI}) \tag{H.7}$$

$$\text{StdDevTTI} = 0.71 * (\text{MeanTTI} - 1)^{0.56} \tag{H.8}$$

$$\text{PctTripsOnTime50mph} = e^{(-2.0570 * [\text{MeanTTI} - 1])} \tag{H.9}$$

$$\text{PctTripsOnTime45mph} = e^{(-1.5115 * [\text{MeanTTI} - 1])} \tag{H.10}$$

$$\text{PctTripsOnTime30mph} = 0.333 + \left[0.672 / \left(1 + e^{(5.0366 * [\text{MeanTTI} - 1.8256])}\right)\right] \tag{H.11}$$

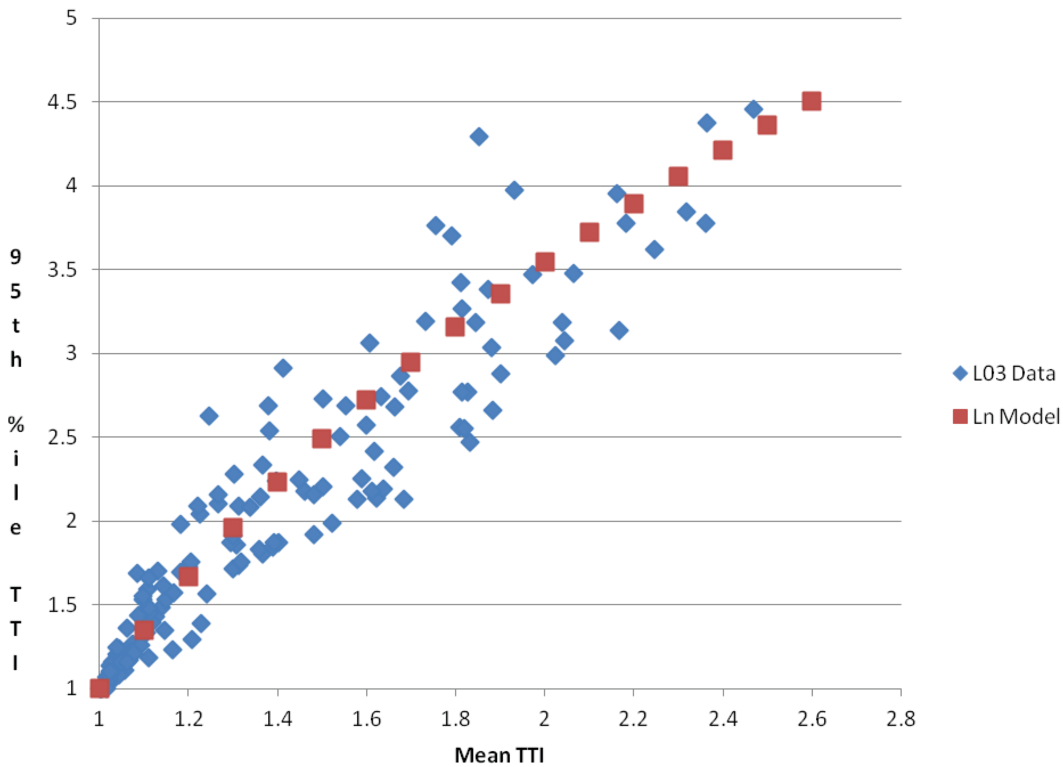


Figure H.1. Relationship between mean TTI and 95th percentile TTI: predicted model superimposed on the data.

