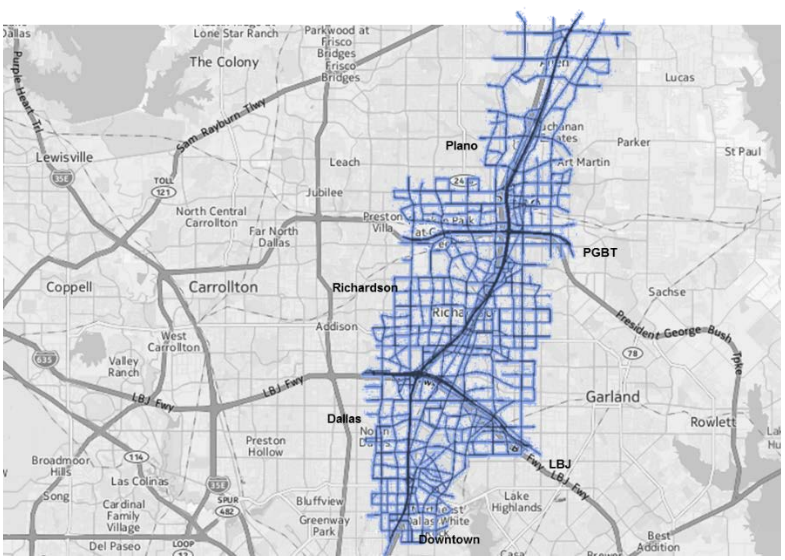
Analysis, Modeling, and Simulation (AMS) Testbed Development and Evaluation to Support Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs

Dallas Testbed Analysis Plan

www.its.dot.gov/index.htm

Final Report — May 11, 2016

FHWA-JPO-16-373



U.S. Department of Transportation

Produced by Booz Allen Hamilton
U.S. Department of Transportation
Intelligent Transportation System (ITS) Joint Program Office (JPO)

Notice

This document is disseminated under the sponsorship of the Department of Transportation in the interest of information exchange. The United States Government assumes no liability for its contents or use thereof.

The U.S. Government is not endorsing any manufacturers, products, or services cited herein and any trade name that may appear in the work has been included only because it is essential to the contents of the work.

[Cover Image by Booz Allen Hamilton]

Technical Report Documentation Page

<table>
<tr><td>1. Report No.
FHWA-JPO-16-373</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Analysis, Modeling, and Simulation (AMS) Testbed Development and Evaluation to Support Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Programs — Dallas Testbed Analysis Plan</td><td colspan="2">5. Report Date
June 16, 2016</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s)
Balaji Yelchuru, Khaled Abdelghany (SMU), Ismail Zohdy, Sashank Singuluri, Raj Kamalanathsharma</td><td colspan="2">8. Performing Organization Report No.</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name And Address

Booz Allen Hamilton
20 M St SE, Suite 1000
Washington, DC 20003</td><td colspan="2">10. Work Unit No. (TRAIS)</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
DTFH61-12-D-00041</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address

U.S. Department of Transportation
Intelligent Transportation Systems–Joint Program Office (ITS JPO)
1200 New Jersey Avenue, SE Washington, DC 20590</td><td colspan="2">13. Type of Report and Period Covered</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="4">15. Supplementary Notes

FHWA Government Task Manager: James Colyar</td></tr>
<tr><td colspan="4">16. Abstract
The primary objective of this project is to develop multiple simulation Testbeds/transportation models to evaluate the impacts of DMA connected vehicle applications and the active and dynamic transportation management (ATDM) strategies. The outputs (modeling results) from this project will help USDOT prioritize their investment decisions for DMA and ATDM programs.

The primary purpose of this report is to document the Analysis Plan for AMS Dallas Testbed. The report expands on detailed testbed description including the geographic location, modes, operational conditions and cluster analysis details. In addition, the plan also provides details on the analysis scenarios, ATDM strategies that are evaluated using the Testbed and the plan to answer ATDM-specific research questions. The analysis plan provides details on the evaluation approach used to answer specific research questions. Additional data used for the testbed development and evaluation are provided in the Appendix</td></tr>
<tr><td colspan="2">17. Key Words

ATDM, DMA, AMS, Selection criteria, Testbeds, active transportation demand managements, modeling, dynamic mobility application, ICM Dallas</td><td colspan="2">18. Distribution Statement</td></tr>
<tr><td>19. Security Class if. (of this report)</td><td>20. Security Class if. (of this page)</td><td>21. No. of Pages
93</td><td>22. Price</td></tr>
</table>

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Acknowledgements

The Booz Allen Hamilton team thanks the U.S.DOT and project team members for their valuable input.

Name	Organization
Alex Skabardonis	Kittelson & Associates
Brandon Nevers	Kittelson & Associates
Chung Tran	Federal Highway Administration (FHWA)
David Roden	AECOM
James Colyar	Federal Highway Administration (FHWA)
Jim Sturrock	Federal Highway Administration (FHWA)
John Halkias	Federal Highway Administration (FHWA)
Karl Wunderlich	Noblis
Matthew Juckes	Transport Simulation Systems (TSS)
Meenakshy Vasudevan	Noblis
Peiwei Wang	Noblis
Pitu Mirchandani	Arizona State University (ASU)
Ram Pendyala	Arizona State University (ASU)
Richard Dowling	Kittelson & Associates
Roemer Alferor	Federal Highway Administration (FHWA)
Thomas Bauer	Traffic Technology Solutions (TTS)

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

The United States Department of Transportation (USDOT) initiated the Active Transportation and Demand Management (ATDM) and the Dynamic Mobility Applications (DMA) programs to achieve transformative mobility, safety, and environmental benefits through enhanced, performance-driven operational practices in surface transportation systems management. In order to explore a potential transformation in the transportation system's performance, both programs require an Analysis, Modeling, and Simulation (AMS) capability. Capable, reliable AMS Testbeds provide valuable mechanisms to address this shared need by providing a laboratory to refine and integrate research concepts in virtual computer-based simulation environments prior to field deployments.

The foundational work conducted for the DMA and ATDM programs revealed a number of technical risks associated with developing an AMS Testbed which can facilitate detailed evaluation of the DMA and ATDM concepts. Therefore, instead of selecting a single Testbed, it is desirable to identify a portfolio of AMS Testbeds and mitigate the risks posed by a single Testbed approach by conducting the analysis using more than an "optimal" number of Testbeds. At the conclusion of the AMS Testbed selection process, four (4) AMS Testbeds were selected to form a diversified portfolio to achieve rigorous DMA bundle and ATDM strategy evaluation: San Mateo (US 101), Pasadena, ICM Dallas, and Phoenix Testbeds. The ICM San Diego Testbed and the Chicago Testbed is planned to be added to the selected Testbeds. The analysis plan helps to test the hypotheses of the DMA and ATDM Programs and evaluate the implementation costs of their applications.

The primary purpose of this report is to document the analysis plan approach for the ICM Dallas Testbed. The ICM Dallas Testbed is developed for the US 75 Corridor in Dallas, Texas. The corridor is a major north-south radial corridor connecting downtown Dallas with many of the suburbs and cities north of Dallas. The corridor is a 20.1 mile long stretch of the US 75 freeway with continuous frontage roads and several parallel and crossing major regional arterial streets. The corridor includes a light-rail line (DART Red Line) and 10 park-and-ride lots. This Testbed will be used to test several ATDM strategies considering a proactive network management approach that adopts simulation-based prediction capabilities. These strategies include Dynamic Shoulder Lane, Dynamic Signal Control, Dynamic Routing, Ramp Metering and Dynamic Priced Parking. The Testbed is developed using the DIRECT software (Dynamic Intermodal Routing Environment for Control and Telematics), which was developed by researchers at Southern Methodist University (SMU).

This report is organized into ten chapters in addition to an Appendix as follows:

- Chapter 1 – Introduction: This chapter presents the report overview and objectives
- Chapter 2 – Testbed Description: This chapter presents the regional characteristics of the Testbed (e.g., geographic characteristic) and the proposed operational conditions.
- Chapter 3 – Analysis Hypotheses: This chapter identifies the ATDM hypotheses that will be tested by the Testbed. The hypotheses to be tested will, in many cases, determine the analysis approach and the operational scenarios to be considered for the specific Testbed.
- Chapter 4 – Analysis Scenarios: This chapter describes the analysis scenarios (combination of operational conditions and alternatives) to be evaluated. The description will include demand

- considerations, vehicle type mix and characteristics, weather conditions, presence and severity of incidents, traveler characteristics, user acceptance rates (key consideration), and others.
- Chapter 5 – Data Needs and Availability: This chapter illustrates the data needs and gaps for the Testbed. In addition, this chapter will provide a detailed plan for data collection and data mining to fill the identified gaps.
- Chapter 6 – Key Assumptions and Limitations: This chapter identifies assumptions, including behavioral responses of drivers, travelers, and system managers, communication technology, and others.
- Chapter 7 – Modeling Approach: This chapter details the modeling approach to test the hypothesis and generate performance measure statistics to compare alternatives and thus evaluate them.
- Chapter 8 – Model Calibration: This chapter outlines the calibration approach and criteria. It is especially important to establish a consistent calibration approach and criteria across multiple Testbeds in order to effectively compare and combine the results.
- Chapter 9 – Evaluation Approach: This chapter presents the system evaluation plan to answer the ATDM research questions based on the analysis conducted and the sensitivity analysis.
- Chapter 10 – Execution Plan: This chapter presents the proposed schedule, budget and resources required to complete the analysis, and key roles and responsibilities.
- Appendix – Cluster Analysis: This chapter documents the process used to identify four baseline scenarios, combining different levels of demand, incident, and weather conditions for testing the performance effects of Active Transportation and Demand Management (ATDM) Program improvements on the ICM Dallas Testbed.

Chapter 2. Testbed Description

2.1 Regional Conditions

The US 75 Corridor in Dallas, Texas is used as one of the AMS Testbeds. As illustrated in Figure 2-1, the US 75 Corridor is a major north-south radial corridor connecting downtown Dallas with many of the suburbs and cities north of Dallas. It contains a primary freeway, an HOV facility in the northern section, continuous frontage roads, a light-rail line, park-and-ride lots, major regional arterial streets, and significant intelligent transportation system (ITS) infrastructure. The length of the corridor is about 21 miles and its width is in the range of 4 miles. The corridor is equipped with 13 Dynamic Message Signs (DMSs) and numerous cameras that cover all critical sections of the US 75 freeway.

The US 75 corridor is a multimodal corridor where travelers can use the following mode options: a) private car; b) transit; c) park-and-ride; and d) carpooling. Transit and park-and-ride travelers are estimated to represent less than 2% of the traveler population. The freeway consists of four lanes per direction for most of its sections with the exception of the section at the High-Five interchange which consists of three lanes only. This lane reduction creates a major bottleneck during the morning and afternoon peak periods. Traffic incidents are also frequently observed nearby this bottleneck.

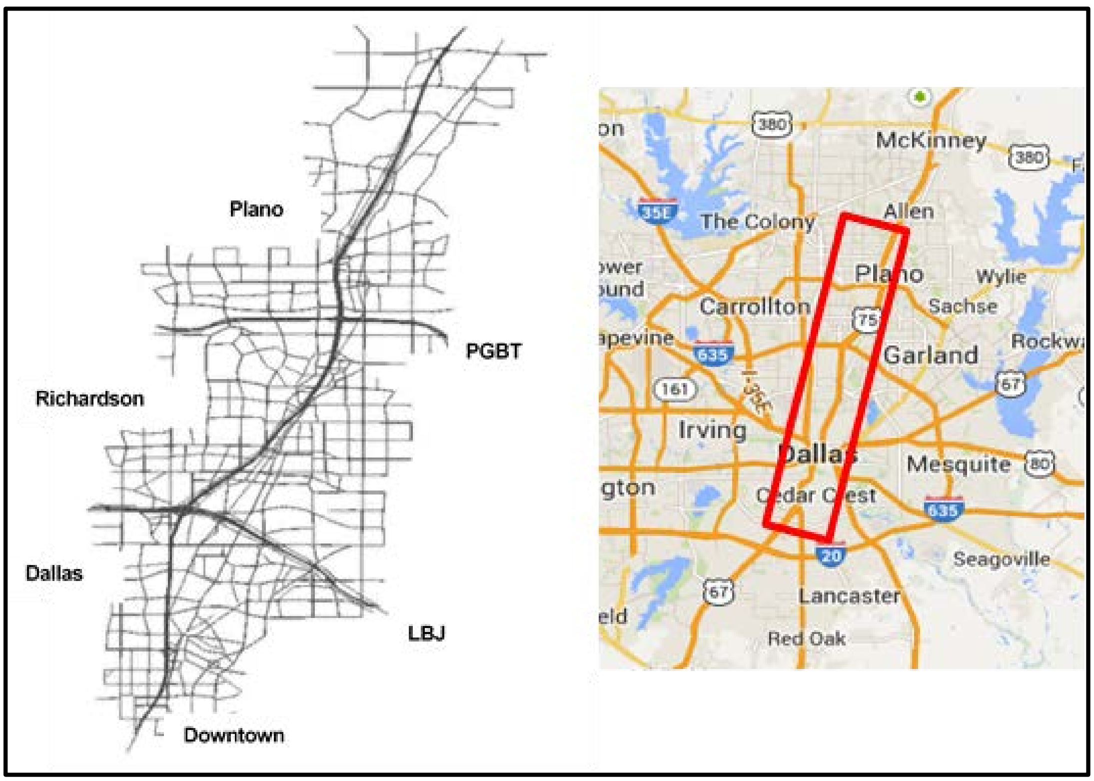


Figure 2-1: US 75 Corridor in Dallas, Texas [Source: SMU & Google Maps]

As presented in details hereafter (see the Appendix), freeway incidents occur at an average frequency of about two incidents per day; resulting in severe congestion especially during the peak periods. In general, the travel time for about 50% of the peak periods is greater than the average travel time recorded during the peak period for the US 75 freeway. This pattern is observed for the northbound and southbound directions. Congestion related to adverse weather conditions has also been observed along the corridor. While such conditions are not frequently encountered, their impact on the overall operational performance of the corridor is significant as drivers are generally not used to driving in such conditions. Based on data collected in 2013, the highest level of congestion is observed along the NB direction in the afternoon peak period with an average speed of about 25 miles per hour. In the morning peak period, congestion is typically observed along the SB direction with an average speed of about 32 miles per hour. The measured daily VMT varies by no more than ±10% from the average value of all days observed. Another important observation is that the morning peak period is generally subjected to more variability in the demand level than the afternoon peak period. The VMT ratio - which is defined as the ratio between the VMT recorded for a peak period and the average VMT for all peak periods in the analysis horizon - ranges from 0.2 to 1.4 in the morning peak period, and it ranges from 0.3 to 1.2 in the afternoon peak periods.

Several operation management strategies have been developed for the US 75 corridor as part of the ongoing ICM project. These strategies focus primarily on a) providing real-time multimodal traveler information that allows travelers to better plan their trips using a newly-developed regional 511 system; and b) implementing efficient traffic management schemes (response plans) to mitigate non-recurrent congestion. These response plans are designed such that they alert travelers of any downstream congestion and provide route diversion instructions using DMSs along the freeway, while increasing the capacity of the diversion routes through dynamically optimizing the timing plans at signalized intersections along these routes. Depending on the severity of the incident, the traffic could be diverted to the frontage roads only or to the frontage roads and other parallel arterials. In the case of severe incidents (e.g., full closure of the freeway), drivers could be guided to use the light rail system, if parking capacity at the stations permits. A decision support system is developed to map the observed operational conditions associated with the incident to the most suitable response plan. The real-time simulation-based prediction subsystem, DIRECT, is used to quantify the potential benefits associated with deploying a response plan as recommended by the decision support system.

2.2 Operational Conditions

For the purposes of conducting analysis, the ICM Dallas Testbed leads will identify up to four operational conditions or baselines using the Cluster Analysis approach defined in the following section under Data Needs for Cluster Analysis below. The details of the cluster analysis approach are described in the **Appendix**.

2.2.1 Data Needs for Cluster Analysis

In general, there are three types of data needed for conducting the cluster analysis and identifying the prevalent operational conditions (as summarized in Figure 2-2):

1. Type 1 data represents the underlying phenomena, i.e., data which are used as input to simulation models (e.g., traffic flows).
2. Type 2 data considers the non-recurring measurements (e.g., incident and weather data).

3. Type 3 data characterizes the system outcomes in terms of specific measures (e.g., travel time) in order to perform the cluster analysis.

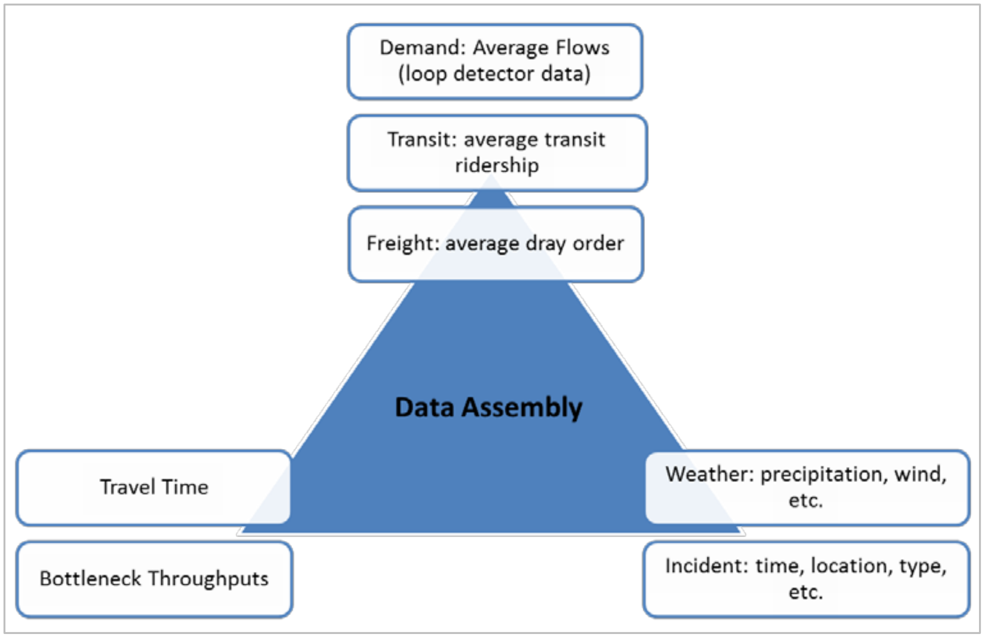


Figure 2-2: Data Assembly Components [Source: SMU]

2.2.1.1 Type 1: Data to Represent Underlying Phenomena

Demand: Traffic flow rate data is available for the US 75 freeway at five minutes resolution. This data is obtained using a series of detectors that are installed along the US 75 freeway with an average spacing of less than two miles. The data for 124 days in 2013 are obtained from DalTrans database (see the Appendix). The vehicle miles traveled (VMT) is used in this analysis to provide information on the demand level in the corridor. The VMT is obtained by multiplying the hourly traffic flow rate observed at each detector by the average spacing between the detectors. The VMT data can be determined for the entire peak period or for each hour in the peak period. The VMT spatial distribution can also be determined to provide information on sections along the freeway that are heavily traveled.

2.2.1.2 Type 2: Data to Represent Non-recurring Measurements

Weather: Weather data was extracted from the national weather service website www.weather.gov for the Love Field airport, which is the closest weather-reporting station to the ICM Dallas Testbed. Out of the 124 days, 26 days with rainy weather were observed in the morning peak period, and 13 days of rainy weather were observed for afternoon peak period. There was no snow, ice, or ground fog conditions during the analyzed horizon.

Incident: Incident logs were obtained for the analysis horizon from the DalTrans database. Incident data includes starting time, duration, location information, type, and number of blocked lanes. About 215 incidents were recorded. The majority of the incidents are due to accidents (about 68%) and stalled vehicles that blocks one or more lanes (about 27%). By way of comparison, for the AM peak period, there are a total of 29 (14%) accidents recorded in the northbound direction, and 41 (19%) accidents recorded in the southbound direction. For the PM peak period, there are a total of 95 (44%) accidents recorded in the northbound direction, and 50 (23%) accidents recorded in the southbound direction. The rate of accidents along the US 75 freeway is about two accidents per day.

2.2.1.3 Type 3: Data to Represent System Outcomes

Bottleneck Throughput: Based on the observed speed profile, several bottlenecks are identified along the US 75 freeway. The nearest detectors upstream and downstream of the locations of these bottlenecks are identified, and their time-dependent flow rate records are used to provide an estimate of the traffic throughput at these bottleneck locations. For instance, the US 75 interchange with the I-635 is a major bottleneck for both freeway directions. Flow rate data for the detectors at Spring Valley Road and Forest Lane are used to estimate the throughput of this bottleneck.

Travel Time: Travel time data for the US 75 freeway for both directions are obtained based on speed data recorded by the detectors. The travel time data, which is available at five minutes resolution, is recorded for the entire length of the freeway section. Thus, it incorporates delays observed at all bottlenecks identified along the freeway.

2.2.2 Cluster Analysis Approach

Once the data are assembled as given in the Appendix, cluster analysis may be performed over all peak periods using cluster analysis algorithms or a statistical package that offers cluster analysis. The potential of using cluster analysis to reduce the number of baseline scenarios was examined. This is a non-traditional use of clustering analysis, since cluster analysis is normally used during the early explorative stage of data analysis to discover structure in the data that has already been collected. For the Dallas Testbed, cluster analysis will be used to condense the amount of data into several scenarios identified by a combination of various traits. These clusters will represent a significant portion of the actual events.

The experimental objective is to estimate the travel time performance and safety benefits of ATDM. The hypothesis is these benefits will be a function of the severity of the baseline congestion and the degree to which the congestion is caused by non-recurring events (such as adverse weather and lane blocking incidents) in addition to factors related to the implementation of ATDM strategies. Based on this hypothesis the following factors were identified as relevant to identifying the baseline scenarios for analysis: demand, weather, and incidents.

The approach to reducing the number of operational scenarios that need to be tested with full simulation analysis is a clustering analysis approach employing the steps listed below.

1. Examine real world conditions at the test site,
2. Identify all of the possible combinations of demand, incidents, weather, and travel time that occurred on approximately 124 days including morning and evening peak periods,
3. Perform a clustering analysis to identify opportunities for collapsing several scenarios into fewer scenarios.
4. Identify the frequency of occurrence for each scenario
5. Assemble a set of operational scenarios that span the range of observed conditions on the corridor.

The final number of operational scenarios to be used in the analysis was determined to be four, based on the twin objectives of the selection process:

- To identify a full range of operational conditions for testing the improvements
- To ensure remaining sufficient project resources for adequate testing options related to the specific design and implementation of the ATDM improvements

The details of the cluster analysis approach and results are presented in the ***Appendix***. A summary of these results for the morning and evening peak periods are given in the next two subsections.

2.2.3 Cluster Analysis Results

Morning Peak Period

The results for the cluster analysis for the morning peak period are presented in Table 2-1. As shown in this table, the analysis resulted in six main clusters. The table gives the number of peak periods and the average value for each variable used in the analysis. Comparing the values of these variables against the average values for all data records, meaningful description of these six clusters can be obtained. For example, comparing the VMT level of these six clusters with the average VMT value, it can be suggested that Clusters 1 and 2 represent low demand operational conditions. Clusters 3, 4 and 5 represent the medium-high demand level. Finally, Cluster 6 represents the high demand level. For the incident severity level, one can describe Cluster 5 as the major incident cluster. In this cluster, the total lane closure is recorded at about 90 minutes. All other clusters are characterized by lower incident severity. The level of precipitation recorded for these clusters is low (less than 7 mm) suggesting that they represent dry operational conditions.

Based on this analysis, the following four operational scenarios are proposed to represent the main operational conditions in the morning peak period:

- Scenario 1: High Demand + Minor Incident + Dry Conditions (Cluster 6)
- Scenario 2: Medium-High Demand + Major Incident + Dry Conditions (Cluster 5)
- Scenario 3: Medium-High Demand + Minor Incident + Dry Conditions (Clusters 3-4)
- Scenario 4: Low Demand + Minor Incident + Dry Conditions (Clusters 1-2)

Table 2-1: Clusters Obtained for the AM Peak Period

Variables	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
No. Records	124	23	18	21	18	9	35
Records (%)	100%	19%	15%	17%	15%	7%	28%
Cluster Description		Low Demand + Minor Incident + Dry	Low Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	Medium to High Demand + Major Incident + Dry	High Demand + Minor Incident + Dry
VMT (vehicle miles)	278,304	97,860	176,172	347,133	338,595	338,045	361,739
Incident severity (min.)	11.72	2.26	7.78	6.43	13.22	90.44	2.11
Level of precipitation (mm)	4	4	3	4	0	7	4
Travel Time (min)	27	20	20	24	29	33	34

Evening Peak Period

The cluster analysis is also conducted for the evening peak periods. Table 2-2 provides a description of the main five clusters obtained based on this analysis. The Table gives the number of peak periods and the average value for each variable used in the analysis. Meaningful description of these five clusters can be obtained by comparing the values of these variables against the average values for all data records. For example, comparing the VMT level of these five clusters with the average VMT value, it can be suggested that Cluster 1 represents low demand operational conditions. Clusters 2 and 5 represent the medium-high demand level. Finally, Clusters 3 and 4 represent the high demand level. For the incident severity level, Cluster 5 is described as the major incident cluster where the total lane closure is recorded at about 140 minutes. Clusters 1, 2, and 3 are characterized as lower incident severity. Cluster 4 is be characterized as medium severity incident. Only Cluster 3 is has a precipitation record of 1.0 mm, suggesting mostly dry operational conditions.

Based on this analysis, the following four operational scenarios are proposed to represent the main operational conditions in the evening peak period.

- Scenario 1: Medium-High Demand + High Severity Incident + Dry Conditions (Cluster 5)
- Scenario 2: High Demand + Medium Severity Incident + Dry Conditions (Cluster 4)
- Scenario 3: Medium-High Demand + Minor Severity Incident + Dry Conditions (Clusters 2)
- Scenario 4: High Demand + Minor Incident + Dry Conditions (Clusters 3)

Table 2-2: Cluster Obtained for the PM Peak Period

Variables	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
No. Records	124	15	25	42	32	10
Records (%)	100%	12%	20%	34%	26%	8%
Cluster Description		Low Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	High Demand + Minor Incident + Dry	High Demand + Medium Severity Incident + Dry	Medium to High Demand + High Severity Incident + Dry
VMT (vehicle miles)	334,175	239,333	324,504	362,694	349,158	332,891
Incident severity (min.)	27.0	10.5	12.6	10.2	32.2	141.6
Level of precipitation (mm)	0	0	0	1	0	0
Travel Time (min)	32	22	23	32	40	45

2.2.4 Hypothetical Operational Conditions

Two hypothetical scenarios are considered for the US 75 Corridor Testbed. These scenarios include:

2.2.4.1 Icing Operational Conditions

The Dallas-Fort Worth region is occasionally subject to icing and light snow conditions for few days in the winter season. The lack of adequate equipment for icing treatment and snow removal as well as the drivers' unfamiliarity with such road conditions usually result in significant operation disruptions. Icy conditions scenario should be modeled where multiple roadways in the network are fully or partially closed. In this scenario, the expected drop in the demand level due to possible closure of schools and businesses, and the choice of some commuters to work from home will be considered. In addition, the change in the drivers' behavior as a result of the icy road conditions will be represented in the model.

2.2.4.2 Evacuation Operational Conditions

The Dallas-Fort Worth region falls along the tornado alley. As such, the area is occasionally under the threat of possible dangerous tornados. While evacuation is rarely instructed for the region, it would be interesting to model an evacuation scenario in which the residents along the US 75 corridor are instructed to evacuate to one or more safe destinations inside or outside the boundaries of the corridor. Demand patterns that represent different evacuation scenarios will be developed. In addition, traffic management strategies such as dynamic shoulder lane and contra-flow operations could be considered in these scenarios.

2.3 Existing Testbed Modeling and Tools Capabilities

The traffic network simulation-assignment model, Dynamic Intermodal Routing Environment for Control and Telematics (DIRECT), is used to model the US 75 Corridor. The DIRECT model is a mesoscopic dynamic traffic assignment simulation model which is developed by researchers at Southern Methodist University (SMU). The model is designed to support multi-resolution modeling and analysis for urban intermodal transportation networks through its capability to interface with regional travel demand models and microscopic simulation models. DIRECT can be used in the offline mode to simulate peak periods considering different combinations of operational conditions and traffic network management strategies. The model can also be used in the online mode to provide real-time traffic network state estimation and prediction as well as emulating the system management process.