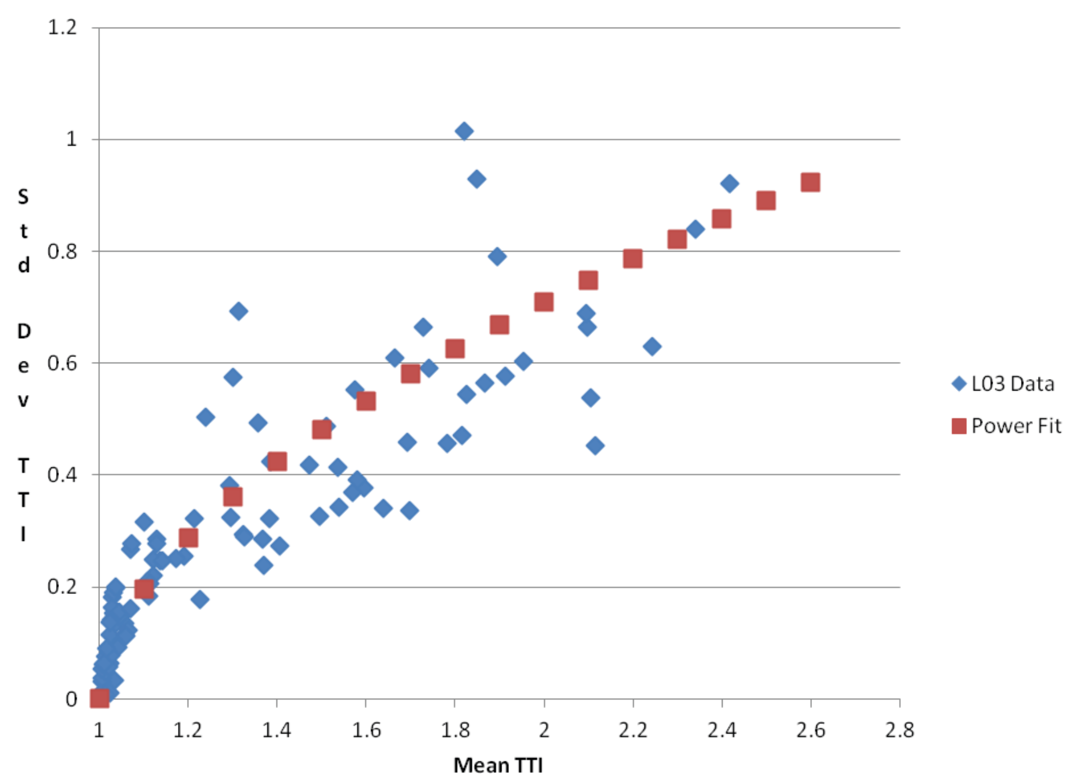


Figure H.2. Relationship between mean TTI and standard deviation of TTI: predicted model superimposed on the data.

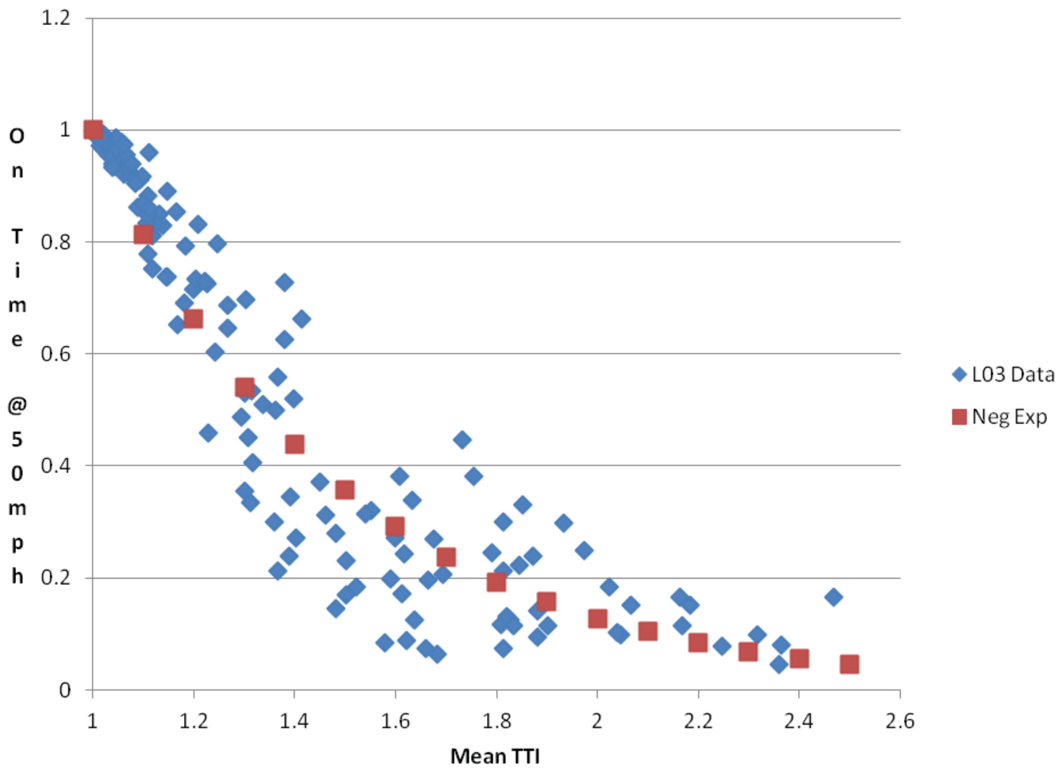


Figure H.3. Relationship between mean TTI and percentage of trips with travel speeds ≥50 mph: predicted model superimposed on the data.

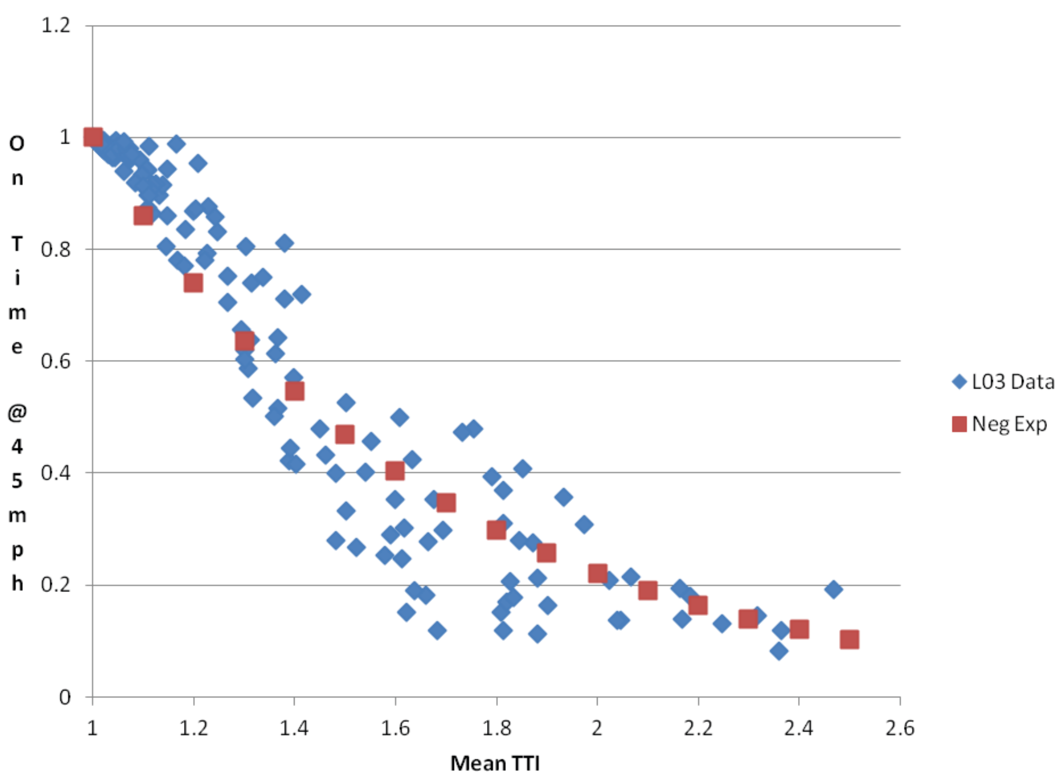


Figure H.4. Relationship between mean TTI and percentage of trips with travel speeds ≥45 mph: predicted model superimposed on the data.

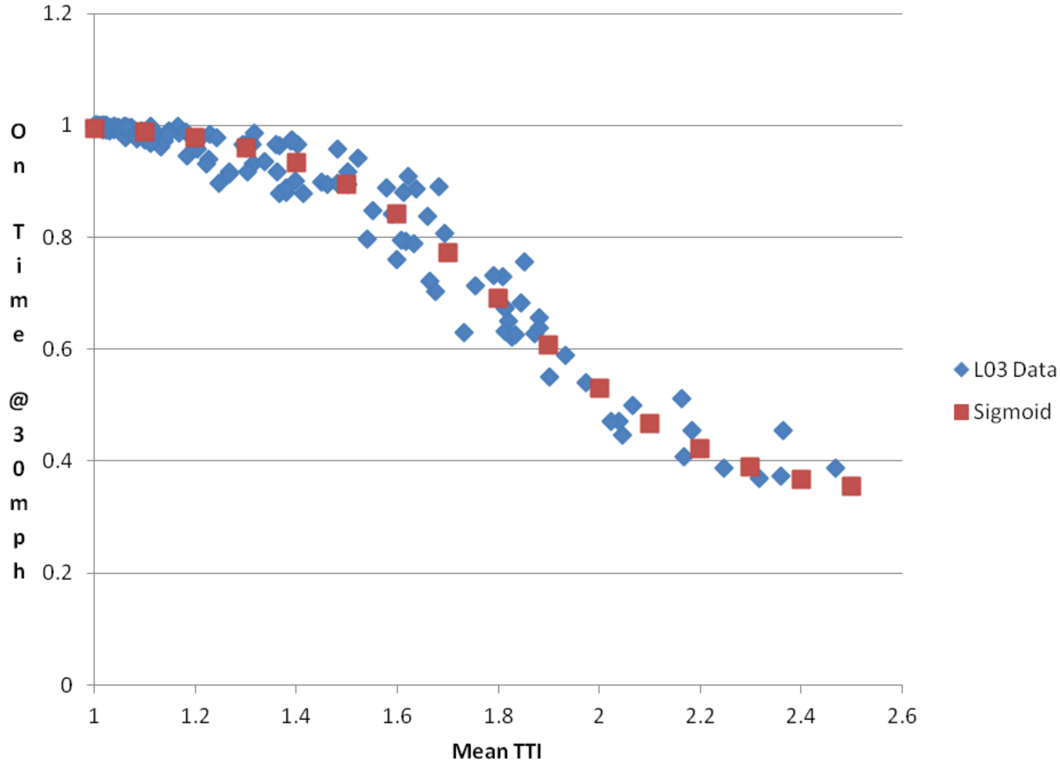


Figure H.5. Relationship between mean TTI and percentage of trips with travel speeds ≥30 mph: predicted model superimposed on the data.

Related SHRP 2 Research

Incorporating Reliability Performance Measures into the Transportation Planning and Programming Processes (L05)

Evaluation of Cost-Effectiveness of Highway Design Features (L07)

Validation of Urban Freeway Models (L33)

Local Methods for Modeling, Economic Evaluation, Justification and Use of the Value of Travel Time Reliability in Transportation Design Making (L35)

Pilot Testing of SHRP 2 Reliability Data and Analytical Products (L38)

Development of Improved Economic Analysis Tools Based on Recommendations from Project C03 (C11)