DIRECT represents several modal networks through a single integrated multidimensional network. The model represents the travelers' mode and route choice decisions as a function of the congestion evolution in the network which is modeled using a mesoscopic vehicle simulation logic. There is no restriction on the number and types of vehicle classes that may be considered in the model. Typical classes of relevance to the study of intermodal networks include auto, trucks and various types of transit modes. They may also include HOV vehicles. The associated cost vector provides the principal mechanism for designating certain links for particular classes. For example, a very high cost for a single occupant auto on a certain link, coupled with the actual travel time for an HOV, could indicate a special HOV facility. Similarly, a transit network may be represented to allow both exclusive (e.g. underground rail) and shared right of way (e.g. buses). Transfer penalties at major transfer nodes in the network are explicitly modeled. For each traveler, the waiting time till the arrival of the next vehicle that serves the chosen transit line, and the parking cost at the park-and-ride facility are considered while evaluating the different travel options.

The model captures explicitly the dynamic interactions between mode choice and traffic assignment in addition to the resulting evolution of the network conditions. It determines the time-dependent assignment of individual trips to the different mode-routes in the network, including the corresponding arc flows and transit vehicles loading. As illustrated in Figure 2-3, DIRECT, consists of several interconnected components including (a) demand generation; (b) travel behavior; (c) shortest path algorithm; (d) vehicle/transit simulation; and (e) statistics collection. The model can accept as demand input a file listing the population of travelers and their attributes including trip starting time, trip generation location, final destination, and a distinct identification number. The historical route for each travel is also assigned, if available. Alternatively, the model accepts as an input the time-dependent origin-destination demand matrix where a dynamic route assignment is performed internally reflecting the network's congestion dynamics. Each generated traveler is assigned a set of attributes, which include the trip starting time, generation link, final destination and a distinct identification number. A binary indicator variable is also assigned to each traveler to denote car ownership status. In parallel, transit vehicles are generated according to a pre-determined timetable and follow pre-determined routes. Prevailing travel times on each link are estimated using the vehicle simulation component, which moves vehicles capturing the interaction between autos and transit vehicles, as described later. The model also estimates other measures that may be used by travelers as criteria to evaluate the different mode-route options, including travel distances, parking cost, highway tolls, transit fares, out of vehicle time, and number of transfers along the route.

A mode-route decision module is activated at fixed intervals to provide travelers with a superior set of mode-route options. The activation interval (usually in the range of 3 to 5 minutes) is set such that the variation in network conditions is captured, while retaining desirable computational performance for the procedure. The route-mode decision module consists of a multi-objective shortest path algorithm designed for large-scale intermodal transportation networks, which is described separately. This multi-objective shortest path algorithm generates a set of superior paths in terms of the set (or a suitable subset) of attributes listed above. Considering diverse set of travelers' behavioral rules as well as different levels of information availability and response, travelers evaluate the different mode-route options and choose a preferred one. These behavior rules and response mechanisms are implemented through a behavior component within the model as described in a subsequent section.

Each option represents an initial plan that a traveler follows (unless he/she receives en-route real-time information of a better plan) to reach his/her final destination. This plan describes the used mode(s) and the route to be followed including any transfer node(s) along this route. Based on the available options, a traveler may choose a "pure" mode or a combination of modes to reach his/her final destination. If a traveler chooses private car for the whole trip or part of it, a car is generated and moved into the network with a starting time equals to its driver starting time. Each newly generated vehicle is assigned an ID number that is unique to this vehicle. Vehicles are then moved in the network subject to the prevailing traffic conditions until they reach their final destinations or the next transfer node along the pre-specified route (in the case of an intermodal trip).

If a traveler chooses a transit mode, he/she is assigned to a transit line such that the destination of this passenger is a node along the route followed by the bus line. If no single line is found or if the passenger is not satisfied with the available single line, the passenger is assigned to a path composed of two lines with one transfer node, such that the destination of the passenger is a node along the route followed by the second bus. If no such two lines are found, the search is continued for three lines with two transfers. It is assumed that no passenger would be willing to incur more than two transfers in his/her trip. Thus, if no path with a maximum of two transfers is available, the trip is indicated as infeasible. Given the passenger's origin node, the nearest transit stop along the first line in the passenger's path is determined, and he/she waits until the arrival of the next vehicle that serves that transit line. When a transit vehicle arrives at a certain stop, all passengers waiting for a vehicle serving this specific line board this vehicle (subject to a capacity constraint) and head towards either their final destination or the next transfer node along their route.

Upon the arrival of a vehicle (private car or transit vehicle) to a certain destination node, this destination is compared to the final destinations of the travelers on board. If it matches the final destination of a traveler, the current time is recorded for this traveler as his/her arrival time. If they are different, the traveler transfers to the next transit line in his/her plan. The nearest stop is again determined and the traveler waits for his/her next transit vehicle. The time difference between arrival at the transfer node and boarding of the next line is calculated as the waiting time at the current transfer node for this traveler. This process is continued till all vehicles reach their final respective destinations. If a traveler misses the initially assigned transit vehicle because of late arrival or because the vehicle does not have enough space, the model allows the traveler to re-plan his/her trip. The available options are regenerated for this traveler and he/she makes a selection according to the decision process described in a subsequent section.

Prevailing travel time on each link is estimated using the vehicle simulation component which adopts a mesoscopic simulation approach. In addition, a shortest path algorithm is activated at fixed intervals to generate the set of superior paths between every origin-destination pair. The activation interval (usually in the range of three to ten minutes) is set such that the variation in network conditions is captured, while retaining desirable computational performance. The updated routing information is assumed to be available to travelers with access to en-route information (e.g., dynamic message signs (DMSs)). Vehicles move in the network subject to the prevailing traffic conditions until they reach their final destinations along the pre-specified routes. If a driver receives en-route information and she/he presumably complies with the provided information, the route of this driver is updated accordingly.

As mentioned earlier, each traveler is assigned a route to represent her/his historical route. If the traveler encounters non-recurrent congestion along her/his route, this traveler might decide to change the historical route to avoid this congestion. The model is capable of modeling travelers route diversions based on I) their own perception of the congestion ahead, II) received information from DMSs along their routes, or III) received in-vehicle rerouting information. For the first case, given the travelers on a certain link, if the traffic density of the next few links along their routes is higher than a pre-defined threshold, a percentage of those travelers are assumed to change their routes only if the anticipated saving in the travel time by following the new routes is acceptable. For the other two cases, a bounded-rational behavior is assumed. Travelers who are willing to comply with the information compare the new route with their current route and divert only if the travel time saving is greater than a certain threshold. While all travelers are assumed to access the DMSs information, only a pre-determined percentage of the travelers are assumed to have access to in-vehicle re-routing information. For DMSs installed on the freeways, travelers are assumed to exit from one of the downstream ramps according to a pre-defined distribution. For in-vehicle information, the diversion occurs at the next node in their routes after the information is received.

DIRECT is capable of modeling dynamic signal control in which the timing plan could vary by time of day following a known schedule, or due to implementing a specific traffic management plan in response to a non-recurrent congestion situation. For each timing plan, the phases are defined in terms of permissible maneuvers and the green/red time split. Lanes associated with each permissible maneuver are also defined. In each simulation interval, if a lane is serving a movement that is part of the green phase, the saturation flow rate for this lane is used to discharge the vehicles in that lane. As the phase changes to red, a queue is formed and incoming vehicles are assumed to join this queue. For normal operations, the schedule for these timing plans is assumed to be given. If the time meets the start time of a new timing plan, this plan is activated. The phasing and time split data for all intersections are updated according to this timing plan. Similarly, a new timing plan could be activated as part of a deployed response scheme. Once the response scheme is deactivated, due to the clearance of the incident, the original timing plan is resumed or the next scheduled plan is activated if its starting time has been reached while the response scheme was active.

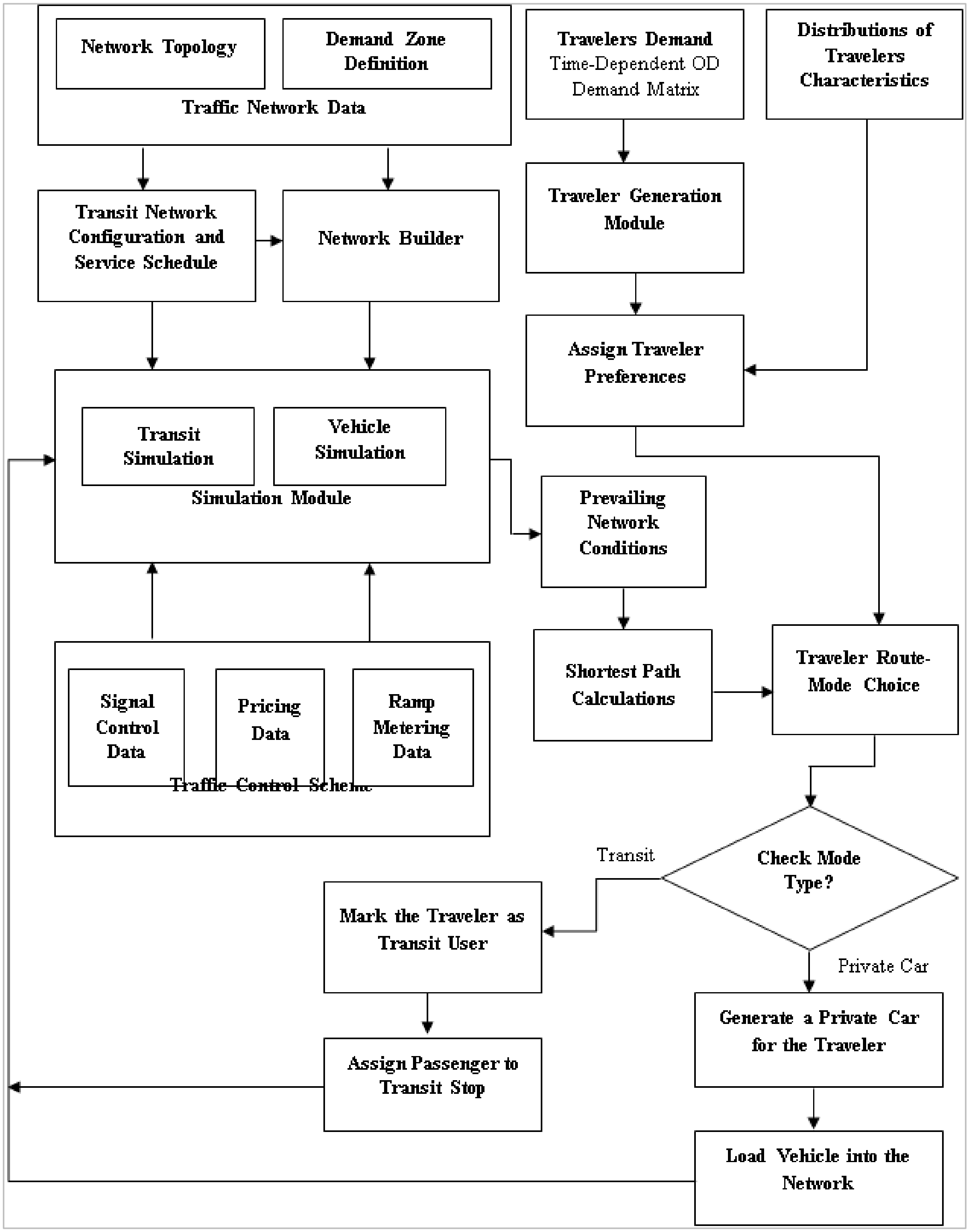


Figure 2-3: DIRECT Modeling Framework [Source: SMU]

Chapter 3. Analysis Hypotheses

The ICM Dallas Testbed analysis will focus on the ATDM applications evaluation. This section details the analysis hypotheses to address the different ATDM research questions by the ICM Dallas Testbed. Table 3-1 presents the general hypothesis corresponding to each ATDM research question.

Table 3-1: ATDM Research Questions and the Corresponding Hypothesis

ID	Research Question Category	ATDM Research Question Category	Hypothesis
1	**Synergies and Conflicts**	1. Are ATDM strategies more beneficial when implemented in isolation or in combination (e.g., combinations of ATM, ADM, or APM strategies)? 2. Which ATDM strategy or combinations of strategies yield the most benefits for specific operational conditions? 3. What ATDM strategies or combinations of strategies conflict with each other?	Some ATDM strategies could result in more benefits when deployed together, while other strategies could be conflicting with each other; resulting in a reduction in the overall benefits. The extent of synergy or conflict among ATDM strategies depend on the prevailing traffic network conditions and the settings used for these strategies.
2	**Prediction Accuracy**	4. Which ATDM strategy or combination of strategies will benefit the most through increased prediction accuracy and under what operational conditions? 5. Are all forms of prediction equally valuable, i.e., which attributes of prediction quality are critical (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction) for each ATDM strategy?	The value of prediction will vary depending on the operational conditions experienced in the system (e.g., incidents, special events, severe weather). The value of prediction will be higher under non-recurrent congestion situations.

3	**Active Management or Latency**	6. Are the investments made to enable more active control cost-effective? 7. Which ATDM strategy or combinations of strategies will be most benefited through reduced latency and under what operational conditions?	ATDM is most effective when time lag (latency) between detection/prediction of queues, shockwaves, bottlenecks, incidents, and breakdown conditions, and strategies deployed by System Managers is reduced.
4	**Operational Conditions, Modes, Facility Types with Most Benefit**	8. Which ATDM strategy or combinations of strategies will be most beneficial for certain modes and under what operational conditions? 9. Which ATDM strategy or combinations of strategies will be most beneficial for certain facility types (freeway, transit, arterial) and under what operational conditions? 10. Which ATDM strategy or combinations of strategies will have the most benefits for individual facilities versus system-wide deployment versus region-wide deployment and under what operational conditions?	Most benefits will be achieved in the high congestion and for severe incident scenarios. ATDM strategies generally enhance freeway operations more than arterial streets.
5	**Prediction, Latency, and Coverage Tradeoffs**	11. What is the tradeoff between improved prediction accuracy and reduced latency with existing communications for maximum benefits? 12. What is the tradeoff between prediction accuracy and geographic coverage of ATDM deployment for maximum benefits? 13. What will be the impact of increased prediction accuracy, more active management, and improved robust behavioral predictions on mobility, safety, and environmental benefits? 14. What is the tradeoff between coverage costs and benefits?	Increased prediction accuracy, more active management (reduced latency), and improved robust behavioral predictions result in significant mobility, safety, and environmental benefits. Key attributes of prediction quality (e.g., prediction horizon, prediction accuracy, speed of prediction, and geographic prediction cordon) vary criticality depending on ATDM strategies considered and operational conditions encountered. Increasing the prediction horizon and the size of coverage area enhances decision making on ATDM

			strategies to be used, and hence improves the overall network performance. Longer execution time is expected (i.e., prediction latency) with increasing the prediction horizon and the size of the coverage area.
6	**Connected Vehicle Technology and Prediction**	15. Are there forms of prediction that can only be effective when coupled with new forms of data, such as connected vehicle data?	Prediction can be most effective only when coupled with data capture and communications technologies that can systematically capture motion and state of mobile entities, and enable active exchange of data with and between vehicles, travelers, roadside infrastructure, and system operators.
7	**Short-Term and Long-Term Behaviors**	16. Which ATDM strategy or combinations of strategies will have the most impact in influencing short-term behaviors versus long term behaviors and under what operational conditions?	Accurate travel time information enables travelers to better plan their trips and activities. Departure time shift to non-peak periods and mode shift to transit/carpooling enhance the overall network performance. Travelers' behavior related to route, mode, departure time choices could change from day-to-day based on perceived travel experience in previous days.

Chapter 4. Analysis Scenarios

This section describes the analysis scenarios to test the different ATDM strategies. An analysis scenario is defined as “a combination of operational conditions, applications (or combination of applications) and the alternatives to be used to test hypotheses”.

Scenarios should be developed for the range of operational conditions of greatest interest (to be determined using historical data) to the Testbed site in light of its analysis objectives and based on the current conditions of the Testbed. This section presents a description of the analysis scenarios to be created as part of this analysis in addition to the baseline description.

4.1 ATDM Strategies to be addressed by Testbed

This section presents the proposed applications evaluated by the Testbed. The ICM Dallas Testbed will only focus on the ATDM applications as summarized in Table 4-1. ATDM strategies are divided among the Testbeds while taking into consideration the suitability of the strategy to the testbed and the amount of effort needed to model a strategy using the testbed,

Table 4-1: ATDM Applications Evaluated/Addressed by the ICM Dallas Testbed

ATDM Strategy Type	Application	Dallas
Active ***Traffic*** Management Strategies	Dynamic Shoulder Lanes	Yes
	Dynamic Lane Use Control	-
	Dynamic Speed Limits	-
	Queue Warning	-
	Adaptive Ramp Metering	Yes
	Dynamic Junction Control	-
	Dynamic Merge Control	-
	Dynamic Traffic Signal Control	Yes
	Transit Signal Priority	-
	Dynamic Lane Reversal Or Contraflow Lane Reversal	-
Active ***Demand*** Management Strategies	Dynamic Ridesharing	-
	Dynamic Transit Capacity Assignment	-
	On-demand Transit	-
	Predictive Traveler Information	Yes
	Dynamic Pricing	-
	Dynamic Fare Reduction	-
	Transfer Connection Protection	-
	Dynamic HOV / Managed Lanes	-
	Dynamic Routing	Yes
Active ***Parking*** Management Strategies	Dynamically Priced Parking	Yes
	Dynamic Parking Reservation	-
	Dynamic Wayfinding	-
	Dynamic Overflow Transit Parking	-

4.2 Performance Measures

The performance measures should provide an understanding of travel conditions in the study area; and demonstrate the ability of ATDM strategies to improve corridor mobility, throughput, and reliability. Below is the list of performance measures for each tested ATDM scenario:

- Mobility – travel time and delay;
- Reliability – the relative predictability of the travelers travel time;
- Emissions – carbon monoxide (CO), carbon dioxide (CO_2), Nitrogen Oxides (NOx) and Hydrocarbons (HC);
- Fuel Consumption – The consumed gallons per mile (Gallons/mile).

The modeling framework for the ICM Dallas testbed adopts mesoscopic simulation logic, which is not suitable to directly evaluate safety. However, safety benefits will be estimated indirectly as a function of travel time savings and associated congestion reduction. To estimate safety improvements, models in the literature will be reviewed for correlation level of safety to independent variables such as VMT and total travel time. For example, the final report for SHRP 2 Reliability Project L07 titled Further Development of the Safety and Congestion Relationship for Urban Freeways, August 2014, could be a good source for such models[1].

As the simulation Testbed is used to emulate real-time traffic network management decisions, the travel time is recorded every five minutes to capture the dynamic effect of any deployed strategies. The travel time associated with activating the ATDM strategies could be compared to the travel time in the do-nothing scenario. The percentage saving in the travel time is a good measure for the effectiveness of the ATDM strategies deployed in the network. Figure 4-1 provides an example of the proposed measures of performance (MOP) for a typical operational day. As shown in the figure, the traffic management scheme deployed in this example was successful in most parts of the day as positive travel time savings is obtained.

[1] I. B. Potts, D. W. Harwood, C. A. Fees, and K. M. Bauer, Further Development of the Safety and Congestion Relationship for Urban Freeways, Final report for SHRP 2 Reliability Project L07, August 2014,
http://onlinepubs.trb.org/onlinepubs/shrp2/SHRP2prepubL07SupplementalReport.pdf: Access Date December 2015.

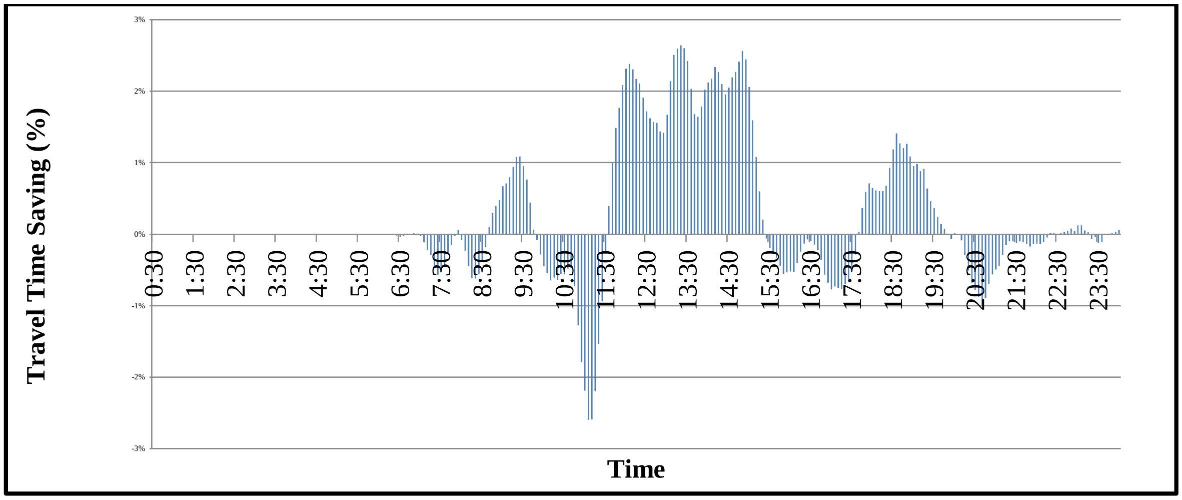


Figure 4-1: Example of MOP for Real-time Traffic Management System [Source: SMU]

4.3 Analysis Phases and Scenarios

This section provides more details on the different simulation experiments that will be conducted as part of this study. These simulation experiments are grouped into three main phases. The multi-phase approach also enables knowledge sharing among the different Testbeds, and also facilitates the integration of any newly developed models/methodologies generated from other ongoing projects that are related to this project. The tables below provide a summary of the scenarios that are considered in each of these phases. As shown in the tables, each scenario is described in terms of the combination of operational conditions and ATDM strategies to be modeled and the prediction attributes to be considered for each scenario. The list of research questions that each scenario contributes towards their answer is also given.

4.3.1 Phase 1 of the Analysis Plan

Table 4-2 provides the list of base case scenarios to be modeled in Phase 1. These base cases represent the four main operational conditions identified using the cluster analysis. As shown in the table, no ATDM strategies are considered. Thus, these scenarios are used to represent the do-nothing condition. The results of these simulation runs will be used as benchmarks to evaluate the effectiveness of the ATDM strategies.

Table 4-3 provides the list of scenarios to be conducted in phase 1. In general, these scenarios are used to:

a) Quantifying the synergy and conflict among the different ATDM strategies
b) Quantifying the benefits for the different facilities and modes considering different operational conditions

The four main operational conditions scenarios, identified in the cluster analysis, are considered in this phase. These four scenarios are:

- High Demand + Minor Severity Incident + Dry Conditions
- High Demand + Medium Severity Incident + Dry Conditions

- Medium/High Demand + Minor Severity Incident + Dry Conditions
- Medium/High Demand + High Severity Incident + Dry Conditions

Scenarios 7 to 13 are devoted to studying the effectiveness of different ATDM strategies in the high demand conditions, while scenarios 14 to 20 examine their effectiveness in the medium/high demand conditions. Different combinations of ATDM strategies were examined in these set of experiments to allow evaluating the potential synergy and conflict among these strategies. For example, scenario 9 examines the dynamic signal control strategy. Scenario 10 examines the effect of combining the dynamic signal control strategy with the dynamic routing strategy. Scenario 12 further examines the possible additional improvement in the network performance if the ramp metering strategy is considered. To summarize the following list of ATDM strategies and combinations of strategies will be considered in this phase:

Group 1: Dynamic Shoulder Lane
Dynamic Shoulder Lane + Dynamic Routing

Group 2: Dynamic Signal Control
Dynamic Signal Control + Dynamic Routing

Group 3: Ramp Metering
Dynamic Signal Control + Dynamic Routing + Ramp Metering

Group 4: Dynamic Priced Parking

For both demand levels, different levels of incident severity are considered. For example, scenario 8a is a replication of scenario 8 (both are high demand scenarios) with the only difference is the severity of the incident. Similarly, both scenario 15 and 15a represents medium/high demand level with different incident severity. Such experiments allow examining the effectiveness of the ATDM strategies considering different demand levels and different incident severities.

In this phase, the following will be examined: a) the effect of being able to predict future congestion/demand; and b) exploring the effect of travelers' response to information on the effectiveness of the ATDM strategies are considered.

For example, the demand prediction is assumed to be an input to the simulation model. The effect of the weather conditions and the ATDM strategies on the level of demand will be estimated and used by the model to capture possible effect on the network performance. Also, to capture the sensitivity of travelers' access and response to traveler information on the effectiveness on the dynamic routing strategies, scenarios that include this strategy will be modeled considering three different values of the model's parameters that represent the travelers' access and compliance with information (e.g., 10%, 15%, and 20%).

Table 4-2: A Summary of Modeled Base Case Scenario in Phase 1

Scenario ID	Scenario Description: Operation Conditions and ATDM Strategies	Prediction Attributes	Research Questions addressed by the Scenario
1	High Demand + Dry Conditions	Do Nothing	Base case
2	High Demand + Minor Severity Incident + Dry Conditions	Do Nothing	Base case
3	High Demand + Medium Severity Incident + Dry Conditions	Do Nothing	Base case

4	Medium/High Demand + Dry Conditions	Do Nothing	Base case
5	Medium/High Demand + Minor Severity Incident + Dry Conditions	Do Nothing	Base case
6	Medium/High Demand + High Severity Incident + Dry Conditions	Do Nothing	Base case

Table 4-3: Summary of Simulation Scenarios Considered in Phase 1

Scenario ID	Scenario Description: Operation Conditions and ATDM Strategies	Prediction Attributes	Research Questions addressed by the Scenario
7	High Demand + Medium Severity Incident + Dynamic Shoulder Lane	Predict Future Congestion/ Demand	1,2,3,5,8,9,10
8	High Demand + Medium Severity Incident + Dynamic Shoulder Lane + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
8a	High Demand + Minor Severity Incident + Dynamic Shoulder Lane + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
9	High Demand + Medium Severity Incident + Dynamic Signal Control	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
10	High Demand + Medium Severity Incident + Dynamic Signal Control + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
10a	High Demand + Minor Severity Incident + Dynamic Signal Control + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
11	High Demand + Medium Severity Incident + Ramp Metering	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
12	High Demand + Medium Severity Incident + Dynamic Signal Control + Dynamic Routing Ramp Metering	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
13	High Demand + Medium Severity Incident + Dynamic Priced Parking	Predict Future Congestion Traveler Response	1,2,3,8,9,10

14	Medium/High Demand + High Severity Incident + Dynamic Shoulder Lane	Predict Future Congestion/ Demand	1,2,3,5,8,9, 10
15	Medium/High Demand + High Severity Incident **+** Dynamic Shoulder Lane + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
15a	Medium/High Demand + Minor Severity Incident **+** Dynamic Shoulder Lane + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
16	Medium/High Demand + High Severity Incident **+** Dynamic Signal Control	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9, 10
17	Medium/High Demand + High Severity Incident + Dynamic Signal Control + Dynamic Routing	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
17a	Medium/High Demand + Minor Severity Incident + Dynamic Signal Control + Dynamic Routing	Predict Future Congestion/ Demand Time Horizon Sensitivity Traveler Response	1,2,3,5,8,9,10
18	Medium/High Demand + High Severity Incident + Ramp Metering	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10
19	Medium/High Demand + High Severity Incident + Dynamic Signal Control + Dynamic Routing Ramp Metering	Predict Future Congestion/ Demand Traveler Response	1,2,3,5,8,9,10
20	Medium/High Demand + High Severity Incident + Dynamic Priced Parking	Predict Future Congestion/ Demand Traveler Response	1,2,3,8,9,10

4.3.2 Phase 2 of the Analysis Plan

Table 4-4 provides a summary of scenarios that are modeled in phase 2. These scenarios are designed to:

a) Capturing the effect of prediction horizon sensitivity
b) Examining the effect of the overall prediction accuracy on the effectiveness of the ATDM strategies.

In addition, similar to the experiments conducted in phase 1, these scenarios will also help in quantifying the synergy and conflict among the different ATDM strategies and also quantifying these benefits for the different facilities and modes considering different operational conditions.

The four main operational conditions scenarios, identified in the cluster analysis, are also considered in this phase. These scenarios are:

- High Demand + Minor Severity Incident + Dry Conditions
- High Demand + Medium Severity Incident + Dry Conditions
- Medium/High Demand + Minor Severity Incident + Dry Conditions
- Medium/High Demand + High Severity Incident + Dry Conditions

In this phase, Dynamic Signal Control Strategy and a strategy combination in which the Dynamic Signal Control Strategy is integrated with Dynamic Routing will be examined.

Group 1: Dynamic Signal Control
Dynamic Signal Control + Dynamic Routing

In these scenarios, the effect of two prediction attributes will be examined which are:

I. The prediction horizon
II. The prediction accuracy.

For example, to capture the prediction horizon sensitivity, these simulation runs will be repeated considering different values for the prediction horizon which is set at 20, 30 and 60 minutes, respectively. In addition, the prediction accuracy sensitivity will be modeled through introducing different levels of error for the predicted demand (e.g., 10% and 20%). This error is introduced to be able to examine the robustness of the ATDM strategies considering different levels of prediction accuracy.

Table 4-4: Summary of Simulation Scenarios Considered in Phase 2

Scenario ID	Scenario Description: Operation Conditions and ATDM Strategies	Prediction Attributes	Research Questions addressed by the Scenario
21	High Demand + Medium Severity Incident + Dynamic Signal Control	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10
22	High Demand + Medium Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10

22a	High Demand + Minor Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10
23	Medium/High Demand + High Severity Incident **+** Dynamic Signal Control	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10
24	Medium/High Demand + High Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10
24a	Medium/High Demand + Minor Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/ Demand Prediction Horizon Sensitivity Prediction Accuracy Sensitivity	1,2,3,5,8,9,10

4.3.3 Phase 3 of the Analysis Plan

Table 4-5 provides a summary of the simulation scenarios that will be conducted in phase 3. The scenarios in phase 3 are designed to capture the trade-off between: a) prediction latency; and b) prediction coverage extent.

In addition, similar to the experiments conducted in phases 1 and 2, these scenarios will also help in quantifying the synergy and conflict among the different ATDM strategies and also quantifying these benefits for the different facilities and modes considering different operational conditions.

The four main operational conditions scenarios, identified in the cluster analysis, are also considered in this phase. These scenarios are:

- High Demand + Minor Severity Incident + Dry Conditions

- High Demand + Medium Severity Incident + Dry Conditions
- Medium/High Demand + Minor Severity Incident + Dry Conditions
- Medium/High Demand + High Severity Incident + Dry Conditions

In this phase, Dynamic Signal Control Strategy and a strategy combination where the Dynamic Signal Control Strategy is integrated with Dynamic Routing will be examined.

Group 1: Dynamic Signal Control
Dynamic Signal Control + Dynamic Routing

In these scenarios, the effect of two prediction attributes will be examined which are:

I. Prediction latency
II. Area coverage

To examine the effect of prediction latency, the effectiveness of the ATDM strategies considering three values for the prediction update cycle: 3, 5 and 10 minutes will be compared. The 3 minutes cycle represents the case of frequent update of the network state prediction and active management, while the 10 minutes cycle represents a scenario with excessive prediction and management latency.

The coverage extent is represented by predicting the network state conditions for a subarea rather than the entire network. The boundaries of the subarea could be determined considering a certain distance from the location of the modeled incident. For these set of simulation experiments, a special module will be developed to extract the sub-network of the modeled subarea and properly represent its demand pattern.

Phase 3 will also be used to model the two hypothetical scenarios that are described earlier. The first hypothetical scenario represents a day with icing conditions and low demand. In this scenario, the dynamic routing strategy will be activated to provide travelers with information on road closure and expected delays.

In the second scenario, a hypothetical evacuation scenario is modeled. A combination of ATDM strategies which include dynamic shoulder lane, dynamic signal control and dynamic routing is considered for this scenario.

Table 4-5: Summary of Modeled Scenarios in Phase 3

Scenario ID	Scenario Description: Operation Conditions and ATDM Strategies	Prediction Attributes	Research Questions addressed by the Scenario
25	High Demand + Medium Severity Incident + Dynamic Signal Control	Predict Future Congestion/Demand Prediction Latency Sensitivity Coverage Extension Variation	1,2,3,5,8,9,10
26	High Demand + Medium Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/Demand Prediction Latency Sensitivity	1,2,3,5,8,9,10

		Coverage Extension Variation	
26a	High Demand + Minor Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/Demand Prediction Latency Sensitivity Coverage Extension Variation	1,2,3,5,8,9,10
27	Medium/High Demand + High Severity Incident **+** Dynamic Signal Control	Predict Future Congestion/Demand Prediction Latency Sensitivity Coverage Extension Variation	1,2,3,5,8,9, 10
28	Medium/High Demand + High Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/Demand Prediction Latency Sensitivity Coverage Extension Variation	1,2,3,5,8,9,10
28a	Medium/High Demand + Minor Severity Incident + Dynamic Signal Control+ Dynamic Routing	Predict Future Congestion/Demand Prediction Latency Sensitivity Coverage Extension Variation	1,2,3,5,8,9,10
29	Low Demand + Snow + Dynamic Routing	Predict Future Congestion/Demand	Hypothetical scenario
30	Evacuation + Dynamic Shoulder Lane + Dynamic Signal Control + Dynamic Routing	Predict Future Congestion/Demand	Hypothetical scenario

Chapter 5. Data Needs and Availability

This section discusses the data needs, availabilities, and shortages for the Testbed. In addition, this section will provide a detailed plan for data collection and data mining to fill the identified data shortages. For unresolved data shortages, a plan to overcome issues pertaining to lack of data will be developed to ensure the Testbed can be successfully built.

5.1 Data Needs

The modeled scenarios cover different operational conditions for the US 75 Testbed. In addition to the typical day of operations, these conditions include:

a) High demand with no incident
b) High demand with low/moderate severity incident
c) High demand with high severity incident
d) High demand with adverse weather conditions

The DIRECT model will be calibrated offline to represent these conditions. The calibration effort involves adjusting the time-dependent travel demand matrix and the flow propagation models along the different highway facilities. Data required to perform the model calibration includes:

a) Hourly vehicle counts along a number of critical links and screenlines
b) Speed profile along the freeway facility
c) Travel time along strategic routes.

The appendix provides a summary of the data assembled for 124 days 2013. These data include

a) Traffic flow rate at all freeway detectors
b) Speed and density profiles along the freeway
c) Incident records
d) Time-dependent travel time

This data will be used for the model calibration and validation to ensure that the overall travel pattern and associated congestion phenomena in the corridor are accurately captured.

In addition to the offline calibration effort, the DIRECT platform will be used in the online mode to emulate real-time system management. For that purpose, real-time traffic counts data, incident data, and weather data will be used in estimating and predicting the network state conditions.

5.2 Available Data

Adequate of traffic data is available for the ICM Dallas Testbed. These data include:

a) Historical traffic data for offline calibration of the DIRECT model

b) Real-time traffic data for online calibration and to emulate the system management process
c) Validating the model's prediction accuracy.

Main data elements that are readily available include:

- Time-dependent traffic flow, speed and density data (volume, speed, etc.)
- Time-dependent travel times
- Work zone data
- Incident information, etc.
- Video surveillance data
- Signal plans, traffic control device data
- Parking occupancy for selected park-and-ride facilities
- Transit ridership

The traffic detector data for the freeway links in the US 75 corridor, which is provided as web services by Texas Department of Transportation. The data is published at five minutes resolution and gives the speed, density and volume for the different freeway links. The data is given in an XML format with tag definition for the different data fields. A map view of the data is also provided as illustrated in Figure 5-1.

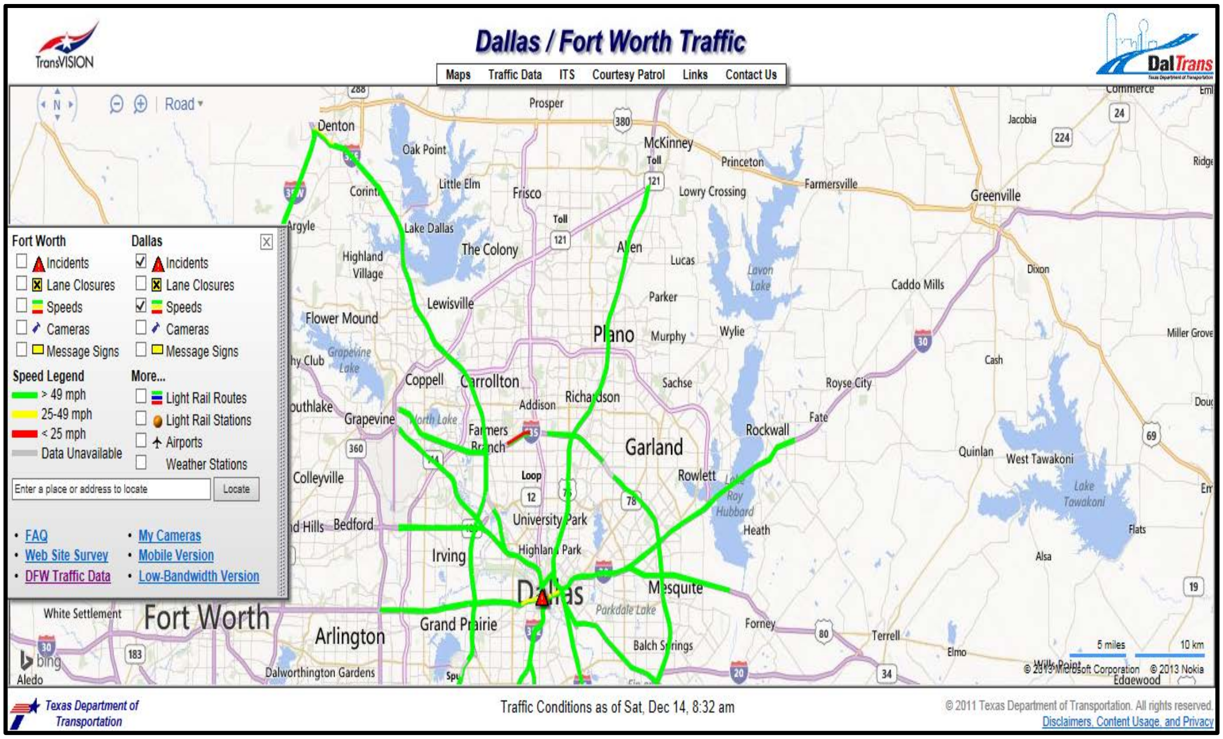


Figure 5-1: Map View of Real-time Traffic Detector Data for US 75 Corridor [Source: DalTrans]

Figure 5-2 and Figure 5-3 provide an example of the speed profile along the US 75 freeway for the southbound and northbound directions respectively. These speed profiles were produced using historical data from Texas Department of Transportation for year 2011. As shown in Figure 5-2 (southbound direction), in the morning peak period (left side of the figure), more congestion is observed on the northern section of the freeway up to the interchange with the Lyndon B. Johnson (LBJ) freeway. In the evening peak period, congestion is observed south of the interchange with the LBJ freeway. For the northbound direction depicted in Figure 5-3, most of the congestion occurs during the evening peak period, which extends along the almost entire section of the freeway.

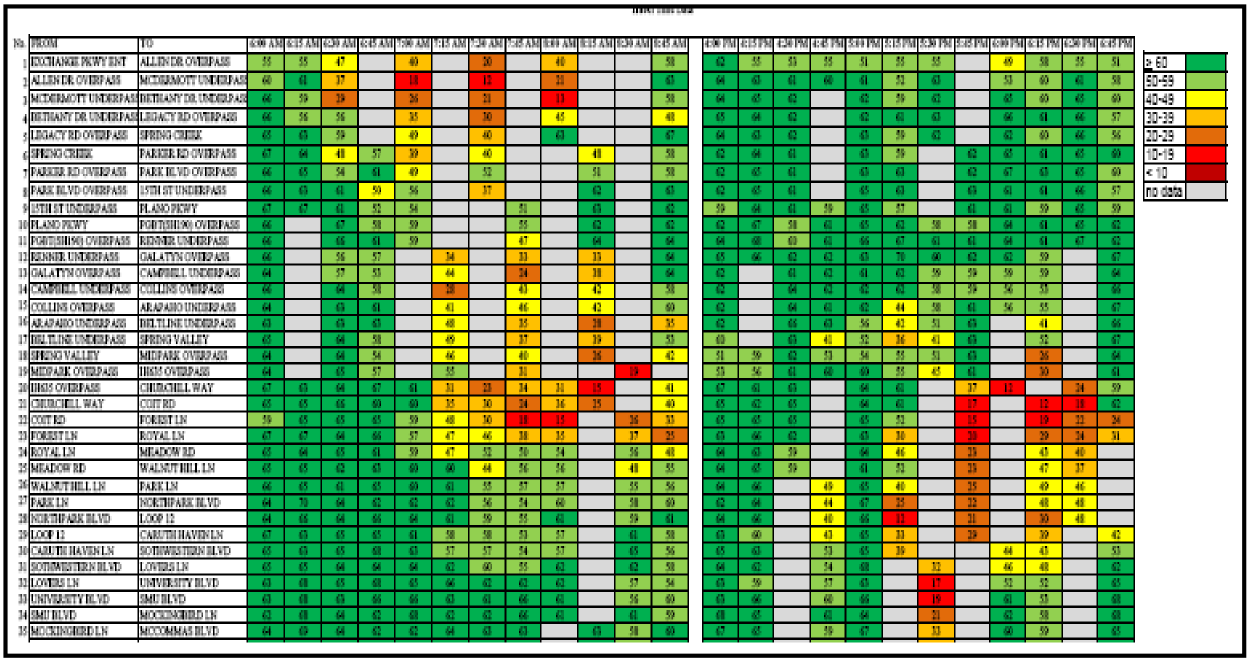


Figure 5-2: Speed Profile for US 75 Southbound Based on Historical Data (Year 2011) [Source: SMU]

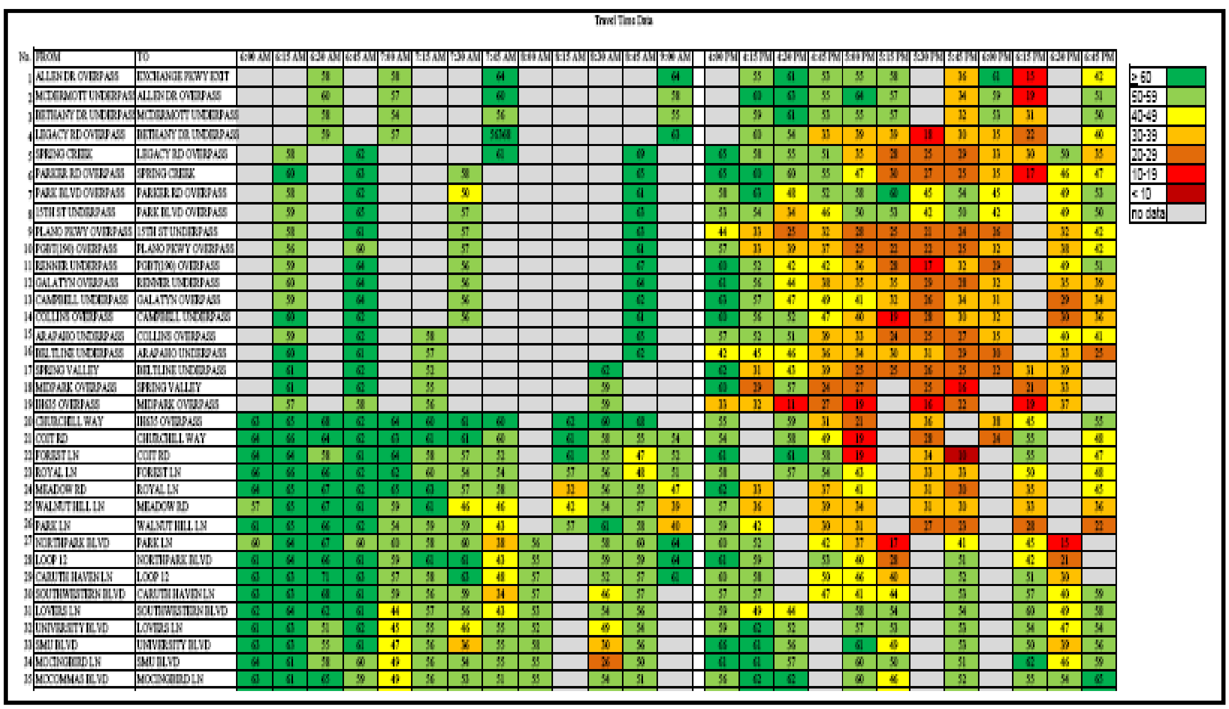


Figure 5-3: Speed Profile for US 75 Northbound Based on Historical Data (Year 2011) [Source: SMU]

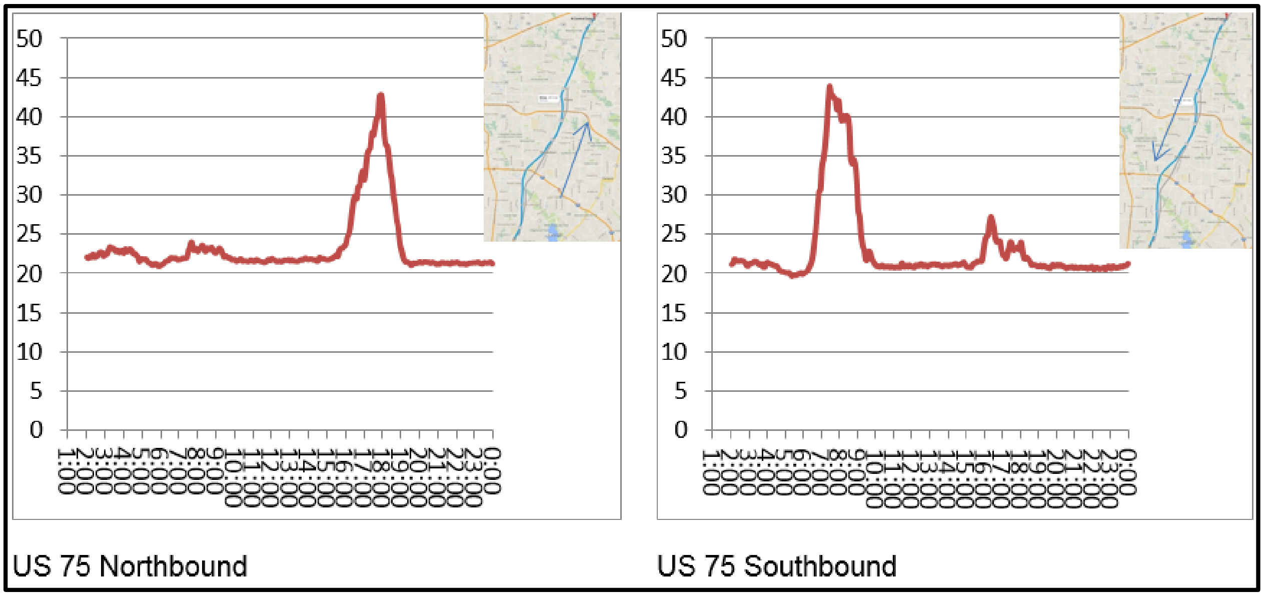


Figure 5-4: Time-dependent travel time data for the US 75 Freeway [Source: SMU]

The time-dependent travel time data for the US 75 freeway are presented in Figure 5-4. This data is obtained using the time-dependent speed data for the different links which is obtained at 5 minutes resolution. Travel time on links with no detectors is obtained by interpolating the data from upstream and downstream detectors.

Incident data are available for the corridor. According to the records of year 2011, traffic incidents are frequently observed along the US corridor with an average rate that is close to two incidents per day. Figure 5-5 gives the distribution of these incidents in terms of their time of occurrence and duration. As shown in the figure, higher accident frequencies are generally observed in the peak periods.

The frequency in the evening peak period is 50% higher than that of the morning peak period. About 33% of these incidents are minor incidents with less than 20 minutes duration. Also, about 50% of the incidents are incidents with medium severity where the duration is greater than 20 minutes and less than one hour. Finally, about 17% of the incidents have a duration that is greater than one hour. These incidents are considered as severe incidents. The incident records will be updated using latest available data to capture the most recent incident pattern.

Finally, as illustrated in Figure 5-6, videos of all cameras on the US 75 freeway could be accessed. These videos are typically used to verify incident data and the associated congestion level as the model is used to run in the on-line mode. Transit data including real-time transit ridership and occupancy of parking facilities at selected station along the Red Line light rail are also available through the SmartNet data repository, which could be accessed by DIRECT.

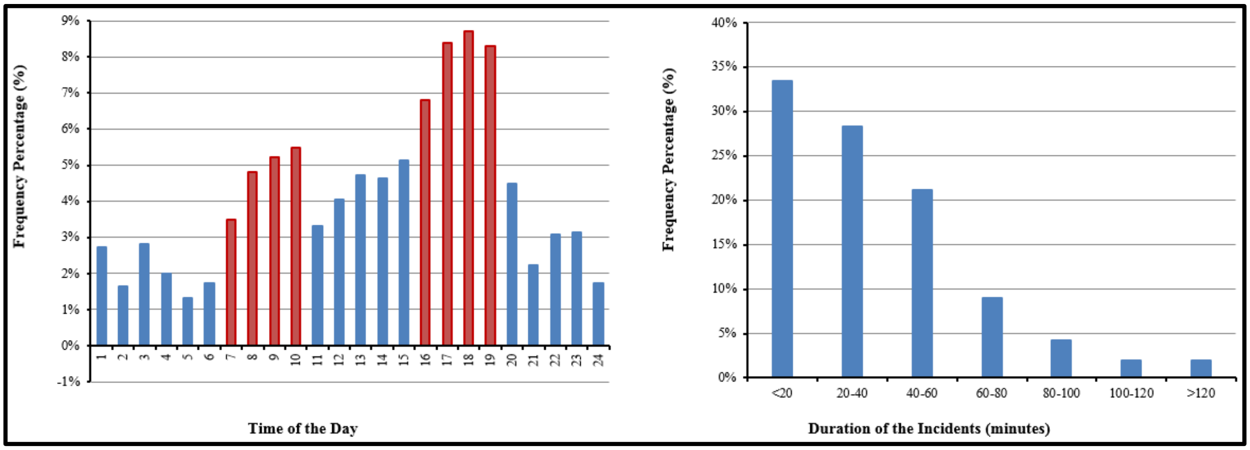


Figure 5-5: The Traffic Incident Distribution Pattern along the US 75 Freeway (Year 2011) [Source: SMU]

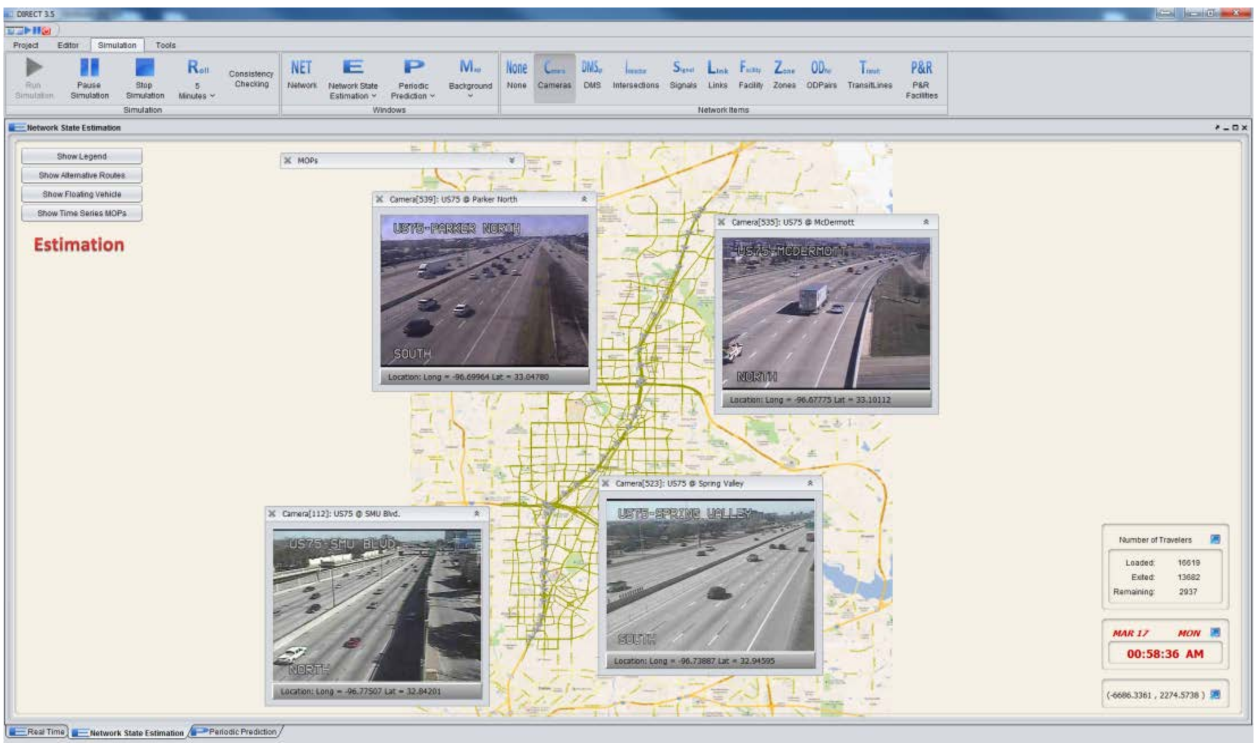


Figure 5-6: Video Surveillance Data for the US 75 Corridor [Source: SMU]

5.3 Preliminary Data Collection Plan to address gaps

Data limitations for the ICM Dallas Testbed are related to three following data items:

a) Travelers' behavior
b) Weather data
c) Arterial data

5.3.1 Travelers' Behavior Data

Data on travelers' behavior is limited with the exception of a recent survey that was conducted as part of the ICM project to capture travelers' responses to accidents and to the provided information (e.g. route diversion). These data were collected before and after the ICM system deployment. The data from the survey will be studied to extract useful information that can be used to better model travelers' route and mode choice behavior in non-recurrent congestion situations. Additionally, if similar data is available in other testbeds, this data could be transferred to the ICM Dallas Testbed to enhance the model predictability.

5.3.2 Weather Data

The national weather survey website will be used to extract historical weather data along the US 75 corridor region. The traffic data for the days when adverse weather conditions were recorded will be extracted from the DalTrans' data system. Weather impact on traffic patterns will be examined. Data sets that represent the traffic pattern associated with adverse weather conditions will be used to calibrate the model to accurately represent these conditions.

5.3.3 Arterial Data

Data reflecting traffic flow patterns and associated travel times along major arterials for multiple complete days are not available. As part of the ICM project, Bluetooth equipment have been recently installed at frontage roads along US 75 and along two other major arterials. Travel time estimates along these arterials were extracted and stored in SmartNet. These data can be made available for the purpose of this study.

Chapter 6. Key Assumptions and Limitations

Three main limitations were identified for the proposed analysis. The first limitation is inadequate data to model the potential change in travelers' short-term and long-term travel behavior in response to the deployed ATDM strategies. Adopting ATDM strategies is expected to change the travel time for the different modes and facilities. Consequently, travelers might change their departure time, route, mode, and destination as a function of their day-to-day travel experience. Real-world data that captures such behavior is limited which could affect the fidelity of any developed models.

The second limitation is determining the optimal settings for ATDM strategy or a combination of strategies. For example, if an active traffic management scheme that includes dynamic pricing strategy and ramp metering strategy, the optimal prices and the optimal ramp inflow rates need to be determined. These optimal values are interdependent. Additional simulation runs might be required to determine the optimal settings for the ATDM strategies. Third, the availability of system-wide measures of performance that can be used to describe the network performance during recurrent and non- recurrent (incidents, weather, special events) congestion situations. The lack of such data limits the capability to validate the system-wide measures of performance that are produced by the models. There are differences between estimating the system-wide ground truth and measuring this ground truth. This challenge primarily pertains to measuring the ground truth.

To address the first two limitations, a sensitivity analysis that covers the possible ranges of the unknown parameters and any assumptions that are considered as part of the modeling logic is proposed. For example, if dynamic pricing strategy is considered and there is no information on the optimal pricing scheme, a sensitivity analysis that covers the possible pricing schemes could be implemented. Similarly, the dynamic pricing is expected to affect the travelers' departure time, route, and mode choice. If no accurate models are available to capture the change in the behavior, sensitivity analysis could be conducted assuming different percentages of travelers would change their behavior in response to the ATDM strategies.

As for the lack of system-wide measures of performance data, one approach to address this challenge is to compare the results obtained from the models across the different testbeds. While this approach will ensure consistency among the different testbeds in terms of the methodology used to compute the different performance measures, it would also provide confidence in the obtained values of these measures.

Chapter 7. Modeling Approach

This section details the modeling approach to test the hypothesis and evaluate the effectiveness of the different ATDM strategies considering different operational conditions. This section also describes the analysis framework, application specific algorithms, analysis tools, and analysis phases or multi-tier approach to be used to conduct the overall modeling effort.

Figure 7-1 and Figure 7-2 illustrate the overall framework of the implemented real-time traffic management system. The framework is designed to virtually emulate the decision making process in a typical traffic network management center. The framework describes main processes for detection, communications, and control/advisory information dissemination technologies; and system management decisions.

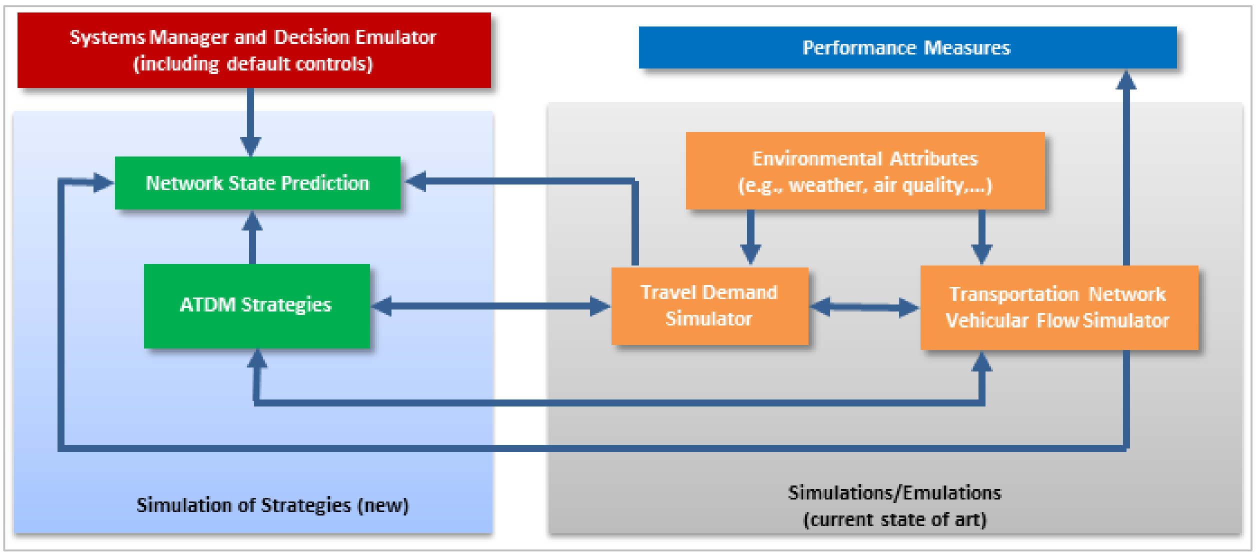


Figure 7-1: Preliminary Analysis Framework [Source: SMU]

As illustrated in Figure 7-2, the DIRECT simulation testbed adopts a rolling horizon framework, which integrates:

1. Network state estimation module
2. Network state prediction module
3. Demand estimation and prediction module
4. Consistency checking module
5. Decision support subsystem (scheme generator)

The network state estimation module is synchronized to real-time and provides an estimate of the current network conditions at any point in time. It is consisted of real-time simulation-based DTA model capable of capturing the network congestion dynamics resulting from the network's demand-supply interaction.

The DTA simulation-based model, DIRECT is used as the basis for the estimation and the prediction modules. DIRECT consists of several interconnected components including:

a) Demand generation
b) Travel behavior
c) Shortest path algorithm
d) Vehicle simulation
e) Statistics collection

The network prediction module is periodically activated (e.g. every 3 to 5 minutes) to predict the network conditions over a predefined horizon (30 minutes to 1 hour). The prediction module consists of another instance of the network simulation model running faster than real-time. The initial conditions for each prediction horizon are obtained from the estimation module which provides a snapshot of the network conditions at the start time of each prediction horizon. This snapshot defines the current location, speed, and assigned route for all travelers in the network. The new vehicles to be loaded during the prediction horizon are obtained through activating the online dynamic demand estimation and prediction module for the prediction horizon, which is described in more details in the next section. The system also allows the use of demand data that are estimated offline. For example, several OD demand tables representing different congestion levels could be estimated offline to reflect the demand levels for the different operational conditions identified based on the cluster analysis. Vehicles already in the network at the start of the prediction horizon and newly generated vehicles are simulated for the pre-specified horizon. In case the prediction module is used to evaluate a traffic management scheme, the parameters of the simulated control devices are updated to replicate this scheme. For example, if a scheme requires a modification to the timing plan of one or more intersections, these plans are fed to the prediction module to simulate their effect.

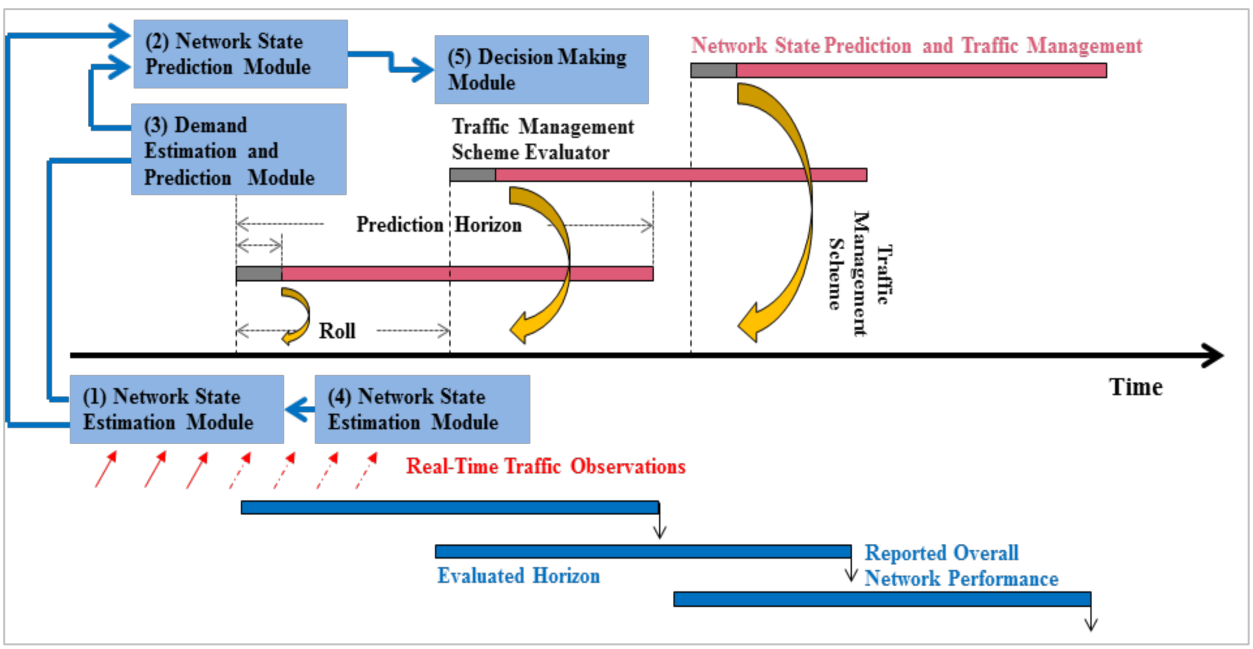


Figure 7-2: Real-time Network State Estimation and Prediction Framework [Source: SMU]

To ensure consistency between the simulation and the real network, the simulation model receives continuous data feeds in the form of speed and flow rate observations for roadway links equipped with surveillance devices. These observations can be used to adjust the model parameters in real-time to achieve better estimation results. The DIRECT framework is ready to integrate correction algorithms to any of its parameters. Under the current implementation, real-world speed observations are used to adjust the flow propagation models used to represent traffic movement on links. In addition, the flow rate observations are used to adjust the OD demand pattern obtained from the offline calibration step.

As illustrated in the figure, the estimation module implements a moving horizon approach to report the estimated measures of performance. Following this approach, statistics that covers a pre-defined horizon (e.g., 30 minutes) are continuously collected and reported at each roll (e.g., 5 minutes). Such approach is more suitable for real-time applications as it continuously monitors the time-varying network performance associated with any emerging congestion and the implemented response plans. Several measures of performances are reported at each roll. In the analysis conducted in this paper, the total travel time for all travelers existing in the network for any part of their trips during the pre-defined past horizon is used as a measure to evaluate the effectiveness of the generated traffic management schemes.

7.1 Application-Specific Algorithm and Needed Tools

This section describes the algorithms and models that need to be used/developed to satisfy the analysis approach. Table 7-1 presents a summary of the different strategies that will be modeled using the ICM Dallas Testbed and an overview of how of these strategies are modeled. In addition, two main modules will be developed:

I. Real-time traffic demand prediction module which accounts for demand adjustments associated with predicted operational conditions and implemented strategies
II. System management module which emulates the decision making process (i.e., system manager) at a typical traffic management center (TMC).

An overview of these two modules is presented below.

7.1.1 Traffic Demand Adjustment Module

This section describes the time-dependent demand estimation and prediction methodology, which is implemented as part of the rolling horizon framework. As illustrated in Figure 7-3, at each roll, the time-dependent OD-demand pattern is first estimated using the demand estimation methodology described hereafter. Based on available information of the demand dynamic transition pattern the demand for the next prediction horizon is determined. This transition pattern takes into account:

a) Current and predicted network operational conditions
b) ATDM strategies to be implemented

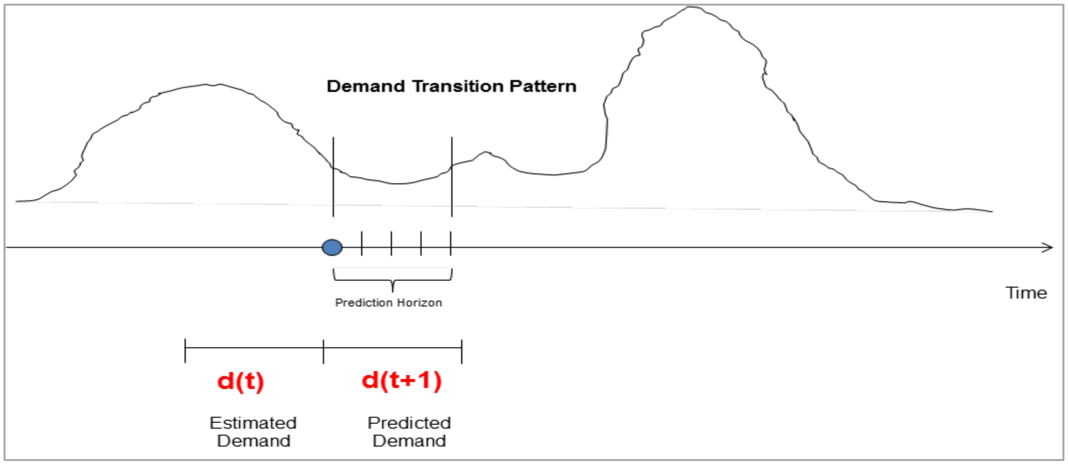


Figure 7-3: Demand Estimate and Prediction [Source: SMU]

The main objective of the demand estimation step is to estimate the time-dependent demand pattern for a pre-defined horizon using link-based vehicle counts observations in that horizon. The methodology for demand estimation takes advantage of the structure of the conventional least-square error minimization formulation of the OD demand estimation problem. It adopts a separable programming approach to derive an approximate linear formulation of the problem, which can be efficiently solved to meet the system's real-time requirement.

Assume the network is divided into a set of zones, Z. Also, the estimation horizon R is divided into R^d departure intervals and R^s observation intervals. Traffic originates from origins $I \in Z$ to destinations $J \in Z$ during the different departure time intervals $\tau \in R^d$. Define P as the demand assignment matrix such that an element $p_{ij\tau}^{at}$ in this matrix represents the portion of vehicles observed on link $a \in A$ in interval $t \in R^s$ that belongs to the OD pair ij and departure interval $\tau \in R^d$.

This link-flow proportion matrix is generated using the network state estimation module. The simulation-based DTA model, DIRECT, assigns the vehicle trips to routes and tracks their movements along the links of these routes till these reach their final destination. Thus, the link proportion values $p_{ij\tau}^{at} \in P$ are estimated for the demand estimation horizon. The conventional formulation of the OD demand estimation problem in the form of a least-square error minimization as follows.

Minimize	$\sum_{a\in A}\sum_{t\in R^s}\left(y_{at} - \sum_i\sum_j\sum_\tau p_{ij\tau}^{at}.\hat{d}_{ij\tau}\right)^2$		(1a)
Subject to:	$\hat{d}_{ij\tau} \geq 0$	$\forall$ i, j and τ	(1b)

Where, y_{at} is the observed vehicle count on link a in observation interval t, and $\hat{d}_{ij\tau}$ is the estimated demand between OD pair ij in departure interval τ.

The program above consists of a quadratic objective function with linear constraints, which can be decomposed into terms such that each term includes only one variable that is represented by a convex function. Such structure of the problem allows the use of the separable programming approach to efficiently solve the problem. The idea is to solve an approximation of the problem through providing a piecewise-linear approximation of the non-linear terms. Given the maximum possible range $c_{ij\tau}$ of decision variable $\hat{d}_{ij\tau}$ and dividing this range into n equal intervals, the value of $\hat{d}_{ij\tau}$ at interval s is equal to

$(s.\ u_{ij\tau})$, where $u_{ij\tau} = c_{ij\tau}/n$. The corresponding value of a non-linear term at interval s can then be numerically evaluated for all intervals in the range of $\hat{d}_{ij\tau}$. Let's use $v^s_{ij\tau}$ to denote the value of this numerical evaluation. Thus, the mathematical program given above could be rewritten in the form of the following linear mathematical program using the new decision variable $\lambda^s_{ij\tau}$,

Minimize	$\sum_i \sum_j \sum_\tau \sum_s v^s_{ij\tau}.\lambda^s_{ij\tau}$		(2a)
Subject to:	$\sum_s \lambda^s_{ij\tau} = 1$	$\forall$ i, j and τ	(2b)
	$\lambda^s_{ij\tau} \geq 0$	$\forall$ s, i, j and τ	(2c)

The optimal value of $\lambda^{s^*}_{ij\tau}$ determines the optimal interval s^* for $\hat{d}_{ij\tau}$. Given the convexity of each term, the mathematical program yields either $\lambda^{s^*}_{ij\tau}$=1 for s^* and $\lambda^{s'}_{ij\tau}$=0 $\forall\ s' \neq s^*$ or $\lambda^{s^*}_{ij\tau} = \alpha\ (s^*) + (1-\alpha)(s^*+1)$ and $\lambda^{s'}_{ij\tau}$= 0 $\forall\ s' \neq s^*$, where $0 < \alpha < 1$. The solution of this mathematical program gives the optimal $s^*\ \forall$ i, j and τ, and hence the optimal demand $\hat{d}^*_{ij\tau} =\ s^*.\ u_{ij\tau}\ \forall$ i, j and τ that minimizes the difference between the estimated and measured vehicle counts. It is important to note that the number of decision variables $\lambda^s_{ij\tau}$ in this mathematical program depends primarily on the number of OD pairs and departure time intervals that contribute to the observed vehicle counts. It also depends on the number of discretization intervals n that are used to approximate each nonlinear term. While increasing the value for n is expected to provide a better approximation of the nonlinear problem, it also increases the size of the problem and hence its execution time. Thus, the tradeoff between the accuracy of the solution and possible increase in the execution time needs to be carefully examined to choose the proper value for the parameter n.

As illustrated in Figure 7-3, the demand transition pattern between every two successive loading intervals in the operation horizon is assumed to be given. The transition pattern accounts for the predicted operation conditions in the network and the effect of any implemented strategies. It describes the expected demand level for a loading interval as a function of the estimated demand level at the previous loading interval for all OD pairs. The estimation model described above is activated at the end of each demand loading interval (e.g., 10 minutes). Given the estimation results for the current loading interval, the demand pattern for a pre-determined number of future intervals is recursively determined. The predicted demand is passed to the estimation and prediction modules.

7.1.2 Traffic Network Management Module

As mentioned above, the ICM Dallas simulation Testbed provides decision support capabilities by developing efficient traffic management schemes that are consistent with the predicted network conditions. The traffic management scheme determines the optimal settings for available traffic control devices in the network.

In the current implementation, Genetic Algorithm (GA) approach was adopted to generate efficient traffic management schemes. GA is a machine-learning model, which adopts its behavior from the processes of evolution in nature. The process starts with the creation of a population of individuals represented by chromosomes. Chromosomes in this population continuously pass through a process of evolution to increase their fitness and adaptiveness to their environments. The evolution occurs by exchanging characteristics with other chromosomes of the population (crossover) or through self-changes in the chromosome (mutation). New generations appear from clones of the current population, in proportion to their fitness. The fitness is a single objective function of the chromosome that returns a numerical value to differentiate between good and bad chromosomes.

A traffic management scheme is modeled in the form of a chromosome. As illustrated in Figure 7-4, a gene in a chromosome defines a control action implemented as part of the scheme. A timing plan at a signalized intersection, a route diversion message on a dynamic message sign, a speed limit advisory, and a ramp meter flow rate are examples of possible control actions.

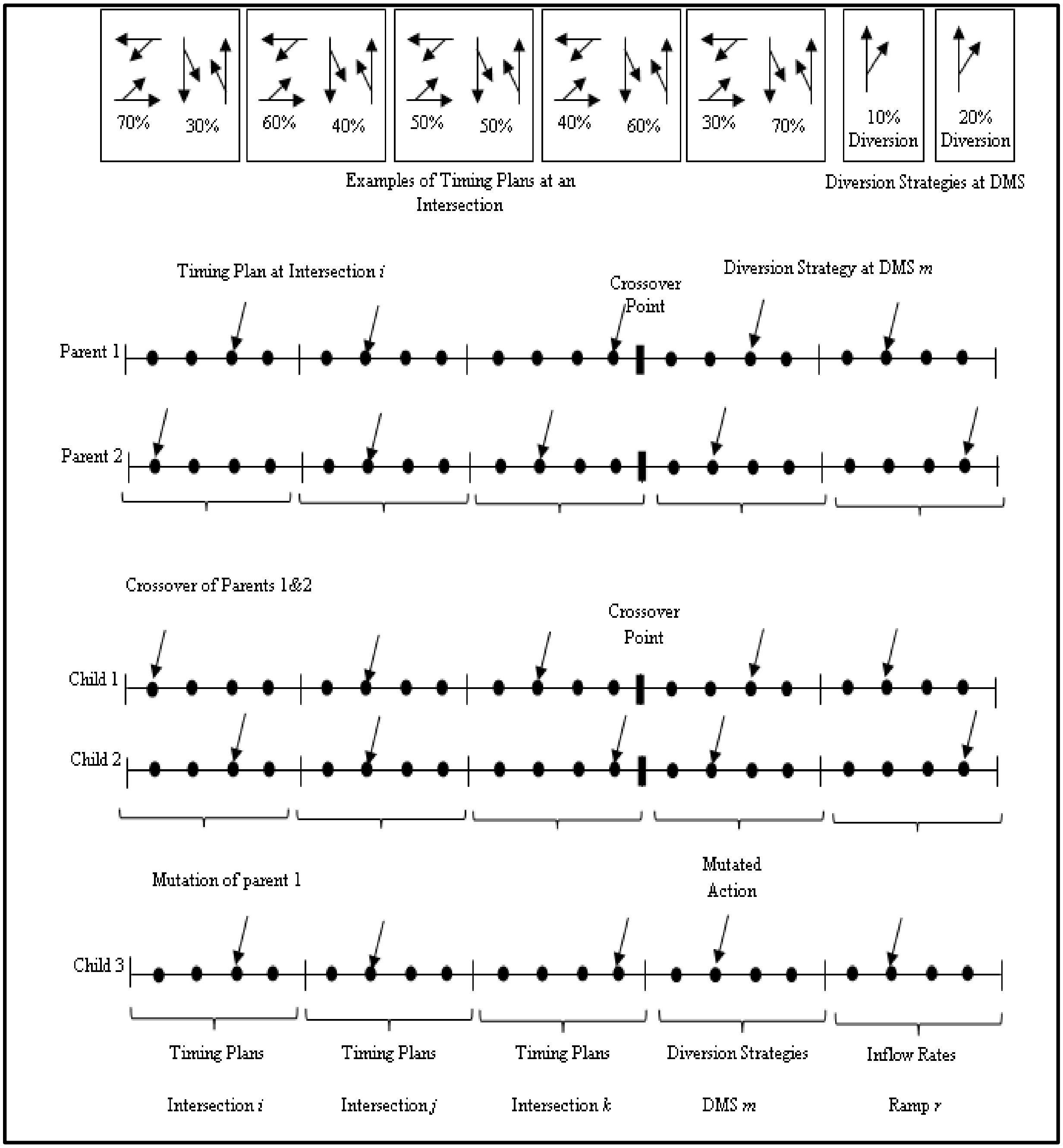


Figure 7-4: GA Representation of the Traffic Management Schemes [Source: SMU]

Figure 7-4 gives examples of multiple schemes with different combinations of actions. The figure illustrates the structure of two parent schemes (1 and 2) in a generation. These two schemes are used to produce three new schemes as part of a subsequent generation. Children 1 and 2 are two new schemes formed by the crossover of Parents 1 and 2. A crossover point is randomly selected to execute the action exchange. Child 3 is obtained by the mutation of Parent 1 by randomly changing one or more of its actions. In the presented example, the DMS action is mutated.

Each scheme is evaluated by its fitness, measured as the average travel time over the prediction horizon when the scheme represented by this chromosome is implemented. The prediction module is activated to estimate the average travelers' travel time for each considered scheme. The traffic network is simulated after modifying the settings of the control devices to represent their corresponding values in the generated scheme. The use of the DTA simulation model to evaluate the fitness of each scheme not only ensures accurate evaluate of the performance of the generated schemes but also ensures that the scheme is consistent with the drivers route choice behavior.

The GA procedures used are as follows. First, the initial population and fitness values of all its schemes are obtained. Schemes in the population are sorted according to their fitness value and top elements are used to produce the next generation using crossover and mutation strategies. Schemes in the new population are again evaluated and ranked. The process continues until the improvement in the fitness of the best scheme in two successive generations is smaller than a pre-defined threshold.

Steps of the GA

Step 1: Set iteration number itr = 0.
Step 2: Generate initial feasible population of traffic management schemes P(itr).
Step 3: Using the prediction module, identify the fitness of each scheme in the population.
Step 4: While convergence is not obtained:
Step 4a: Update the counter.
Step 4b: Select a sub-population with the highest fitness from the population P(itr-1).
Step 4c: Elements of the sub-population are then used to generate a new population P(itr) using crossover and mutation strategies.
Step 4d: Each traffic management scheme in the population is evaluated using the simulation model.
Step 5: Output the traffic management scheme with the best fitness.

7.1.3 Modeling ATDM Strategies using the DIRECT Model

Table 7-1 presents an overview of the logic used to model the different ATDM strategies that will be considered for the ICM Dallas Testbed. These strategies include:

- Dynamic Shoulder Lane
- Adaptive Ramp Metering
- Predictive Traveler Information
- Dynamic Routing
- Dynamically Priced Parking
- Dynamic Traffic Signal Control

The table provides a description of each strategy as well as a pseudo-code of how these strategies are modeled using the DIRECT simulation platform.

Table 7-1: ATDM Strategies Modeled Using the ICM Dallas Testbed

<table>
<tr><th rowspan="2">ATDM Strategy</th><th colspan="2">Modeling Logic</th></tr>
<tr><th>Description</th><th>Logic</th></tr>
<tr><td>Dynamic Lane Shoulder</td><td>DIRECT represents highway links at the lane level. To model the dynamic lane shoulder strategy, a shoulder lane, with pre-defined characteristics, could be added to the link. This shoulder lane would be configured to serve the traffic as long as the strategy is active (e.g., peak period, incident, evacuation, etc.).</td><td>if (shoulder lane strategy starts){
for (selected freeway links){
- Define a new Lane Object (speed limit, capacity, jam density)
- Mark Lane as a shoulder lane
- Add Lane to Link
}
}
if (shoulder lane strategy terminates){
for (selected freeway links){
- Shift traffic from shoulder lane to adjacent lanes
- Remove Lane from Link
}
}</td></tr>
<tr><td>Adaptive Ramp Metering</td><td>Ramp metering is modeled in DIRECT by adjusting the outflow rate for each ramp. The considered resolution is six seconds. When the ramp is open, the outflow rate is equal to the saturation flow rate. When the ramp is closed, the outflow rate is set to zero. The logic (e.g., ALINEA or any other logic) that determines the optimal timing is external to DIRECT. However, it can be developed as an additional task.</td><td>Assumption: the optimal inflow rate for each ramp is determined exogenously to the simulation model
if (Adaptive Ramp Metering Scheme is activated){
for (Ramps in this schemes){
outflowRate = newOutflowRate
}
}</td></tr>
<tr><td>Predictive Traveler Information</td><td>DIRECT implements a simulation-based short-term traffic network state prediction module, which runs in a rolling horizon framework. The prediction module provides information on the time-dependent link travel times for a pre-defined future horizon (e.g., 30 minutes). These predicted travel times could be used to develop different predictive traveler information strategies. The impact of the provided information on the travelers' route-mode choice decisions could be captured in the simulation.</td><td>- Conduct Prediction for a pre-defined horizon
- Generate Predicted Travel Times for all links for the predicted horizon
Generate time-dependent shortest routes for all departure time intervals in the horizon.
If a vehicle is equipped and the driver complies with the information, assign the vehicle to the new route.</td></tr>
<tr><td>Dynamic Routing</td><td>DIRECT is capable of modeling dynamic routing based on the provided traveler information. Drivers with access to information are assumed to be able to compare their current routes with the new routes. If the difference in the travel time is greater than a pre-defined</td><td>Assumptions:
- Travelers are assumed to be assigned to their historical routes.
- The percentage of travelers with access to pre-trip and en-route information is assumed given.
Logic:</td></tr>
</table>

ATDM Strategy	Modeling Logic	
	Description	**Logic**
	threshold, drivers are assumed to switch to the new route. The route diversion could be occurring at any junction along their routes including the DMS locations.	- At each SP update interval, the shortest paths from all origin nodes to all destinations are generated. - For all travelers with access to information, if the travel time (cost) of the new path is better than the time of the current path by a pre-defined threshold, the traveler is assumed to switch to the new path.

Dynamically Priced Parking	Following the dynamic route assignment logic in DIRECT, travelers are assigned to routes that minimize a generalized cost measure. This measure is in the form of a weighted linear function which includes the total travel time and the total travel cost. The travel cost component includes the expected vehicle operation cost and any out-of-pocket cost elements (e.g., parking cost, tolls). The set of optimal routes are periodically updated to capture congestion dynamics in the network as well as changes in the parking cost associated with implementing a dynamic parking pricing scheme.	Assumption: the parking cost for each parking facility is determined exogenously to the simulation model
		for (all parking facilities){
		if (a new parking cost is implemented){
		- read the new cost value
		- modify the generalized travel cost
		for all private car and park-and-ride paths
		to include this cost
		}
		}

Dynamic Traffic Signal Control	The DIRECT model allows modifying the signal timing plan for all or a subset of the intersections in the network at any point of time during the simulation horizon. A signal control scheme is described in terms of its activation start and end times and the timing plan for all intersections considered in this scheme. Multiple schemes could be a priori defined for the simulation horizon. These schemes are implemented in the simulation based on their activation times. If a traffic management module is used to generate a control scheme at any point in time, this scheme can also be deployed in the network according to its activation time.	Assumption: Each control scheme is defined by its start and end times. All junctions in this scheme are defined in terms of their new timing plans.
		if (Control Scheme is activated){
		for (Junctions in this scheme){
		for (all signal phases at this junction){
		GreenInterval = newGreen
		RedInterval = newRed
		Offset = newOffset
		}
		}
		}

7.2 Risks

Technical risk is controllable for the US 75 Testbed. The multi-phase approach minimizes the technical risk as it enables incorporating the knowledge and lessons learned from each phase into the subsequent phases. In addition, developing a detailed analysis plan is expected to minimize any uncertainty regarding the settings of the modeled scenarios.

A conservative estimate of the number of simulation runs for the US 75 Testbed is within the range of 300 runs. These simulation runs are more sophisticated compared to traditional simulation studies (e.g., traditional what-if analysis) due to their configurations. For instance, every simulation run would require integration with real-time data, online demand adjustment/prediction, activation of the prediction module, activation of system management, etc. The risk associated with using a tight schedule is also augmented by the amount of allocated budget. The budget allows the hiring of only one full time analyst with mid-level experience (5 years). Several time demanding tasks are involved in this project, which include cluster analyses, model calibration, input data preparation, model configuration, ATDM strategies model refinement, model runs execution, MOPs extraction and summarization, report preparation, etc. Based on experience from previous projects, most of these tasks require implementing quality assurance procedure which is usually difficult to achieve by one person. Thus, assigning inadequate manpower and man-hours raises the risk of tasks incompletion, late deliverables, and deliverable quality compromise.

7.3 AMS Requirements

This section enumerates the AMS requirements which every Testbed attempts to satisfy. Table 7-2 shows the list of AMS requirements and the Testbed capability when it is fully developed are classified into three levels:

1= The AMS requirement is **addressed** by the Testbed,

2= The AMS requirement is **partially addressed** by the Testbed or

3= The AMS requirement is **not addressed** by the Testbed.

Table 7-2: AMS Requirements and Capability of the Testbed

No	ID	Requirement	ICM Dallas Testbed
1	SU-1	The AMS Testbed shall emulate and track each Traveler's time-referenced geographic location (position) as he/she plans, executes, and completes a trip within the transportation system.	1
2	SU-2	The AMS Testbed shall emulate and track each Travelers' time-referenced state and transition among various potential states (pre-trip, pedestrian, non-motorized traveler, light vehicle driver, light vehicle passenger, and transit rider) as they plan, execute, and complete trips within the transportation system.	1
3	SU-3	The AMS Testbed shall emulate each Traveler's time-delimited tour planning, both in the pre-trip as well as en route states, subject to the nature and accuracy of available data on travel cost (parking fee, toll, fuel consumption, and transit fare),.	1
4	SU-4	The AMS Testbed shall emulate decision making by Pedestrians and Travelers in Non-motorized Modes of travel in the absence and presence of mobile devices, subject to the nature and accuracy of data available to support decision making.	1
5	SU-5	The AMS Testbed shall emulate decision making by Light Vehicle Drivers in the absence and presence of mobile devices, carry-in devices, integrated devices, and message signs subject to the nature and accuracy of data available to support decision making.	1

No	ID	Requirement	ICM Dallas Testbed
6	SU-6	The AMS Testbed shall emulate decision making by Light Vehicle Passengers in the absence and presence of mobile devices subject to the nature and accuracy of data available to support decision making.	1
7	SU-7	The AMS Testbed shall emulate decision making by Transit Riders in the absence and presence of mobile devices subject to the nature and accuracy of data available to support decision making.	1
8	SU-8	The AMS Testbed shall emulate tactical driving decisions made by Light Vehicle Drivers with respect to lane selection, lane changing, gap acceptance, following headway, speed, acceleration, deceleration, stopping, braking, hard braking, yielding, and merging subject to the nature and accuracy of data available to support decision making.	3
9	SU-9	The AMS Testbed shall emulate and track each Transit Driver and associated transit vehicle's time-referenced geographic location (position) within the transportation system.	1
10	SU-10	The AMS Testbed shall emulate tactical driving decisions made by Transit Drivers with respect to lane selection, lane changing, gap acceptance, following headway, speed, acceleration, deceleration, stopping, braking, hard braking, yielding, and merging su	3
11	SU-11	The AMS Testbed shall emulate fixed route/fixed schedule transit, flexible route bus, rail transit and paratransit.	1
12	SU-12	The AMS Testbed shall emulate a Transit Driver's adherence to dynamic transit dispatch plans (e.g., to counteract bus bunching) when received subject to the nature and accuracy of data available to support decision making.	2
13	SU-13	The AMS Testbed shall emulate decision making by Transit Drivers in the absence and presence of mobile devices, carry-in devices, integrated devices, and message signs subject to the nature and accuracy of data available to support decision making.	2
14	SU-14	The AMS Testbed shall emulate and track each Truck Driver and associated freight vehicle's time-referenced geographic location (position) within the transportation system.	2
15	SU-15	The AMS Testbed shall emulate tactical driving decisions made by Truck Drivers with respect to lane selection, lane changing, gap acceptance, following headway, speed, acceleration, deceleration, stopping, braking, hard braking, yielding, and merging subject to the nature and accuracy of data available to support decision making.	3
16	SU-16	The AMS Testbed shall emulate a Truck Driver's adherence to plans when received on dynamic routing, tours, and actions at waypoints subject to the nature and accuracy of data available to support decision making.	3
17	SU-17	The AMS Testbed shall emulate decision making by Truck Drivers in the absence and presence of mobile devices, carry-in devices, integrated devices, and message signs subject to the nature and accuracy of data available to support decision making.	2
18	SU-18	The AMS Testbed shall emulate and track each Public Safety Worker and public safety vehicle's time-referenced geographic location (position) within the transportation system, including in an active incident zone.	3
19	SU-19	The AMS Testbed shall emulate tactical driving decisions made by Public Safety Vehicle Drivers with respect to lane selection, lane changing, gap acceptance, following headway, speed, acceleration, deceleration, stopping, braking, hard braking, yielding,	3
20	SU-20	The AMS Testbed shall emulate a Public Safety Vehicle Driver's adherence to plans when received on dynamic routing, and response staging subject to the nature and accuracy of data available to support decision making.	3
21	SU-21	The AMS Testbed shall emulate the time-referenced geographic location of Public Safety Workers acting as emergency response personnel within an active incident zone in the	3

No	ID	Requirement	ICM Dallas Testbed
		absence and presence of Mobile Devices subject to the nature and accuracy of data available to support decision making	
22	SU-22	The AMS Testbed shall emulate decision making by Public Safety Vehicle Drivers in the absence and presence of mobile devices, carry-in devices, integrated devices, and message signs subject to the nature and accuracy of data available to support decision	3
23	SU-23	The AMS Testbed shall emulate adherence by Drivers of light, transit, and freight vehicles with directions when received on presence of emergency response personnel subject to the nature and accuracy of data available to support decision making.	2
24	SU-24	The AMS Testbed shall emulate various compliance rates of System Users (drivers, pedestrians, bicyclists, light vehicle passengers, transit riders, transit drivers, truck drivers, and public safety vehicle driver) when presented with advisory and regulations.	1
25	CV-1	The AMS Testbed shall emulate Mobile Devices that are capable of transmitting messages via cellular or DSRC or both.	3
26	CV-2	The AMS Testbed shall emulate the time-referenced geographic location, operational status (ON, OFF, NOT FUNCTIONING), and power status of a Mobile Device, and the state of the device (in use and connected to the vehicle, not in use but within a vehicle, outside a vehicle, and in use and not connected to the vehicle.).	3
27	CV-3	The AMS Testbed shall emulate Carry-in Devices that are capable of transmitting messages via cellular or DSRC or both	2
28	CV-4	The AMS Testbed shall emulate the time-referenced geographic location, and operational status (ON, OFF, NOT FUNCTIONING) of Carry-In Devices.	2
29	CV-5	The AMS Testbed shall emulate Integrated Devices that are capable of Transmitting message via cellular or DSRC or both	2
30	CV-6	The AMS Testbed shall emulate the time-referenced geographic location, and operational status (ON, OFF, NOT FUNCTIONING) of Integrated Devices	2
31	CV-7	The AMS Testbed shall emulate coordinated or independent transmission of messages from Mobile Devices, Carry-in Devices and Integrated Devices when co-located in a vehicle (light, transit, freight, public safety) via cellular or DSRC or both.	3
32	CV-8	The AMS Testbed shall emulate the reception of messages by DSRC-capable Mobile Devices, Carry-in Devices and Integrated Devices from other local DSRC-capable mobile, carry-in, and Integrated Devices	3
33	CV-9	The AMS Testbed shall emulate the reliability of Mobile Devices, Carry-in Devices and Integrated Devices, specifically the reliability of a device to receive or send messages subject to local interference, device malfunction, or user error.	3
34	CV-10	The AMS Testbed shall track the time-referenced geographic- location and emulate the movement of Connected and Unconnected Vehicles within the transportation system, including time parked between trips made as a part of a multi-trip tour.	2
35	CV-11	The AMS Testbed shall reflect differences in vehicle size and weight among Light Vehicles, Transit Vehicles, Trucks and Public Safety Vehicles and associated differences in vehicle performance.	1
36	CS-1	The AMS Testbed shall emulate the geographic location (position), operational status (FUNCTIONING, NOT FUNCTIONING), and range of individual DSRC-capable Roadside Equipment (RSE) deployed as an element of a DSRC Roadside Device Network.	3
37	CS-2	The AMS Testbed shall emulate latency and reliability of messages passing through a DSRC Roadside Device Network, subject to the location and density of nearby roadside devices, relative position and capability of DSRC-capable devices (Mobile Devices,	3

No	ID	Requirement	ICM Dallas Testbed
38	CS-3	The AMS Testbed shall emulate latency and reliability of communications using a Wide-Area Wireless Network, subject to the location of capable devices, sources of interference, and overall communications load.	3
39	CS-4	The AMS Testbed shall emulate provision of roadside/local control by Traffic Control Systems through dynamic message signs, lane control signs, ramp meters, and traffic signals.	1
40	CS-5	The AMS Testbed shall emulate provision of advisory information by Traffic Control Systems through dynamic message signs and other forms of advisory information provision.	1
41	CS-6	The AMS Testbed shall emulate the capability of Traffic Control Systems to receive, process, and implement control setting changes from System Managers, including the latency and reliability of response to System Manager direction.	1
42	CS-7	The AMS Testbed shall emulate the provision of Traveler information via Broadcast Media, including television, radio and through the internet, including a differentiation of information delivered to System Users in pre-trip and en route states.	1
43	CS-8	The AMS Testbed shall emulate data capture from Traffic Detection Systems utilizing passive detection to estimate individual vehicle speed, location, and size or to estimate roadway segment occupancy, travel time, and aggregate vehicle flow where deployed	1
44	CS-9	The AMS Testbed shall emulate the accuracy, precision, latency and reliability of data aggregation and pre-processing actions within the Traffic Detection System prior to those data being made available to System Managers within an Operational Data Environment	1
45	OD-1	The AMS Testbed shall emulate Data Quality Control (QC) and Aggregation processes, including the nature and effectiveness of quality checks and data performed for different data types.	1
46	OD-2	The AMS Testbed shall emulate the processing time associated with performing Data Quality Control and Aggregation processes.	1
47	OD-3	The AMS Testbed shall emulate and differentiate between integrated and independent Data Quality Control and Aggregation processes in support of System Managers.	1
48	OD-4	The AMS Testbed shall emulate the capture and aggregation of data from Connected Vehicles, Mobile Devices, and Detection Systems into Private Sector Data Services.	2
49	OD-5	The AMS Testbed shall account for the processing time associated with performing Data Quality Control and Aggregation processes within Private Sector Data Services.	1
50	OD-6	The AMS Testbed shall emulate the provision of aggregated and quality controlled data products from Private Sector Data Services into Data QC and Aggregation processes supporting System Managers.	1
51	OD-7	The AMS Testbed shall emulate the use of Predictive Tools within an Operational Data Environment, dependent on the flow of data from Data QC and Aggregation processes.	1
52	OD-8	The AMS Testbed shall emulate and differentiate among alternative forms of Predictive Tools, including their prediction horizon, accuracy, scope, and processing time.	1
53	SM-1	The AMS Testbed shall emulate the duration and outcomes of decision-making by Freeway System and Tollway Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1
54	SM-2	The AMS Testbed shall emulate the duration and outcomes of decision-making by Arterial System Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1
55	SM-3	The AMS Testbed shall emulate the duration and outcomes of decision-making by Road-Weather System Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1

No	ID	Requirement	ICM Dallas Testbed
56	SM-4	The AMS Testbed shall emulate the duration and outcomes of decision-making by Transit System Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1
57	SM-5	The AMS Testbed shall emulate the duration and outcomes of decision-making by Parking System Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1
58	SM-6	The AMS Testbed shall emulate the duration and outcomes of decision-making by Freight System Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	2
59	SM-7	The AMS Testbed shall emulate the duration and outcomes of decision-making by Public Safety Managers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	2
60	SM-8	The AMS Testbed shall emulate the duration and outcomes of decision-making by Information Service Providers, subject to the latency, accuracy, reliability and nature of Operational Data Environments available to support this decision-making.	1
61	SM-9	The AMS Testbed shall emulate and differentiate the duration and outcomes of integrated versus independent decision-making among System Managers, including Freeway and Tollway System Managers, Signal System Mangers, Road-Weather System Managers, Parking System Managers, Freight System Managers, Public Safety Managers, and Information Service Providers.	1
62	SM-10	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Freeway System and Tollway Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks	1
63	SM-11	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Arterial System Managers, including messages passed through Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks to control or influence System User decision-making.	2
64	SM-12	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Road-Weather System Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks	2
65	SM-13	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Transit System Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks to control or influence System User decision-making.	2
66	SM-14	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Parking System Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks to control or influence System User decision-making.	2
67	SM-15	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Freight System Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks to control or influence System User decision-making.	3
68	SM-16	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Public Safety Managers, including messages passed through Broadcast Media, Traffic Control Systems, the DSRC Roadside Network or Wide-Area Wireless Networks to control or influence System User decision-making.	3

No	ID	Requirement	ICM Dallas Testbed
69	SM-17	The AMS Testbed shall emulate the forms, scope and limitations of system control exerted by Information Service Providers, including messages passed through Broadcast Media, the DSRC Roadside Network or Wide-Area Wireless Networks to influence System User	3
70	SM-18	The AMS Testbed shall emulate the utilization of Automated Control by one or more System Managers who delegate specific forms of routine decision-making and control message generation.	1
71	DI-1	The AMS Testbed shall emulate the transmission and reception of Information and Data Flows between System Entities over a specific communications system, whether broadcast or point-to-point in nature, the interval at which the data flow occurs, and the co	1
72	DI-2	The AMS Testbed shall emulate the transmission and reception of Basic Safety Messages (BSM) among Connected Vehicles, Mobile Devices, and the DSRC Roadside Network.	3
73	DI-3	The AMS Testbed shall emulate the transmission of Basic Mobility Messages (BMM) from Connected Vehicles and Mobile Devices to the System Entity tasked with managing BMM messaging (either a Private Sector Data Services or a Data QC and Aggregation process)	3
74	DI-4	The AMS Testbed shall emulate the transmission of Signal, Phase and Timing (SPaT) Messages from the DSRC Roadside Device Network to DSRC-capable Connected Vehicles.	3
75	AP-1	The AMS Testbed shall emulate Dynamic Shoulder Lanes.	1
76	AP-2	The AMS Testbed shall emulate driver behaviors in Dynamic Shoulder Lanes that are distinct from behaviors on regular lanes.	1
77	AP-3	The AMS Testbed shall emulate restriction of access to Dynamic Shoulder Lanes by vehicle type (e.g., transit) and vehicle occupancy (e.g., HOV 2+, HOV 3+).	1
78	AP-4	The AMS Testbed shall emulate Dynamic Lane Use Control, including shoulder lanes.	1
79	AP-5	The AMS Testbed shall emulate Dynamic HOV/Managed Lanes.	1
80	AP-6	The AMS Testbed shall emulate detection of position, start time, duration, and length of queues on freeways and arterials in support of a Queue Warning DMA or Queue Warning strategy supporting System Manager decision-making.	1
81	AP-7	The AMS Testbed shall emulate altered driving behavior in response to Queue Warning messages generated by the Q-WARN DMA and delivered to Carry In or Integrated Devices within Connected Vehicles or through local signage within the Traffic Control System.	2
82	AP-8	The AMS Testbed shall emulate the estimation of dynamic target speed recommendations by roadway section and lane made by the SPD-HARM application or the Dynamic Speed Limits strategy deployed in support of System Managers.	2
83	AP-9	The AMS Testbed shall emulate transmission of SPD-HARM enhanced target speed recommendations via message signs; or directly to Carry-In or Integrated Devices running the SPD-HARM application within a Connected Vehicle.	2
84	AP-10	The AMS Testbed shall emulate driver decision-making in response to target speed recommendations made by the SPD-HARM application running on a Carry-In or Integrated Device within a Connected Vehicle.	2
85	AP-11	The AMS Testbed shall emulate altered driving behavior in response to combined queue warning and target speed recommendations made by a combined Q-WARN/SPD-HARM application.	2
86	AP-12	The AMS Testbed shall emulate the creation, movement, and dispersion of a platoon of Connected Vehicles utilizing Coordinated Adaptive Cruise Control (CACC) application, traveling at the same speed and maintaining the same gap with their respective leader	3
87	AP-13	The AMS Testbed shall emulate the identification and implementation of altered signal control settings enhanced by the M-ISIG DMA bundle or the ATDM Adaptive Traffic Signal Control and Adaptive Ramp Metering strategies.	3

No	ID	Requirement	ICM Dallas Testbed
88	AP-14	The AMS Testbed shall emulate the identification and implementation of signal control settings optimized to allow for the rapid and safe movement of Public Safety Vehicles (PREEMPT), Trucks (FSIG), Transit Vehicles (TSP), and Pedestrians (PED-SIG).	2
89	AP-15	The AMS Testbed shall emulate the dynamic creation of high-occupancy vehicles through the DRIDE application running on Mobile Devices or through other Dynamic Ridesharing services supporting informal ridesharing.	
90	AP-16	The AMS Testbed shall emulate multi-modal forms of Traveler information services that include cost, reliability and parking delivered pre-trip through Broadcast Media or pre-trip and en route through Mobile Devices, Carry-in Devices, and Integrated Device	1
91	AP-17	The AMS Testbed shall emulate Active Parking Management Strategies employed to support decision-making by Parking System Managers, including Dynamic Wayfinding, Dynamic Overflow Transit Parking, Dynamic Parking Reservation, and Dynamic Priced Parking	1
92	AP-18	The AMS Testbed shall emulate Dynamic HOV Lane Conversion, including dynamic alterations to access policy (e.g., HOV-2 to HOV-3) and price.	1
93	AP-19	The AMS Testbed shall emulate Intelligent Dynamic Transit Operations (IDTO), including transit connection protection and dynamic dispatch.	2
94	AP-20	The AMS Testbed shall emulate Incident Management practices, including the management of local incident zones, the staging of emergency response vehicles and personnel, and the closure of lanes and facilities required as a part of the incident response.	1
95	AP-21	The AMS Testbed shall emulate Dynamic Pricing and Dynamic Fare Reduction strategies, including dynamic changes to roadway tolls or transit fares.	1
96	AP-22	The AMS Testbed shall emulate the concurrent deployment of two or more DMAs or ATDM strategies, including synergies or conflicts arising from this interaction.	1
97	AP-23	The AMS Testbed shall emulate Dynamic Junction Control	1
98	AP-24	The AMS Testbed shall emulate Dynamic Merge Control	2
99	AP-25	The AMS Testbed shall emulate Dynamic Lane Reversal or Contraflow lanes, including dynamically adjusting the lane directionality in response to real-time traffic conditions.	1
100	AP-26	The AMS Testbed shall emulate freight operations, including drayage optimization and freight Traveler information	3
101	OC-1	The AMS Testbed shall emulate a range of Operational Conditions, including variations in travel demand, weather, and incident patterns.	1
102	OC-2	The AMS Testbed shall be capable of calculating a consistent set of Performance Measures describing mobility, safety, and environmental impacts, over all Operational Conditions and subject to multiple alternative systems linking System Users and System Management	1
103	OC-3	The AMS Testbed shall be capable of being calibrated and validated using relevant Performance Measures against real-world conditions, both in terms of the representation of Operational Conditions and Alternative Systems, where such data are available from actual surface transportation systems.	1

Chapter 8. Model Calibration

The DIRECT model will be calibrated for all base operational scenarios that are identified based on the cluster analysis. A day that represents each operational scenario will be selected (i.e., a core day in the cluster representing this scenario). The traffic operational data for this day will be assembled which includes: hourly volumes on freeway and main arterial links, speed profile for the US 75 freeway, and travel time along strategic routes. The model will be adjusted to replicate the data observed for this day through adjusting the time-dependent OD demand pattern as well as the flow propagation models that are used to represent vehicle movements along the for the different link. Guidelines and criteria presented in the FHWA guidelines on the use and calibration of simulation model will be used as a benchmark for the quality of the calibration process[2].

Several model parameters will be adjusted as part of the calibration effort. First, the modeled time-dependent OD demand matrix will be adjusted to replicate the observed traffic counts for different freeway and arterial links.

As an example of a previous calibration effort that was conducted for the DIRECT model, Figure 8-1 provides a summary of the comparison between the observed and modeled traffic counts using the 2011 traffic count data. The percentage error is presented for the freeway and arterial links for the morning and evening peak periods respectively. Freeway links with observed hourly volume that is greater than 2000 vph and arterial links with observed hourly volume that is greater than 1000 vph are considered in this comparison. As shown in the table, for the AM peak period, an error of 17.4% is observed for the freeway links, while an error of 24.2% is observed for the arterial links. For the PM peak period, these errors are recorded at 20.1% and 24.1% for the freeway and the arterial links respectively. The aggregate errors between the observed and modeled counts are -4% for the freeways, 2% for the arterials, and -2% for the entire network.

Second, the flow propagation models for the different highway facilities will be adjusted using the link speed and travel time data available for the different routes. Figure 8-2 and Figure 8-3 provide the speed profiles for the US 75 freeway produced by the model using data collected in year 2011. Comparing the modeled speed profiles with the observed speed profiles provided in Chapter 1 under Available Data, the model is able to capture the congestion pattern along the US 75 freeway. Congestion is observed in the southbound direction during the morning peak period. Congestion is also observed on the south section (south of LBJ freeway) during the evening peak period. For the northbound direction, the model captures the congestion pattern that forms in the evening peak period. As shown in Figure 8-3, the model produces a speed profile in which the congestion extends along most of the freeway sections, which generally replicates the observed data.

[2] Federal Highway Administration, June 2004, Traffic Analysis Toolbox, Volume III: Guidelines for Applying, Traffic Microsimulation Modeling Software, Publication No. FHWA-HRT-04-040, – available at http://ops.fhwa.dot.gov/trafficanalysistools/index.htm

Sum of All Link Flows

Volume Comparison		Observed	Model	O-M	Error
No. Links	Type	AM-PM			
48	US 75	1,358,749	1,412,052	(53,303)	-4%
97	Arterials	564,141	550,885	13,256	2%
149	Entire Network*	2,016,969	2,055,624	(38,655)	-2%

* Includes four IH 635 links

ValidationReport med baseline.xlsx

OverAll Statistcs

		Location	All Detectors		
		Counts-Weighted Percentage of Error			
Obs. Volume thresholds	AM-PM No. Links	Weighted Index Type	CL AM-PM	06-09	16-19
2000 vph	48	US 75	15.1	17.4	20.1
1000 vph	53	Arterials	21.0	24.2	24.1
	101	Entire Network	16.3	18.4	20.6

Notes:

1. Only links with obs. Volumes higher or equal to thresholds are used.

e.g. US 75 Link X is used if it has 6 hour vol. (06-09 and 16-19) $\geq$ 6000 veh.

2. Counts-Weighted Percentage of Error = sum Error$_{AM\text{-}PM}$/sum obs. Vol$_{AM\text{-}PM}$

Figure 8-1: Summary of Traffic Count Validation Report [Source: SMU]

The adjustment of the flow propagation models is usually verified by comparing the estimated and measured travel time for some strategic routes in the network. Figure 8-4 and Figure 8-5 shows the measured and estimated travel times along the US 75 freeway for the peak hours using 2011 data. Figure 8-4 shows the travel time comparison results for the southbound direction while Figure 8-5 gives these results for the northbound direction. The measured travel times are obtained using Google real-time traffic congestion data. The observed and estimated travel times are recorded for the recurrent congestion conditions.

As shown in the figures, the maximum difference between the estimated and measured travel time in any of the recorded hours is within 12%. The measured and estimated travel time data matches the speed profile observations. For southbound direction, the congestion is observed mainly in the morning peak period which is reflected in the values of the observed and estimated travel times. For the northbound direction, the congestion is observed mainly in the evening peak period. An increase in the observed and estimated travel time values is observed in the afternoon peak period for the northbound direction.

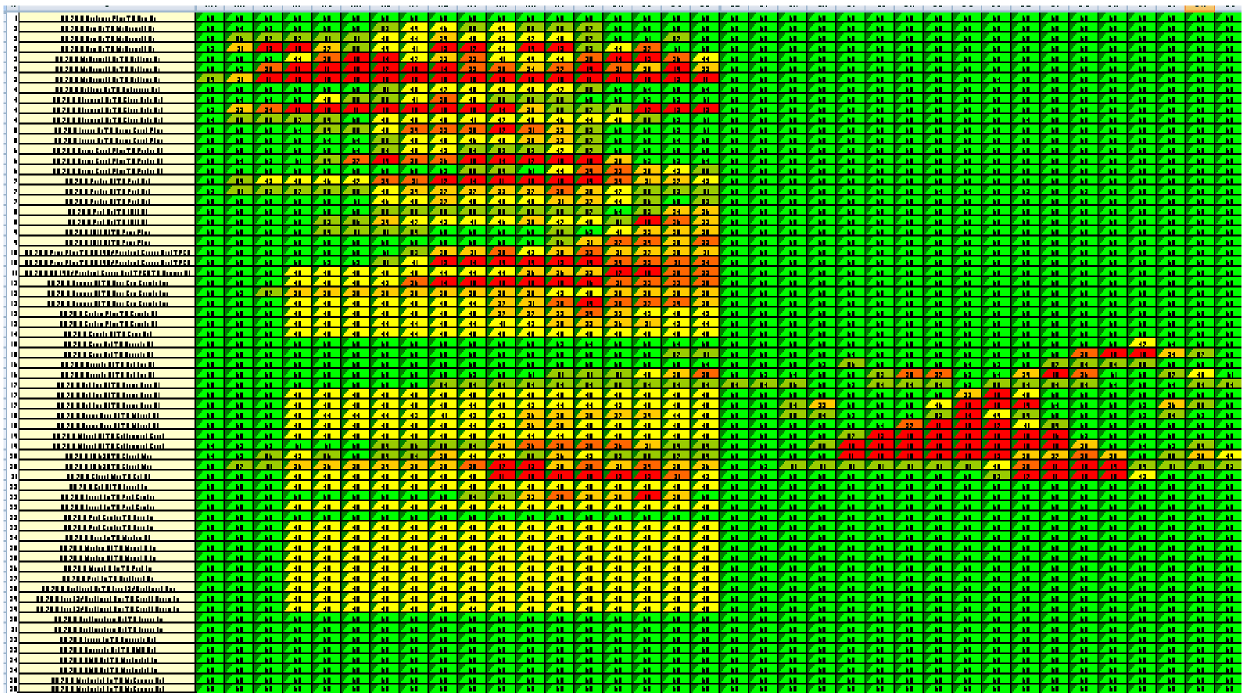


Figure 8-2: Model Speed Profile for US 75 Southbound [Source: SMU]

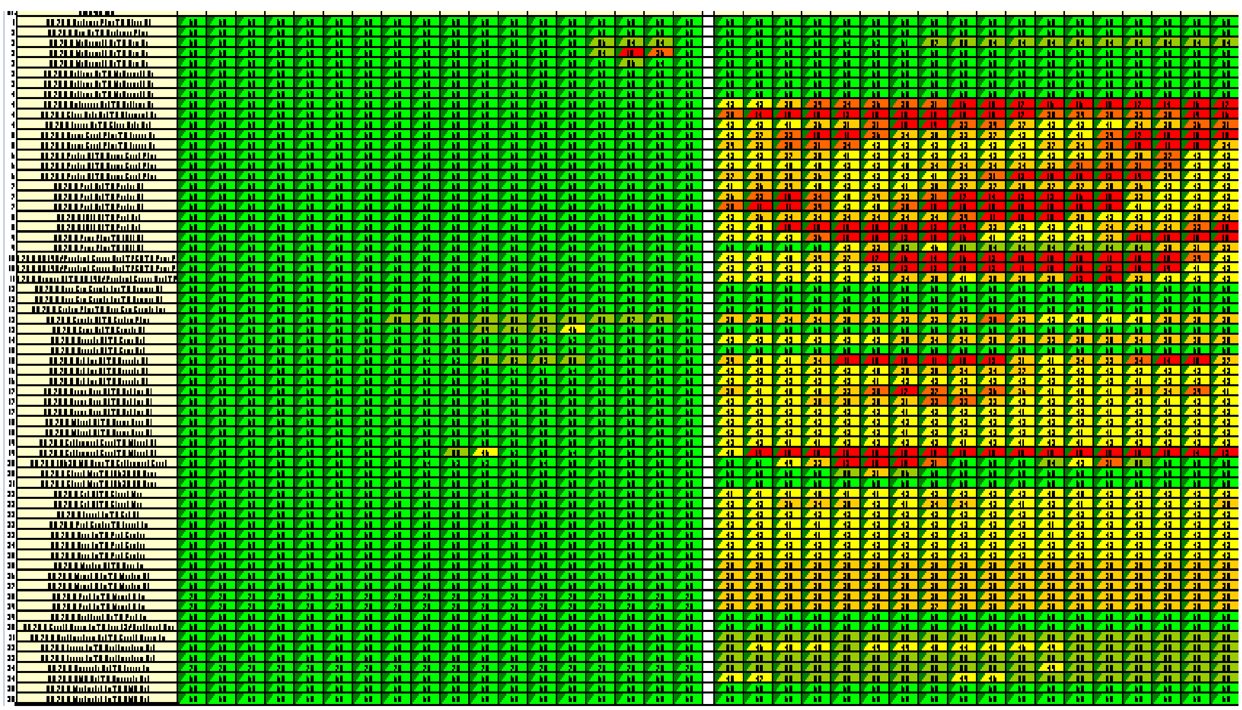


Figure 8-3: Model Speed Profile for US 75 Northbound [Source: SMU]

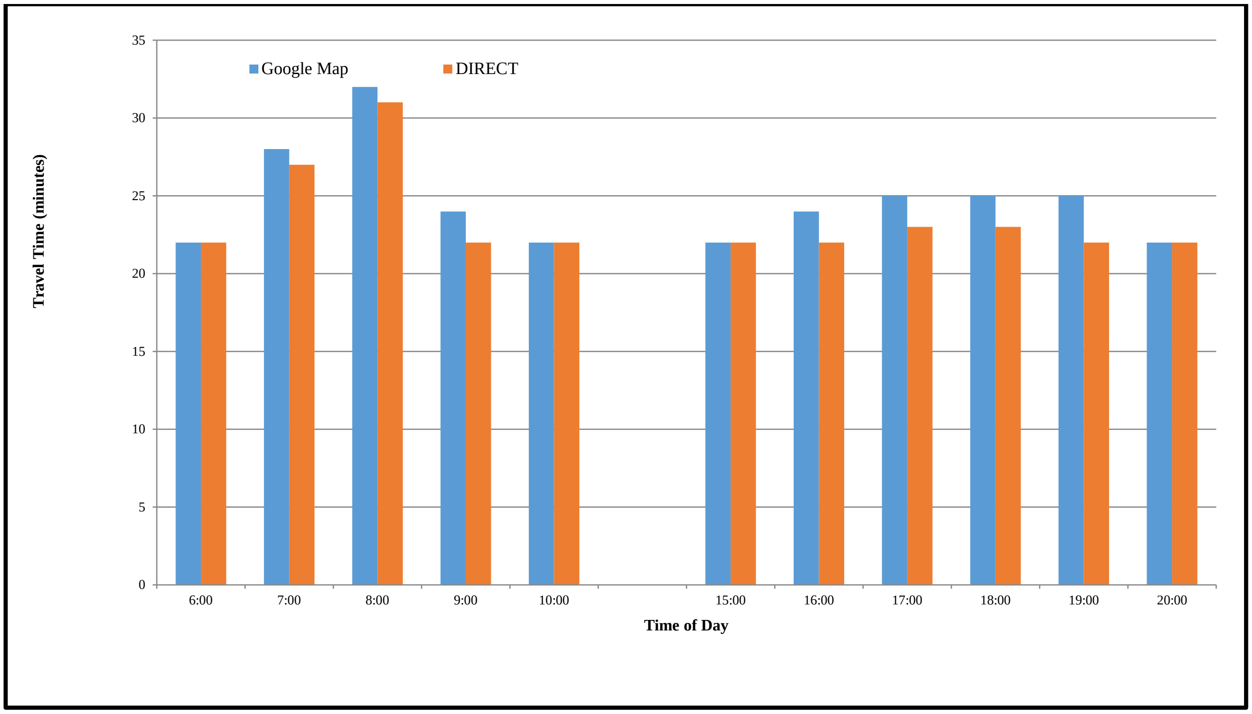


Figure 8-4: Simulated Model travel time for US 75 Southbound [Source: SMU]

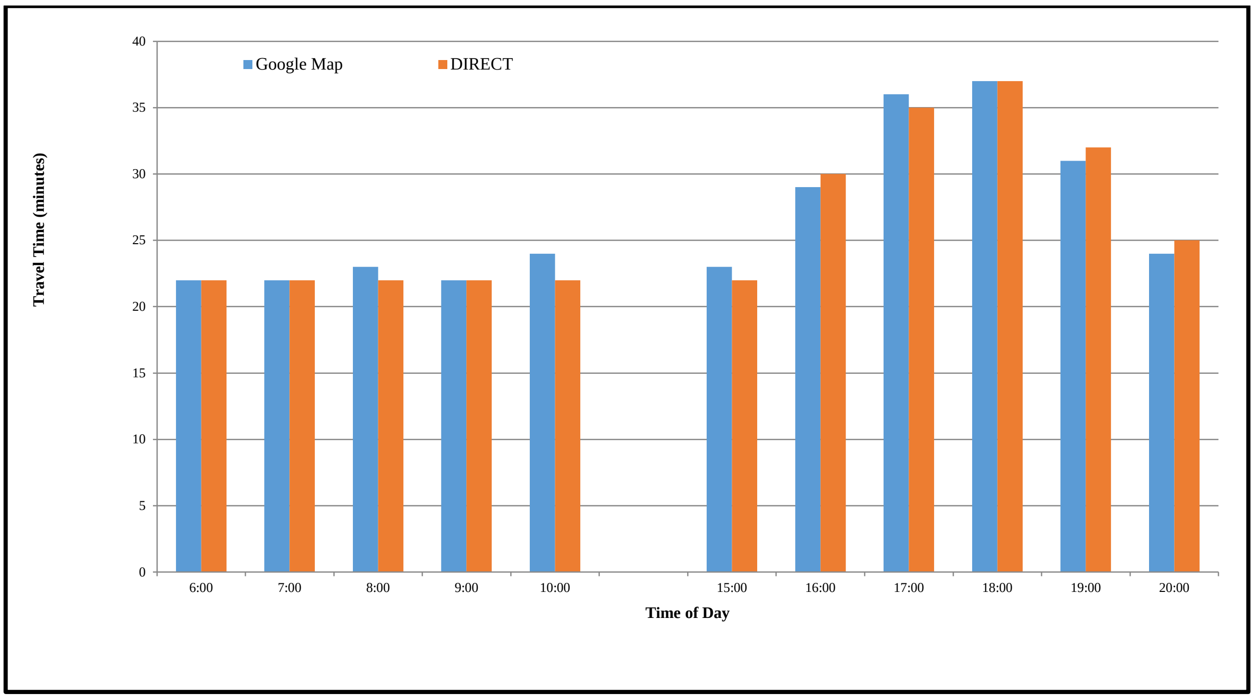


Figure 8-5: Simulated Model travel time for US 75 Northbound [Source: SMU]

Chapter 9. Evaluation Approach

This section shows the system evaluation plan to answer the ATDM research questions based on the analysis conducted and the approach to conducting sensitivity analysis.

9.1 Evaluation Plan to answer ATDM questions based on analysis conducted

As described earlier, the analysis scenarios are designed to answer the different research questions defined for this project. This section maps the analysis scenarios to the research questions categories.

Synergies and Conflicts and Operational Conditions, Modes, Facility Types with Most Benefit: Analysis scenarios 7 to 20 consider cases where single and combination of ATDM strategies are modeled. For example, in scenario 7, the dynamic shoulder lane is modeled considering high demand conditions. In scenario 8, the dynamic routing strategy is activated along with the dynamic shoulder lane strategy. The results from these two scenarios would provide insight on the potential synergy/conflict between these two ATDM strategies. Similarly, scenario 9 examines the dynamic signal control strategy while scenario 10 examines the combination of the dynamic signal control and dynamic routing strategies. Again, the results of these two simulation scenario will provide insight on possible synergy/conflict between these two ATDM strategies.

In addition, this potential synergy/conflict is examined under different operational conditions. For example, in scenarios 8 and 8a, the effectiveness of jointly adopting the dynamic routing strategy and the dynamic shoulder lane strategy is examined under a high demand with two different levels of incident severity (medium and minor). Similarly, scenarios 10 and 10a examine the effectiveness of the dynamic signal control strategy and the dynamic routing strategy considering these two levels of incident severity. In addition, scenarios 14 to 20 were designed to replicate scenarios 7 to 13 to consider different set of operational conditions (medium demand level with both high and minor incident severities).

In all these scenarios, measures of performance will be produced for the different modes and facilities to examine the effect of the ATDM strategies on the performance of these facilities/modes.

Congestion/Demand Prediction and Travelers' Response: As explained earlier, the simulation experiments in phase 1 are devoted to quantifying the importance of congestion/demand prediction and examining the sensitivity of the travelers' response to provided information. For example, the demand prediction is assumed to be an input to the simulation model. The effect of the weather conditions and the ATDM strategies on the level of demand will be estimated and used by the model to capture possible effect on the network performance. Also, to capture the sensitivity of travelers' access and response to traveler information on the effectiveness on the dynamic routing strategies, scenarios that include this strategy will be modeled considering three different values of the model's parameters that represent the travelers' access and compliance with information (e.g., 10%, 15% and 20%).

Prediction Horizon Sensitivity and Prediction Accuracy Sensitivity: The simulation scenarios included in phase 2 will be used to answer research questions related to the effect of the prediction horizon and the prediction accuracy on the effectiveness of the ATDMS strategies. These two prediction attributes will be examined on the Dynamic Signal Control Strategy as well as a combination in which the Dynamic Signal Control Strategy and Dynamic Routing Strategy are integrated in one traffic management plan. The experiments also consider different operational conditions including medium and high demand levels and different incident severity levels.

As explained earlier, to capture the prediction horizon sensitivity, these simulation runs will be repeated considering different values for the prediction horizon which is set at 20, 30 and 60 minutes respectively. In addition, the prediction accuracy sensitivity will be modeled through introducing different levels of error for the predicted demand (e.g., 10% and 20%). This error is introduced to be able to examine the robustness of the ATDM strategies considering different levels of prediction accuracy.

Active Management or Latency and Prediction, Latency, and Coverage Tradeoffs: Scenarios in phase 3 will be used to examine the benefits of active management in terms of the effectiveness of ATDM strategies in improving the overall network performance. The scenarios consider cases in which ATDM strategies are promptly deployed to mitigate congestion and avoid flow breakdown in the network. These cases are compared with cases in which ATDM strategies are deployed after a pre-specified delay. Also, these results of these experiments will focus on examining the trade-off between prediction latency and prediction coverage extent.

To examine the effect of prediction latency, the effectiveness of the ATDM strategies are compared considering three values for the prediction update cycle: 3, 5, and 10 minutes. The 3 minutes cycle represents the case of frequent update of the network state prediction and active management, while the 10 minutes cycle represents a scenario with excessive prediction and management latency.

The coverage extent is represented by predicting the network state conditions for a subarea rather than the entire network. The boundaries of the subarea could be determined considering a certain distance from the location of the modeled incident. For these set of simulation experiments, a special module will be developed to extract the sub-network of the modeled subarea and properly represent its demand pattern.

9.2 Sensitivity Analyses

Sensitivity analysis will be conducted to account for limitation related to lack of adequate input information for some of the model parameters and/or assumptions that are used in developing the simulation logic for the different ATDM strategies. For example, one might anticipate limited data that can be used to develop models that capture the potential change in the travelers' day-to-day behavior in response to the deployed ATDM strategies. Behavioral models that capture the effect of ATDM strategies on travelers' behavior in a dynamic environment do not exist. For example, there is no model capable of capturing how travelers might change their traveling decisions (demand level) in real time due to adopting dynamic lane shoulder as a traffic management strategy. As such, a sensitivity analysis is proposed where the change in the demand level as a function of the saving/increase in the travel time is guess-estimated.

In addition, implementing any ATDM strategy would require the design of this strategy to determine the optimal settings based on the current and predicted network conditions. In most real-world scenarios, determining the optimal settings for ATDM strategy or a combination of strategies is a complex problem. For example, if an active traffic management scheme that includes dynamic pricing strategy and ramp metering strategy is considered, the optimal prices for all tollable links (gantries) and the optimal ramp inflow rates need to be determined.

These optimal values are expected to be interdependent among the two strategies which could complicate the problem significantly. To address these limitations, sensitivity analysis that covers the possible ranges of these unknown parameters is proposed. For example, if dynamic pricing strategy is considered and there is no information on the optimal pricing scheme, sensitivity analysis that covers the possible pricing range could be implemented.

Similarly, the dynamic pricing is expected to affect the travelers' departure time, route and mode choice. If no accurate behavioral models are available, sensitivity analysis could be conducted to examine the effect of assuming different percentages of the travelers changing their behavior.

To summarize, sensitivity analysis might be considered to provide better understanding of different behavioral phenomena and configuration of ATDM strategies to be modeled.

- The optimal settings for the implemented ATDM strategies
- The short-term and long term effects of ATDM strategies on the demand pattern
- The percentage of travelers with access to real-time traveler information and the associated effectiveness of the ATDM strategies

In addition, sensitivity analysis will be conducted to capture the effect of the following prediction attributes:

- The accuracy of the performed prediction
- The prediction horizon
- Prediction Latency
- Prediction extent variation

9.3 Anticipated Implementation Cost

Implementation cost of the ATDM applications will be estimated by assessing similar execution efforts and reviewing cost databases (e.g., IDAS Database).

Chapter 10. Execution Plan

This section presents the execution plan including a detailed schedule, budget and key roles of staff.

10.1 Execution Summary

This section summarizes the process used to conduct the analysis for **ICM Dallas Testbed**. The analysis scenarios for this Testbed will span three analysis phases to demonstrate and evaluate the DMA applications capabilities:

- Phase 1 (September – December 2014):
- Phase 2 (January – May 2015):
- Phase 3 (May – September 2015):

The 5 steps as shown in Figure 10-1 will be followed for the three-Phase approach to completing the analysis as summarized below.

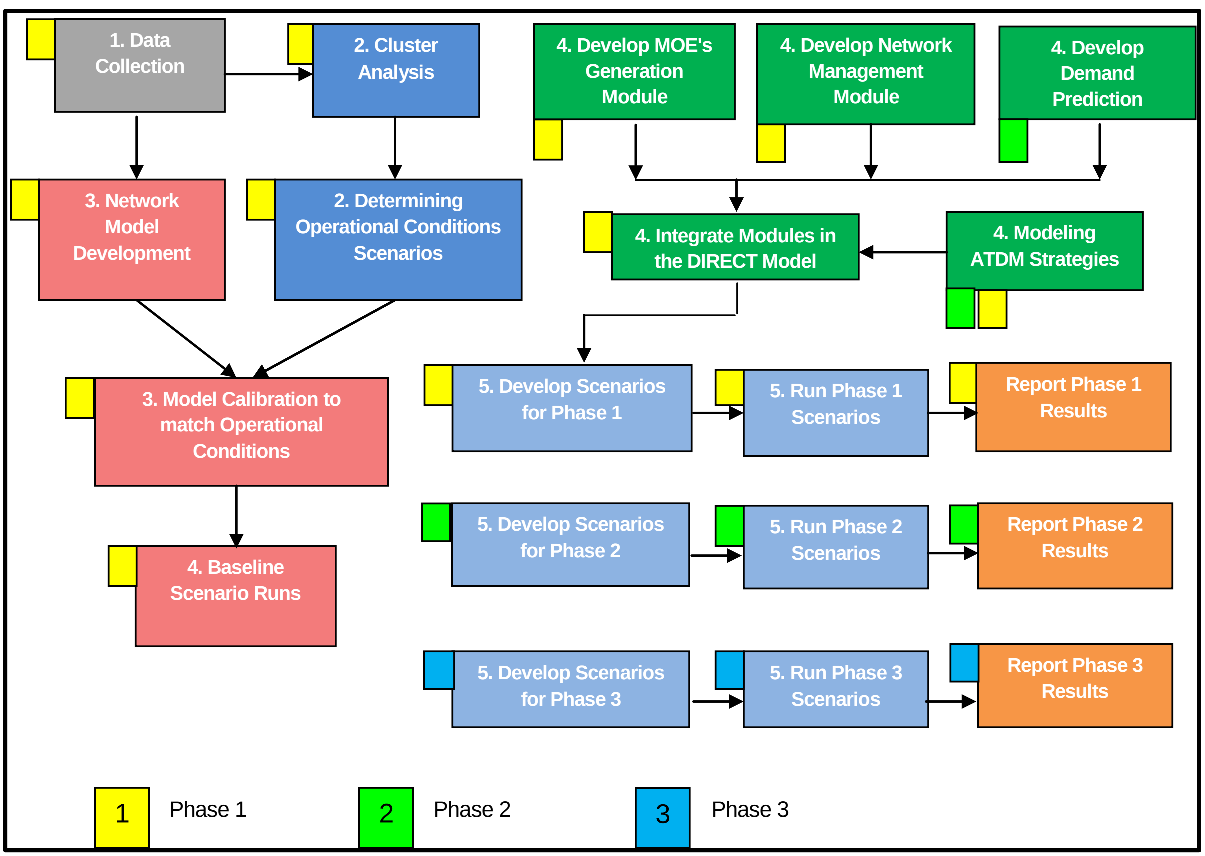


Figure 10-1: Overview of the Project Tasks [Source: SMU]

10.1.1 Data Needs and Availability

10.1.1.1 Available Data

Historical Data, Readily Accessible Data and Real-time Data are already available for the calibration needs and cluster analysis of the Testbed, including:

- Traffic flow counts, density and spot speeds from detectors installed at one to two miles spacing. The data is available at 5 minutes resolution and can be aggregated as appropriate for the purpose of this study.
- Time-varying travel times along the US 75 and I-635 freeway
- Time-varying travel times along the US 75 frontage road and two other strategic arterials using blue tooth technologies
- Signalized intersection peak hour turn counts and signal controller settings, single day only.
- Incident data classified by type, location, and severity
- Park-and-ride lot occupancy during the peak period, single day only.
- Ridership pattern for the Red-Line light rail, single day only.

10.1.1.2 Data Needs/Collection

As part of the cluster analysis performed in this preliminary phase, the traffic data (vehicle counts, travel times, weather and incidents) were assembled for 124 days in 2013. This data will be reexamined to determine the need to extend the analysis horizon to include more days. In addition, the data collection effort will extend to assemble other data elements that are not currently available. These data elements include:

Travel Behavior Data: A recent survey that is conducted as part of the ICM project to capture travelers' responses to incidents and their compliance with travel information (e.g. route diversion). The results of this survey will be studied to extract useful information that can be used to better model travelers' route and mode choice behavior in non-recurrent congestion situations.

Arterial data: Traffic counts for arterial streets are usually collected for the purpose of signals design. The data is limited to one hour in the peak period. Several signal timing studies have been recently performed by NCTCOG. These studies include vehicle count at most signalized intersections. This data will be assembled from these studies. In addition, as part of the ICM project, blue tooth equipment have been recently installed on the frontage road of the US 75 and along two other major arterials. Travel time estimates along these arterials are extracted and stored in the SmartNet system. This data will also be collected for the purpose of the calibration and validation of the model.

<u>Data Collection Tasks:</u>

The following tasks will be performed in Phase 1 during the calibration step

1) Re-examine the data used for the cluster analysis and determine the need to extend the analysis horizon
2) Extracting travel behavior data from the ICM travel behavior survey
3) Extract arterial vehicle count data from signal timing studies
4) Extract blue tooth travel time data from SmartNet

10.1.2 Operational Conditions

10.1.2.1 Existing Operational Conditions

A summary of the proposed operational conditions scenarios are given shown in the table below.

Table 10-1: Summary of Operational Conditions Scenarios

Op. Env. Scenario			Weather Type
1	High Demand	Minor Severity Incident	Dry Pavement
2	High Demand	Medium Severity Incident	Dry Pavement
3	Medium/High Demand	Minor Severity Incident	Dry Pavement
4	Medium/High Demand	High Severity Incident	Dry Pavement

10.1.2.2 Hypothetical Operational Conditions

Up to two “hypothetical” operational conditions which do not exist in the region, but can be modeled by the Testbed with minimal efforts and adjustment factors (e.g. for snow scenario) can be borrowed from other studies to do the analysis. These will be tested as part of Phase 3.

<u>Icing conditions</u>

Icy conditions scenario model is proposed where multiple roadways in the network are fully or partially closed. In this scenario, the expected drop in the demand level due to possible closure of schools and businesses, and the choice of some commuters to work from home would be considered.

<u>Evacuation scenario</u>

An evacuation scenario model is proposed where the residents along the US 75 corridor are instructed to evacuate to one or more safe destinations inside or outside the boundaries of the corridor. Demand patterns that represent different evacuation scenarios will be developed. In addition, traffic management strategies such as dynamic shoulder lane and contraflow operation could be considered in these scenarios.

Table 10-2: Summary of Hypothetical Operational Conditions Scenarios

Hypothetical Operational Conditions	Daily Demand	Incident Type	Weather Type
1	Low/medium Demand	None	Icing
2	High Demand (Evacuation pattern)	None	Dry or wet

10.1.3 Network Modeling and Calibration

As part of the ICM project, the US 75 corridor was calibrated using traffic data collected in year 2011 to represent the so-called "average day". As part of this effort, the time-dependent OD demand matrix was estimated to replicate the time-varying vehicle counts observed along freeway links and some of the arterial links. In addition, the flow propagation models for the freeway links were adjusted to replicate the freeway speed profile and bottleneck patterns. Finally, the model is calibrated to replicate the park-and ride travel behavior in the corridor including a) occupancy of the park-and-ride facilities and b) the spatial ridership pattern for the Red Line. This calibration effort will be updated using a new data set that will be assembled as part of this study. The calibration will be performed for the four operational conditions scenarios identified in the cluster analysis.

Table 10-3: Summary of the Model Calibration Effort

Phases	Procedure
Phase 1 (September – December 2014)	Model the network; calibrate Testbed for existing operational conditions and document results in the “calibration memo”. Set up and verify Performance Measure computations, and execute error check for the model.
Phase 2 (January – May 2015)	Review the network calibration of Phase 1 and make any changes if necessary.
Phase 3 (May – September 2015)	Calibrate Testbed for the hypothetical operational conditions.

10.1.4 Application-Specific Algorithm and Needed Tools

Two main modules will be developed as part of the ICM Dallas Testbed: I) the real-time demand prediction module which accounts for demand adjustments associated with predicted operational conditions and ATDM strategies implemented in the network; and II) the system management module which emulates the decision making process at a typical traffic management center (TMC).

10.1.4.1 Demand Estimation and Prediction Module

The time-dependent demand estimation and prediction methodology is implemented as part of the rolling horizon framework. At each roll, the time-dependent OD-demand pattern is first estimated using a demand estimation methodology that will be developed using a mathematical programming framework. Then, based on available information of the demand dynamic transition pattern, the demand for the next prediction horizon is determined. This transition pattern takes into account a) the current and predicted network operational conditions; and b) the ATDM strategies to be implemented.

10.1.4.2 Traffic Network Management Module

The ICM Dallas simulation testbed emulates the traffic management and decision making process at a typical management center. The traffic management scheme determines the optimal settings for available traffic control devices in the network. A Genetic Algorithm (GA) approach is proposed to generate efficient traffic management schemes that can be deployed based on the predicted network conditions. A traffic management scheme is modeled in the form of a chromosome. A gene in a chromosome defines a control action implemented as part of the scheme. A timing plan at a signalized intersection, a route diversion message on a dynamic message sign, a speed limit advisory, and a ramp meter flow rate are examples of possible control actions. Each scheme is evaluated by its fitness, measured as the average travel time over the prediction horizon when the scheme represented by this chromosome is implemented. The prediction module is activated to estimate the average traveler travel time for each considered scheme.

Table 10-4: Module Development Plan

Phases	Procedure
Phase 1 (January 2015)	The traffic network management module will be developed, tested and applied in Phase 1.
Phase 2 (January – May 2015)	Demand estimation and prediction module will be developed, tested and applied in Phase 2.
Phase 3 (May – September 2015)	Review the module and make any changes if necessary.

10.1.5 Analysis Scenarios

The analysis scenarios for this Testbed will span three different set of test conditions to demonstrate the ATDM strategies as well as to answer the research questions associated with them.

10.1.5.1 Phase 1 (January 2015):

The first phase is devoted to answering research questions related to quantifying the synergy and conflict among the different ATDM strategies and also quantifying these benefits for the different facilities and modes considering different operational conditions. About 18 different scenarios are considered in this phase. ATDM strategies or combinations of strategies that are modeled in this phase include I) dynamic shoulder lane; II) dynamic shoulder lane and dynamic routing; III) dynamic signal control and dynamic routing; IV) ramp metering, V) Dynamic Signal Control + Dynamic Routing + Ramp Metering and VI) dynamic priced parking.

In this phase, the model is used to 1) predict the future congestion; 2) examine the effect of demand prediction y and 3) study the sensitivity of different rates of travelers' response to information on the effectiveness of the ATDM strategies. Operational conditions modeled in this phase include: 1) High Demand + Minor Severity Incident + Dry Conditions; 2) High Demand + Medium Severity Incident + Dry Conditions; 3) Medium/High Demand + Minor Severity Incident + Dry Conditions; and 4) Medium/High Demand + High Severity Incident + Dry Conditions.

Table 10-5: Summary of Operational Conditions Scenarios, ATDM Strategies, and Research Questions Answered in Phase 1

Operational Conditions Scenarios	ATDM Strategies (or combinations of strategies)	Research Questions Answered
- High Demand + Minor Severity Incident + Dry Conditions - High Demand + Medium Severity Incident + Dry Conditions - Medium/High Demand + Minor Severity Incident + Dry Conditions - Medium/High Demand + High Severity Incident + Dry Conditions	- Dynamic shoulder lane - Dynamic shoulder lane and dynamic routing - Dynamic signal control and dynamic routing; - Ramp metering - Dynamic Signal Control + Dynamic Routing + Ramp Metering - Dynamic priced parking	- Demand and Congestion Prediction - Quantifying the benefits of ATDM strategies - Quantifying the synergy and conflict among the different ATDM strategies - Quantifying these benefits for the different facilities and modes considering different operational conditions

10.1.5.2 Phase 2 (January – May 2015):

The second phase considers two additional prediction attributes: a) examining the effect of the prediction accuracy on the performance of the ATDM strategies; and b) examining the effect of the prediction horizon on the performance of the ATDM strategies. The scenarios in phase 2 will also help in answering research questions related to quantifying the synergy and conflict among the different ATDM strategies and also quantifying these benefits for the different facilities and modes considering different operational conditions. Operational conditions modeled in this phase include: 1) High Demand + Minor Severity Incident + Dry Conditions; 2) High Demand + Medium Severity Incident + Dry Conditions; 3) Medium/High Demand + Minor Severity Incident + Dry Conditions; and 4) Medium/High Demand + High Severity Incident + Dry Conditions.

ATDM strategies or combinations of strategies that are modeled in this phase include I) dynamic signal control; and III) dynamic signal control and dynamic routing.

Table 10-6: Summary of operational conditions scenarios, ATDM strategies and research questions answered in Phase 2

Operational Conditions Scenarios	ATDM Strategies (or combinations of strategies)	Research Questions Answered
- High Demand + Minor Severity Incident + Dry Conditions - High Demand + Medium Severity Incident + Dry Conditions - Medium/High Demand + Minor Severity Incident + Dry Conditions - Medium/High Demand + High Severity Incident + Dry Conditions	- Dynamic Signal Control - Dynamic signal control and dynamic routing.	- Examining the effect of the prediction accuracy on the performance of the ATDM strategies - Examining the effect of the prediction horizon on the performance of the ATDM strategies

10.1.5.3 Phase 3 (May– September 2015):

In Phase 3, the modeled scenarios are devoted to capturing the trade-off between prediction latency sensitivity and coverage extent variation. The same combinations of operational conditions and ATDM strategies that are used in Phase 2 are used again in Phase 3 to provide a basis for comparison. Thus, operational conditions modeled in this phase include: 1) High Demand + Minor Severity Incident + Dry Conditions; 2) High Demand + Medium Severity Incident + Dry Conditions; 3) Medium/High Demand + Minor Severity Incident + Dry Conditions; and 4) Medium/High Demand + High Severity Incident + Dry Conditions. ATDM strategies or combinations of strategies that are modeled in this phase include I) dynamic signal control; and III) dynamic signal control and dynamic routing. In addition, two hypothetical operation conditions scenarios representing icing conditions and evacuation scenario will be examined in this phase.

Table 10-7: Summary of Operational Conditions Scenarios, ATDM Strategies and Research Questions Answered in Phase 3

Operational Conditions Scenarios	ATDM Strategies (or combinations of strategies)	Research Questions Answered
- High Demand + Minor Severity Incident + Dry Conditions - High Demand + Medium Severity Incident + Dry Conditions - Medium/High Demand + Minor Severity Incident + Dry Conditions - Medium/High Demand + High Severity Incident + Dry Conditions - Hypothetical Scenario 1: Icing Conditions - Hypothetical Scenario 2: Evacuation	- Dynamic Signal Control - Dynamic signal control and dynamic routing.	- Examine the trade-off between prediction latency sensitivity and coverage extent variation

10.2 Key Roles/Responsibilities

The research team at SMU will be responsible for conducting the analysis plan described above. Obtained results during the different phases will be shared with the project team for further analysis and discussion. The results will be documents and shared with BAH for the preparation of interim and final reports.

Table 10-8: Key Roles and Responsibilities for San Mateo Testbed

Staff	Key Roles	Responsibilities
Khaled Abdelghany	Program Manager	- Budget, Schedule, QA
Ala Alnawaiseh (post-doc) **One graduate student (TBD)**	Technical Lead - ICM Dallas Testbed	- Sim Model Calibration - Baseline Scenarios - Phase 1, 2, 3 Tests - Sensitivity Analysis - Off-model analyses

APPENDIX A. Description

This section documents the process used to identify four baseline scenarios, combining different levels of demand, incident, and weather conditions for testing the performance effects of Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Program improvements on the ICM Dallas Testbed.

The hypothesis is that the traffic congestion and safety benefits of ATDM vary for different levels of recurring congestion (congestion associated with high demand levels) and non-recurring congestion (congestion associated with incidents and bad weather, sometimes in combination with high demand levels). To assess the benefits of ATDM, it is necessary to test various ATDM improvement options on a variety of operational scenarios combining different levels of demand, weather conditions, and incident types. Study resources do not allow modeling every possible combination of the factors. The approach to reducing the number of operational scenarios to be tested with full modeling is a clustering analysis approach employing the steps listed below:

1. Examine real world conditions at the test site
2. Identify all of the possible combinations of demand, incidents, weather and travel time that occurred on approximately 124 days including morning and evening peak periods
3. Perform a clustering analysis to identify opportunities for collapsing several scenarios into fewer scenarios
4. Identify the frequency of occurrence for each scenario
5. Assemble a set of operational scenarios that span the range of observed conditions on the corridor

The experimental objective is to estimate the travel time performance and safety benefits of ATDM. The hypothesis is these benefits is a function of the severity of the baseline congestion and the degree to which the congestion is caused by non-recurring events (such as adverse weather and lane blocking incidents), in addition to factors related to the implementation of ATDM. Based on this hypothesis, the following factors were identified as relevant to the baseline scenarios for analysis: demand, weather, and incidents.

The final number of operational scenarios to be used in the analysis is four, based on the two objectives of the selection process:

- To identify a full range of operational conditions for testing the improvements.
- To ensure remaining sufficient project resources for adequate testing options related to the specific design and implementation of the DMA and ATDM improvements.

The Appendix is divided into the following sections: Data Collection, Cluster Analysis Approach, and Cluster analysis results.

APPENDIX B. Data Collection

The analysis requires travel time, demand, weather, and incident data.

Travel Time Data

Travel time data for approximately 124 days in the year 2013 were obtained from the DalTrans database[3] for about 20 miles of US 75 between Mockingbird Lane (Southern boundary) and Highway 121 (Northern Boundary). For this freeway section, there were 38 mainline loop detector stations in the northbound direction and 43 mainline loop detector stations in the southbound direction (each station recording lane-by-lane speeds for 3, 4 or 5 lanes depending on number of lanes at the station).

The average speed data is archived for each lane at five minutes resolution for each detector. The speed data is averaged for all lanes to obtain one record for each freeway link assuming that all lanes to have the same weight. The spot speeds are then converted to travel time by dividing the length of the link by the speed recorded for this link. The data is finally aggregated to the desired temporal aggregation level. In this case, one hour aggregation was selected.

Figure B-1 and Figure B-2 show the cumulative distribution of the travel time indices for US 75. The distributions are given for the morning and evening peak period and for both freeway directions. The travel time index is obtained by dividing the travel time for each peak period by the average travel time considering the entire data collection horizon. For example, in the AM peak, about 50% of the peak periods are greater than average the travel time. This pattern is observed for the northbound and southbound directions. However, the variability in the travel time is much higher for the southbound direction. For the southbound direction, the travel time index ranges from about 0.75 to 1.4. For the north bound direction, the travel time index varies from 0.9 to 1.37.

[3] http://dfwtraffic.dot.state.tx.us/#showContent%28%27/DfwTrafficData/%27%29%3B, Accessed July-August 2014.

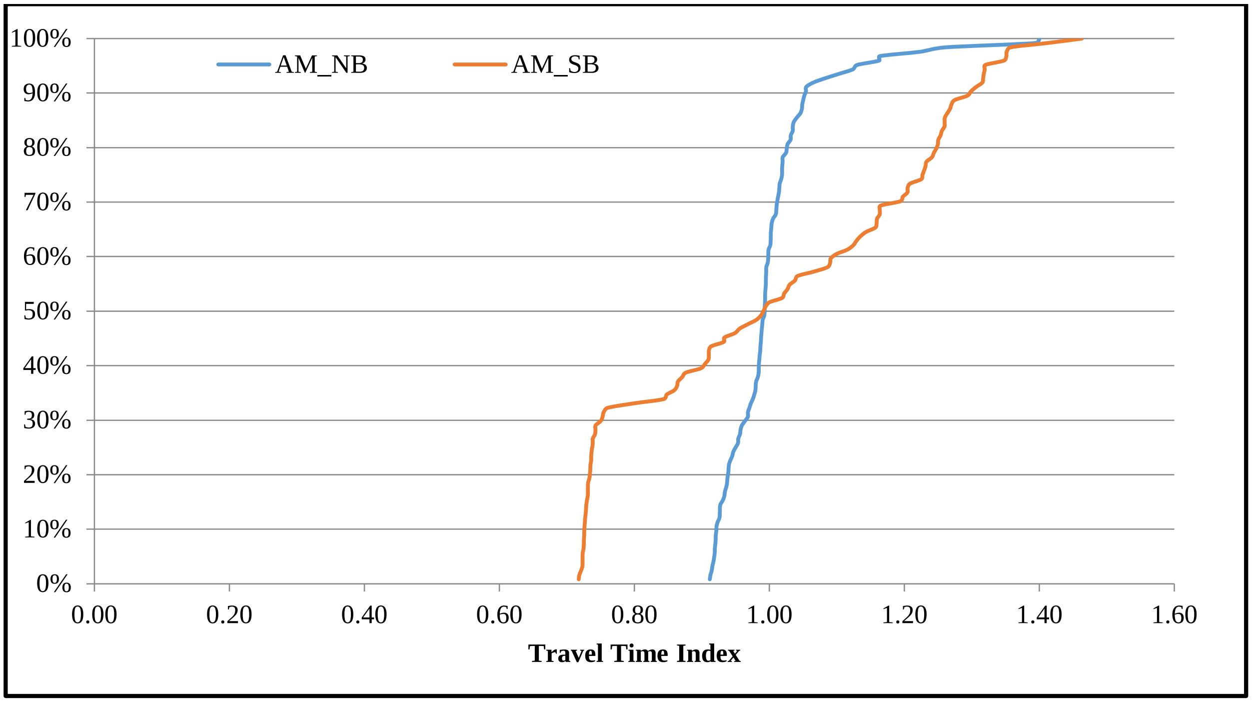


Figure B-1: Cumulative Distribution of Travel Time Indices for US 75 AM Peak Period [Source: SMU]

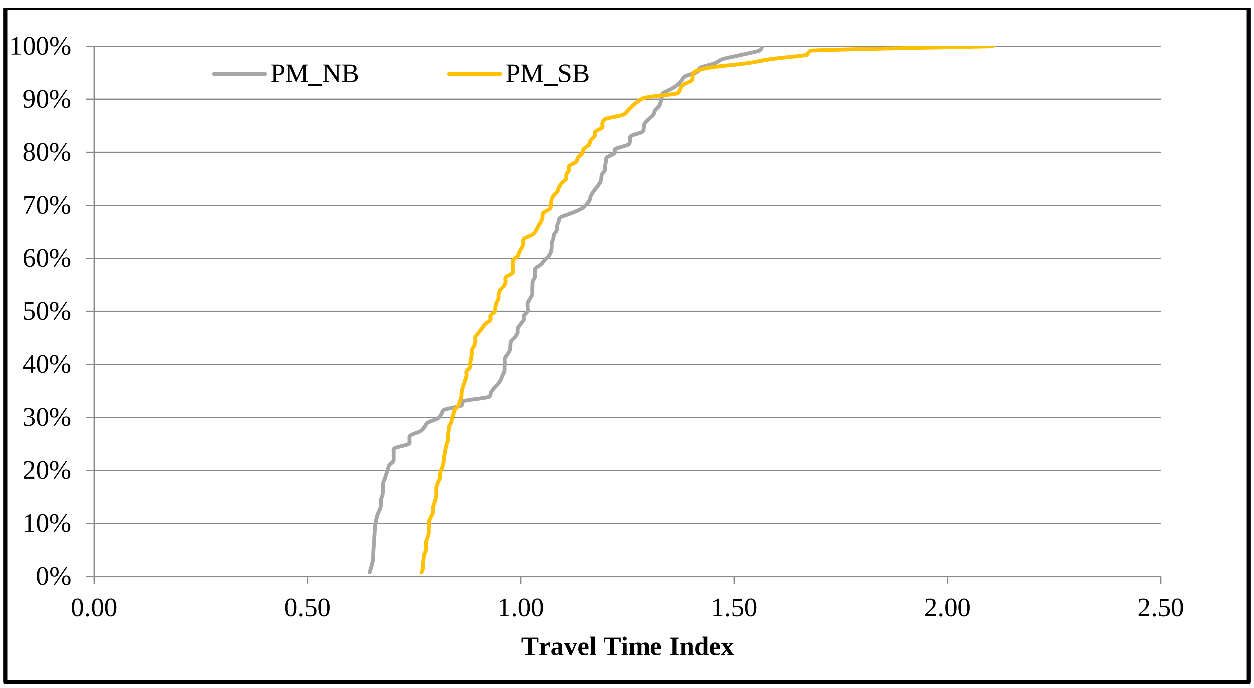


Figure B-2: Cumulative Travel Time Distribution for US 75 PM Peak Period [Source: SMU]

Table B-1: Cumulative Travel Time Index Statistics – US 75

Statistic	AM Peak Period		PM Peak Period	
	Northbound	Southbound	Northbound	Southbound
5th Percentile	0.92	0.72	0.65	0.77
25th Percentile	0.95	0.74	0.74	0.83
Median (50%)	0.99	0.99	1.02	0.94
75th Percentile	1.02	1.23	1.19	1.11
95th Percentile	1.13	1.32	1.41	1.41

Table B-1 Table B-3 provides a summary of the distributions of the travel time for US 75. The travel time indices are recorded for different percentiles of the cumulative distribution for both directions in the AM and PM peak periods. For example, in the AM peak the 95th percentile is recorded at 1.13 for the northbound direction and 1.32 for the southbound direction.

Finally, the hourly variation in the travel time is examined. Figure B-3 to Figure B-6 show the travel time for all hours in the AM and PM peak periods for both directions. The variation is explored for all days in the week. As shown in the figures, some variation in the travel time within the peak periods is observed especially in the dominant commuting direction. For example, in the northbound direction in afternoon peak period, the travel time varies from 34 minutes to 43 minutes in a typical Tuesday. Less travel time variation is generally observed along the less congested direction (i.e., opposite to the commuting direction).

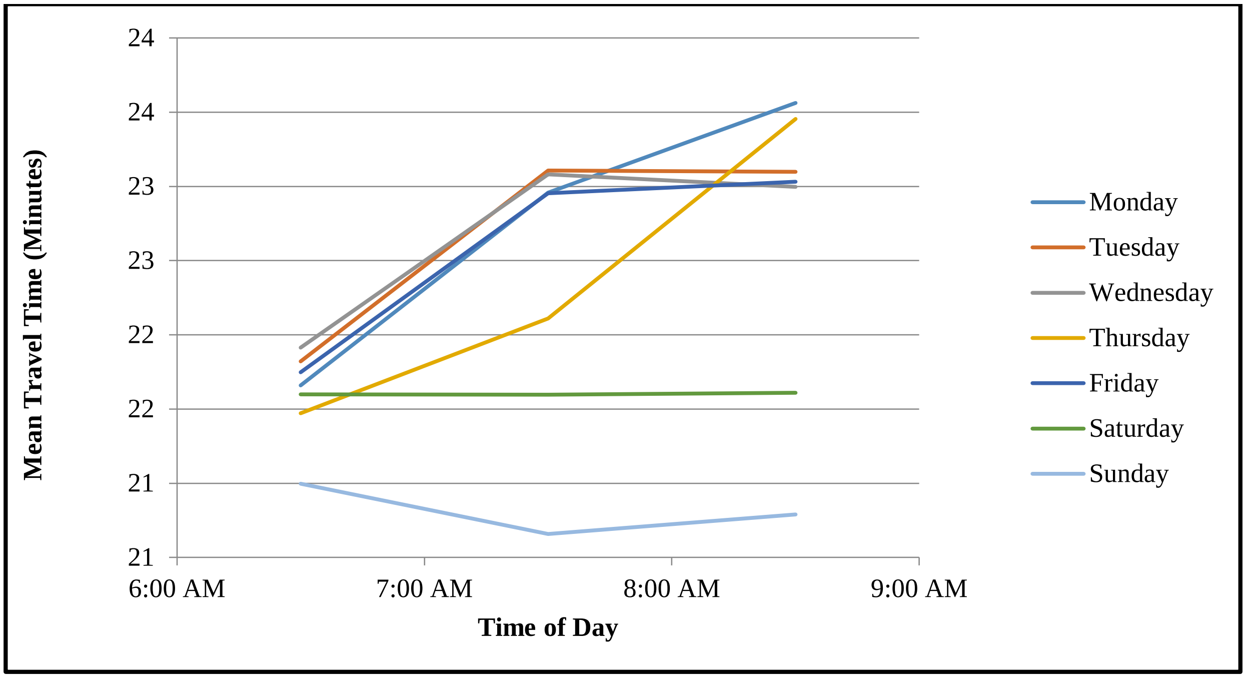


Figure B-3: Hourly Travel Time Variation during AM Peak Period for US 75 Northbound [Source: SMU]

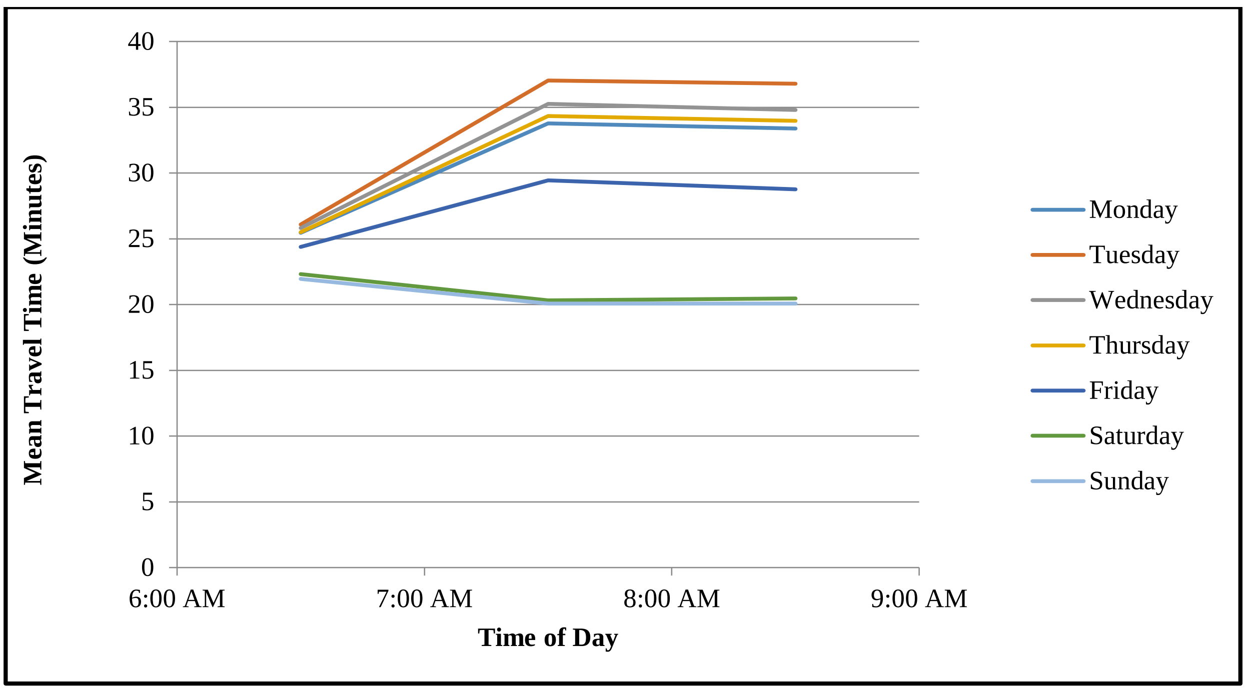


Figure B-4: Hourly Travel Time Variation during AM Peak Period for US 75 Southbound [Source: SMU]

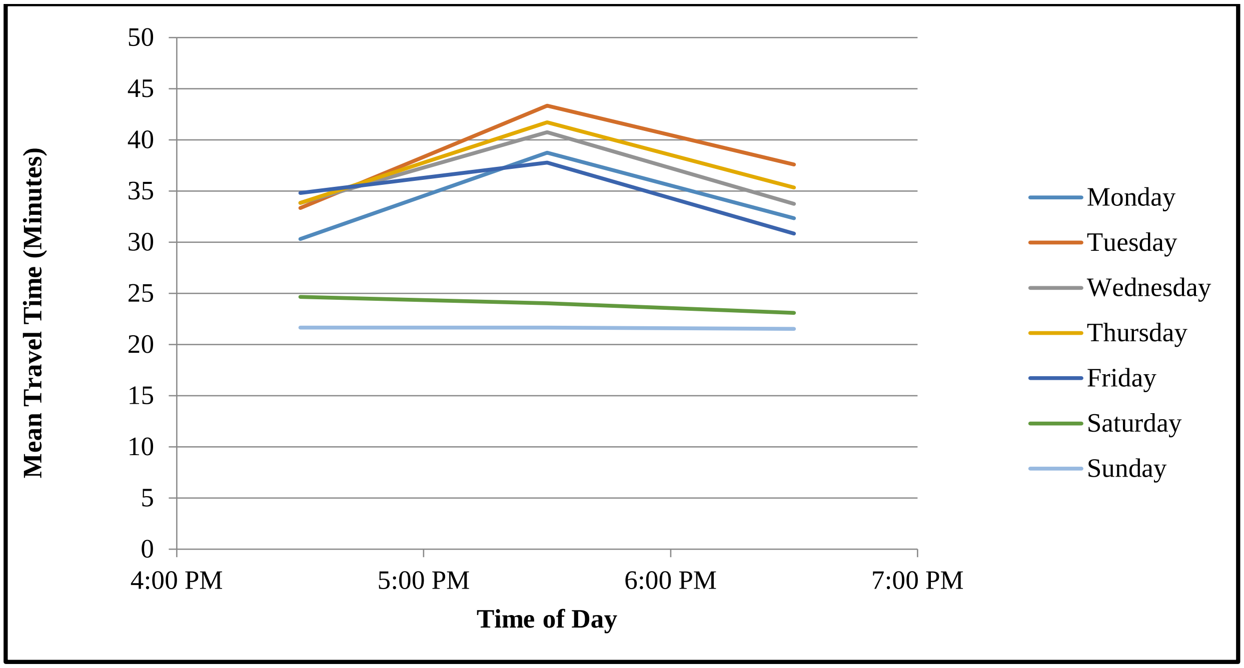


Figure B-5: Hourly Travel Time Variation during PM Peak Period for US 75 Northbound [Source: SMU]

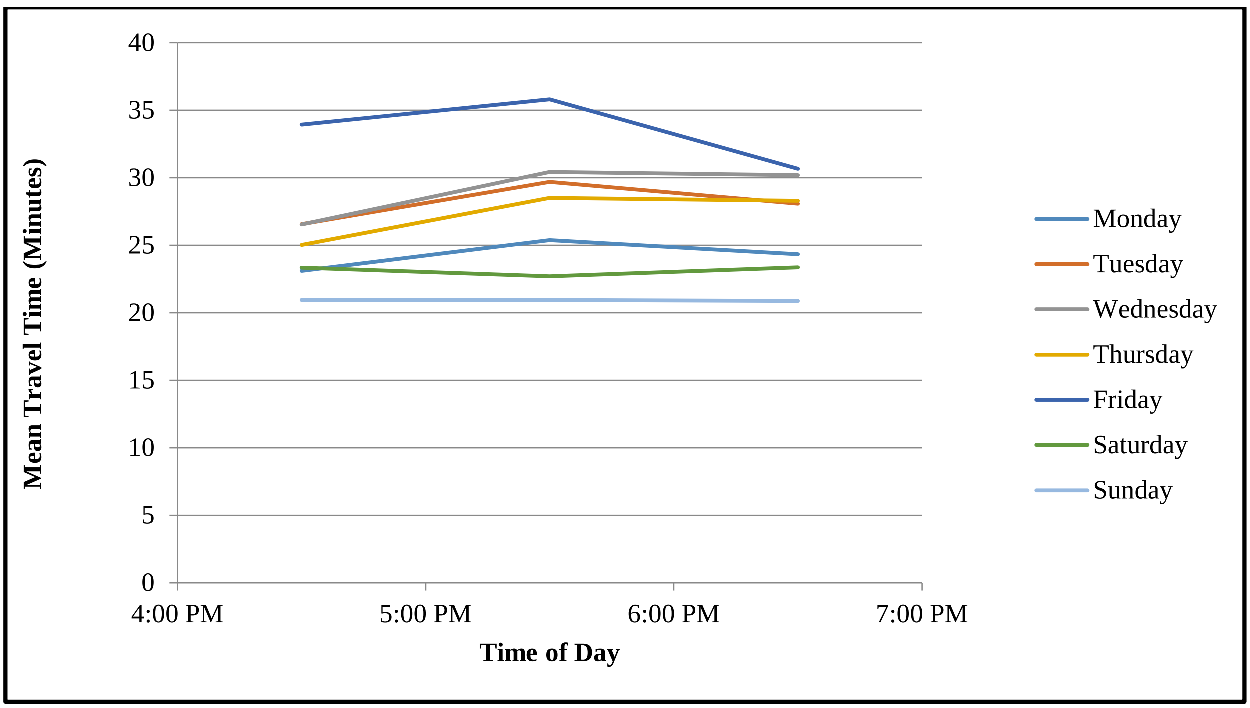


Figure B-6: Hourly Travel Time Variation during PM Peak Period for US 75 Southbound [Source: SMU]

Demand Data

The vehicle miles traveled (VMT) are used as indication for the demand level in the corridor. The VMT data are obtained for both directions of the freeway based on the archived vehicle count data. VMT is estimated by tallying the volume measured at each lane loop detector and multiplying that volume by half the sum of the average distances to the nearest upstream and downstream detectors. The volumes, available at the 5 minute level of aggregation, were aggregated to peak period VMT for each of the study days, by direction, over the length of the freeway study section.

Figure B-7 and Figure B-8 gives the variation in measured daily VMT by direction for the AM and PM peak periods. The charts show that the measured daily VMT varies by no more than plus or minus 10% from the average of the days analyzed. Another important observation is that the AM peak period generally subjects to more variability in the demand level than the PM peak period. The VMT ratio, which is defined as the ration between the VMT value recorded for a peak period and the average VMT for all peak periods in the analysis horizon, ranges from 0.2 to 1.4 in the morning peak period, and it ranges from 0.3 to 1.2 in the afternoon peak period.

Figure B-9 to Figure B-10Figure B-12 illustrate the VMT spatial distribution for the AM and PM peak periods respectively. Each figure gives the VMT spatial pattern for both directions. As shown in these charts, in the AM peak period, the VMT in the southbound direction are generally higher than those recorded for the northbound direction. The opposite pattern is observed for the PM peak period where higher VMT are recorded for the northbound direction. The spatial VMT pattern indicates that the entire corridor is subject to almost the same level of congestion as the highest VMT values are observed at multiple locations along the freeway.

Finally, Figure B-13 and Figure B-14 show the hourly variation in the VMT during the AM and PM peak periods for both directions. Two observations can be made based on this chart. First, as shown above, the demand level in the PM is generally higher than that of the AM peak period. This pattern is observed for both directions. Second, in all peak periods, the hourly variation in the VMT is relatively small, which imply that the congestion is persistent for the entire peak period for both directions of the freeway.

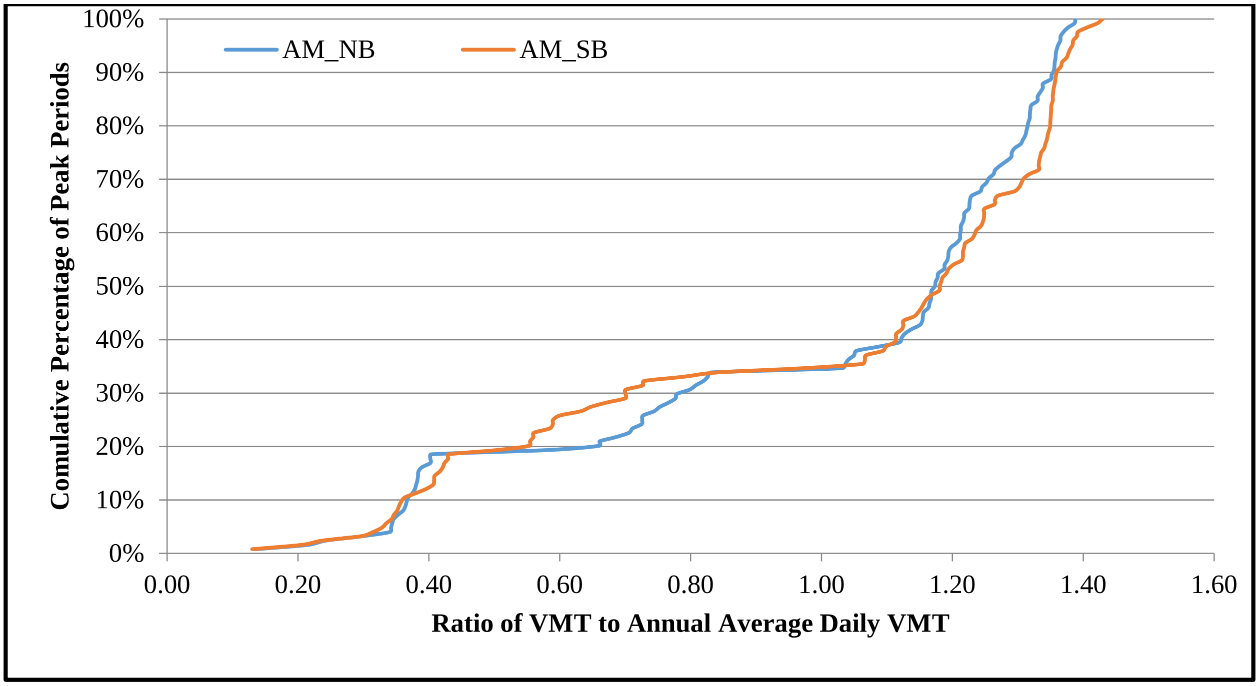


Figure B-7: Cumulative Distributions of Daily VMT for AM Peak Period [Source: SMU]

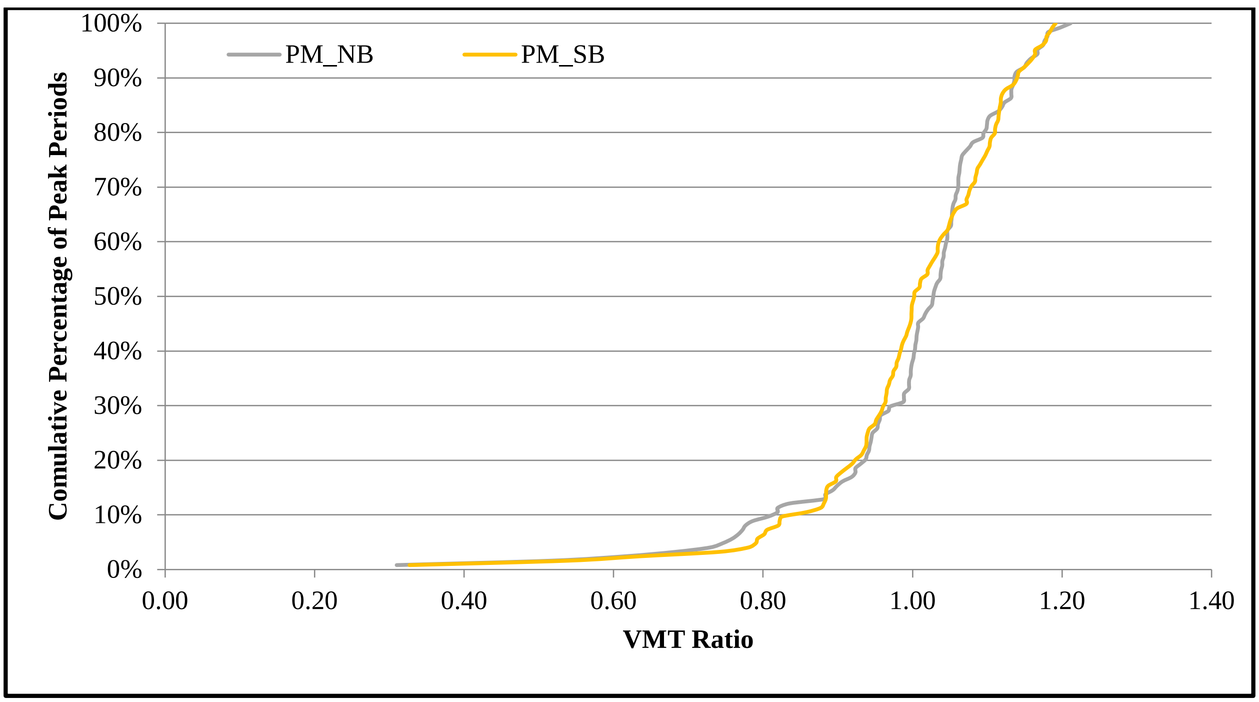


Figure B-8: Cumulative Distributions of Daily VMT for PM Peak Period [Source: SMU]

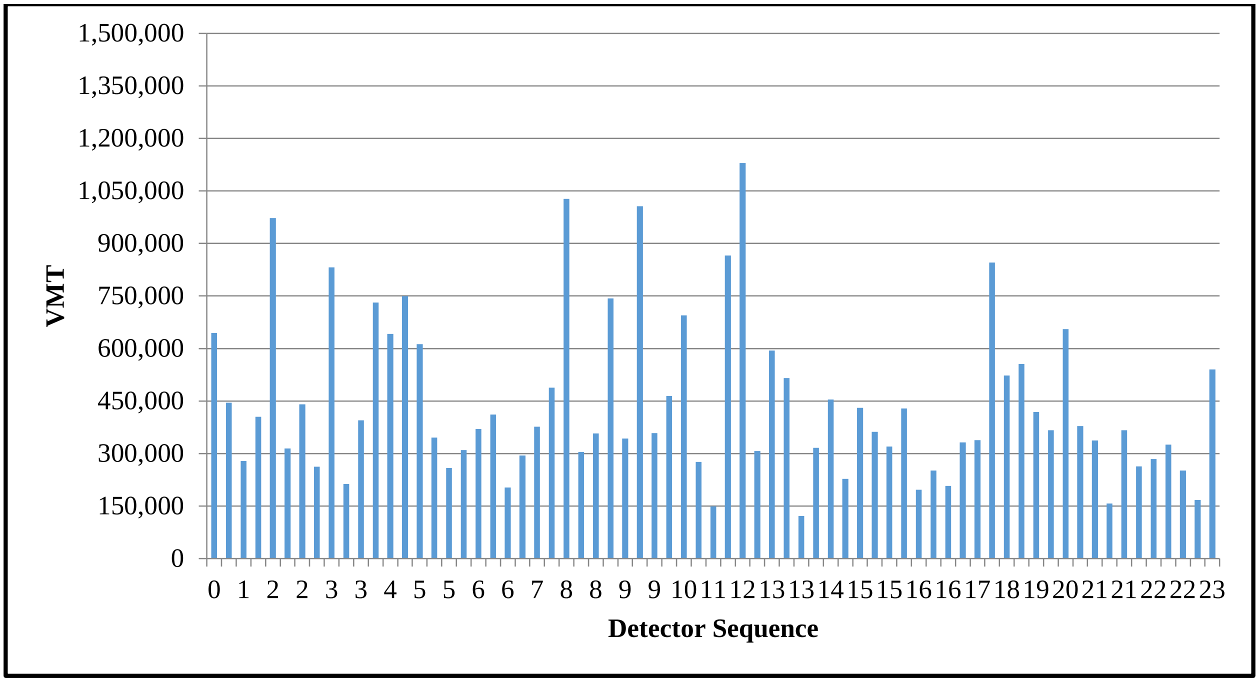


Figure B-9: VMT Distribution for US 75 Northbound, AM Peak Period [Source: SMU]

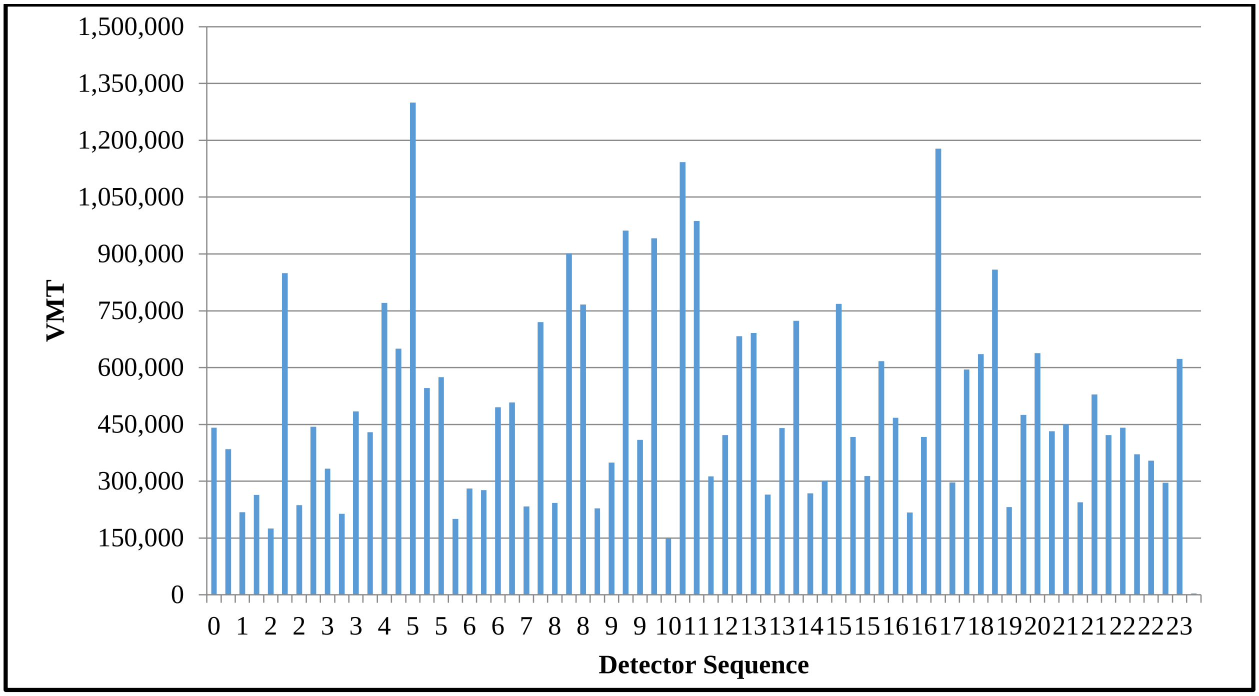


Figure B-10: VMT Distribution for US 75 Northbound, PM Peak Period [Source: SMU]

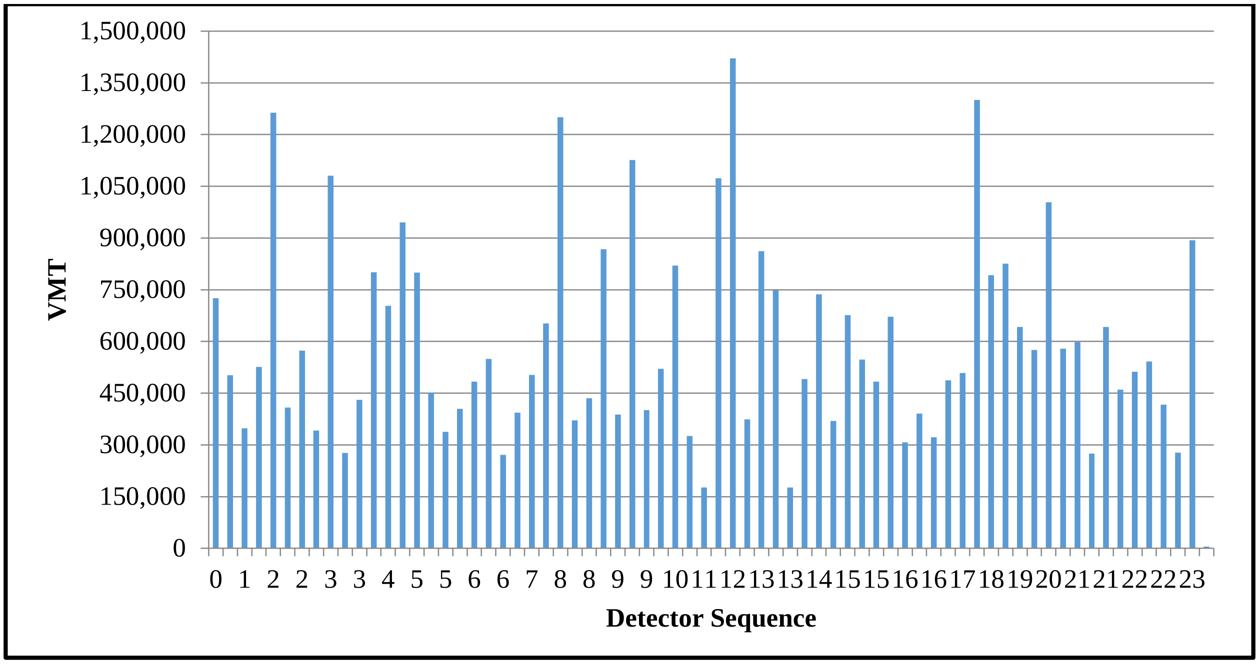


Figure B-11: VMT Distribution for US 75 Northbound, PM Peak Period [Source: SMU]

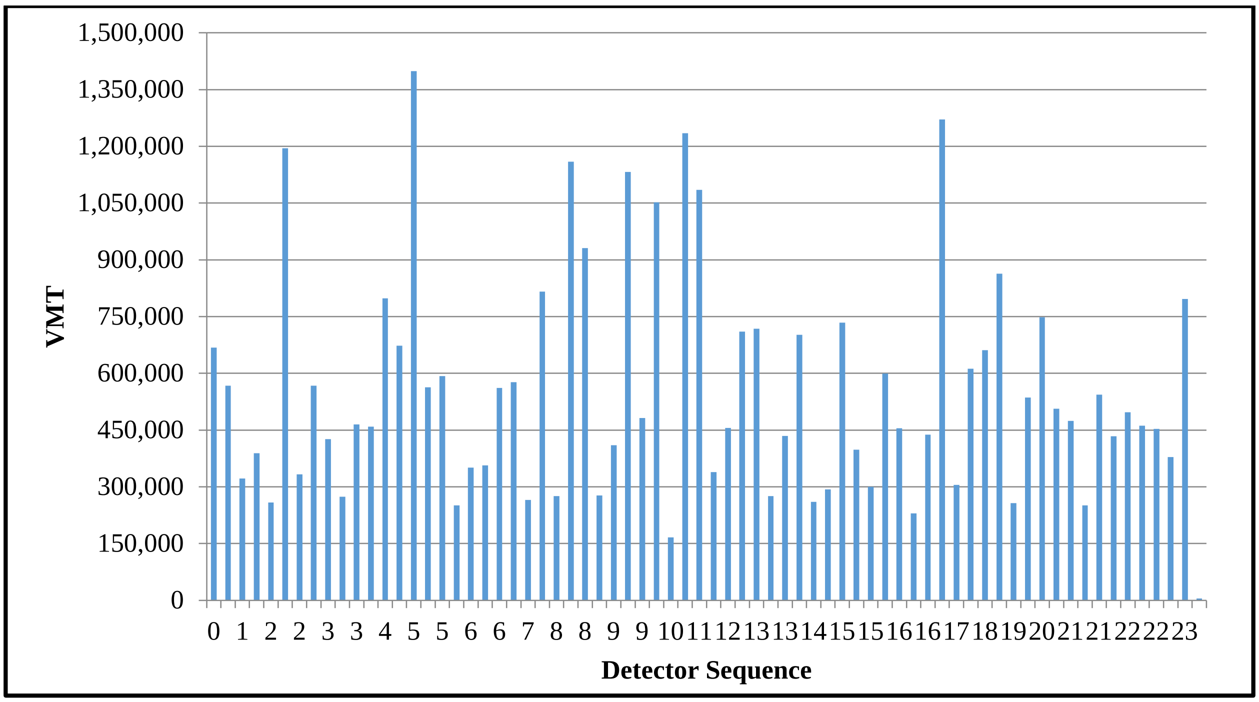


Figure B-12: VMT Distribution for US 75 Southbound, PM Peak Period [Source: SMU]

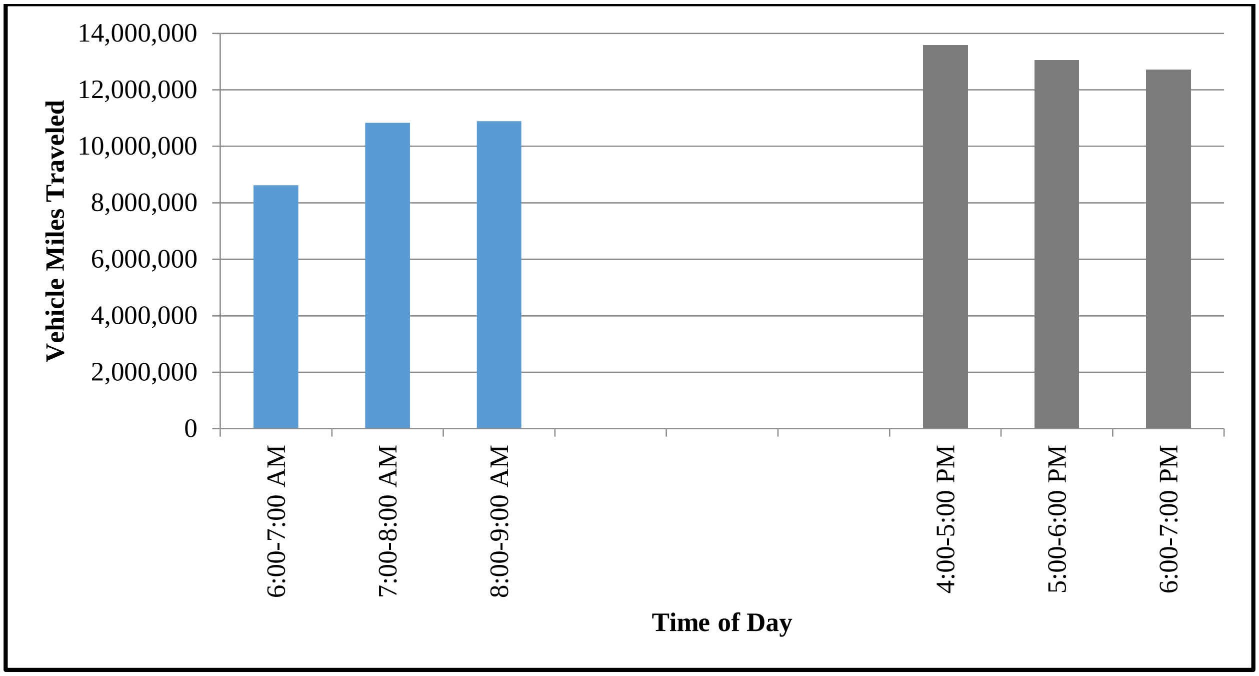


Figure B-13: Hourly Traffic Variation on US 75 Northbound [Source: SMU]

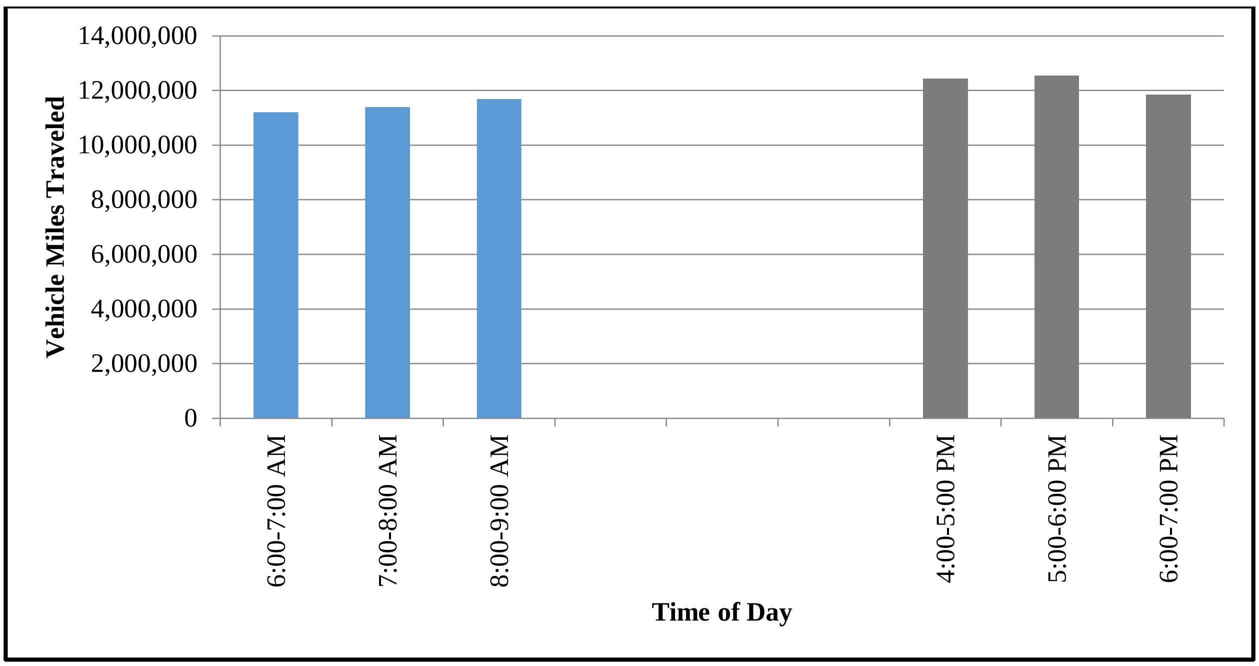


Figure B-14: Hourly Traffic Variation on US 75 Southbound [Source: SMU]

Weather Data

Weather data was extracted from the national weather service website (www.weather.gov) for the Love Field airport, which is the closest weather-reporting station to the Testbed. Out of the 124 days, twenty six days of rainy weather (i.e., the recorded level of precipitation is great than zero) were observed in the morning peak period and thirteen days of rainy weather were observed for afternoon peak period. There was no snow, ice, or ground fog conditions during the analyzed horizon.

Incident Data

Incident logs were obtained for the analysis horizon from the DalTrans database. Incident data includes starting time, duration, location information, type, and number of blocked lanes. About 215 incidents were recorded. Figure B-15 provides a type-based classification of the incidents recorded in the subject horizon.

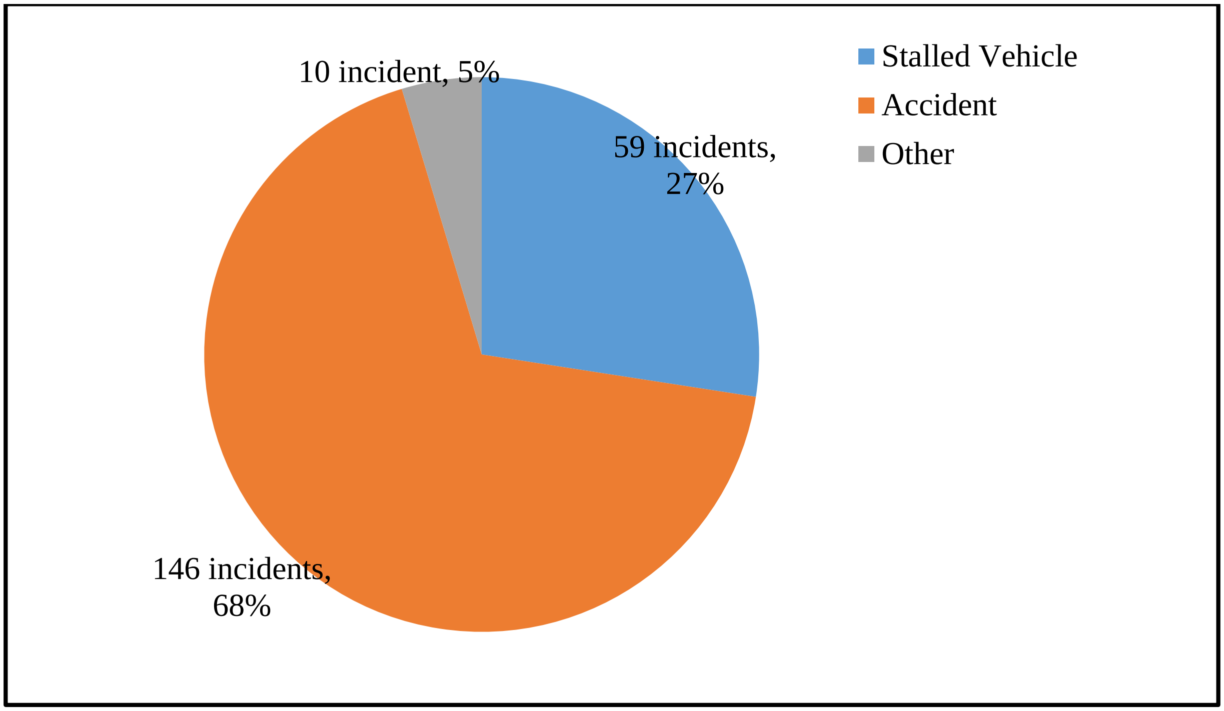


Figure B-15: Incident Classification, US 75 2013 Data [Source: SMU]

By way of comparison, for the AM peak period, there were a total of 29 (14%) incidents recorded in the northbound direction, and 41 (19%) incidents recorded in the southbound direction. For the PM peak period, there were a total of 95 (44%) accidents recorded in the northbound direction, and 50 (23%) incidents recorded in the southbound direction. The rate of incidents along the US 75 freeway is close to two incidents per day.

Figure B-16 and Figure B-17 give spatial distribution of the accident rate (number of accidents per million vehicle mile traveled) for US 75 for both directions. The accident rates are obtained by combining the incident and VMT records for the AM and PM peak periods. A graphical representation of this data is also provided in Figure B-18. For the northbound direction, high accident rates are recorded at Spring Creek Road, Park Blvd, Collins Road, and Forest Lane. For the southbound direction, high accident rates are recorded just north of US 75 interchange with Highway IH 635 and at Renner Road.

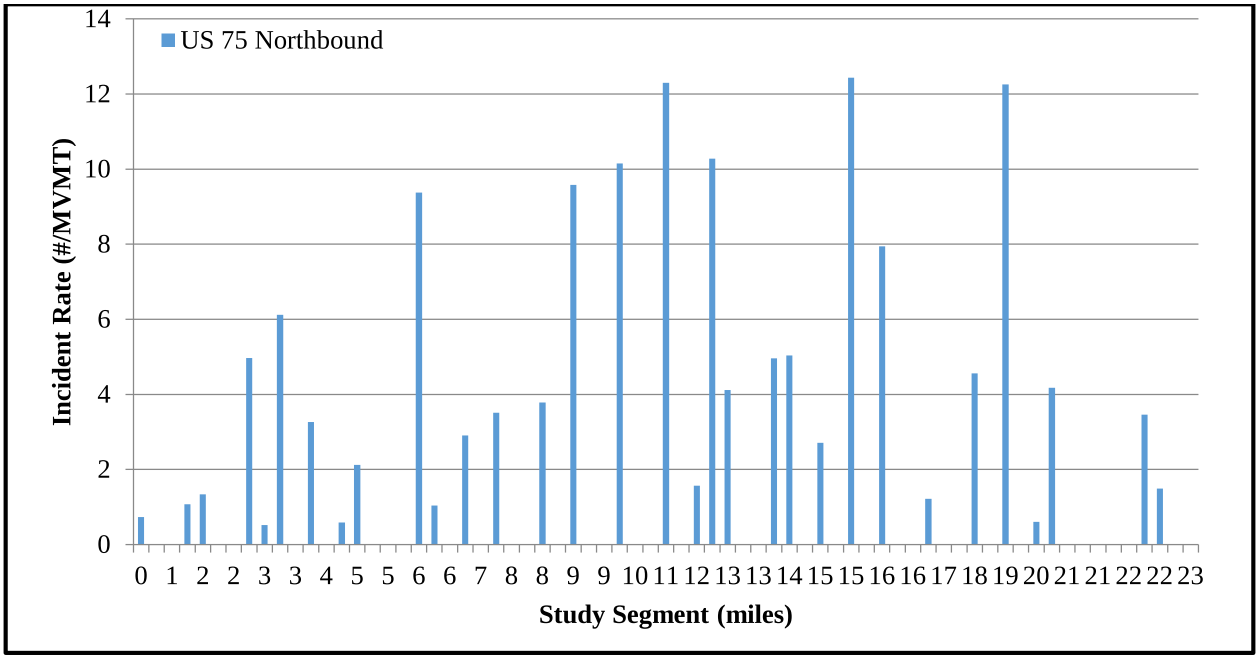


Figure B-16: Incident Spatial Distribution, US 75 Northbound 2013 Data [Source: SMU]

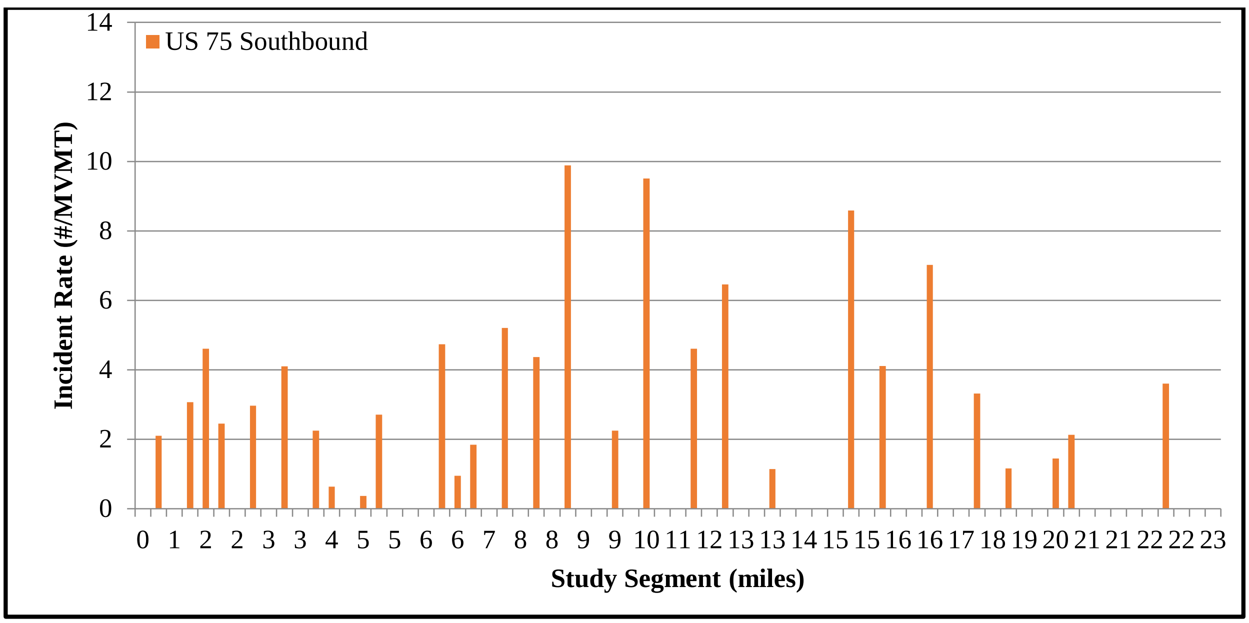


Figure B-17: Incident Spatial Distribution, US 75 Southbound 2013 Data [Source: SMU]

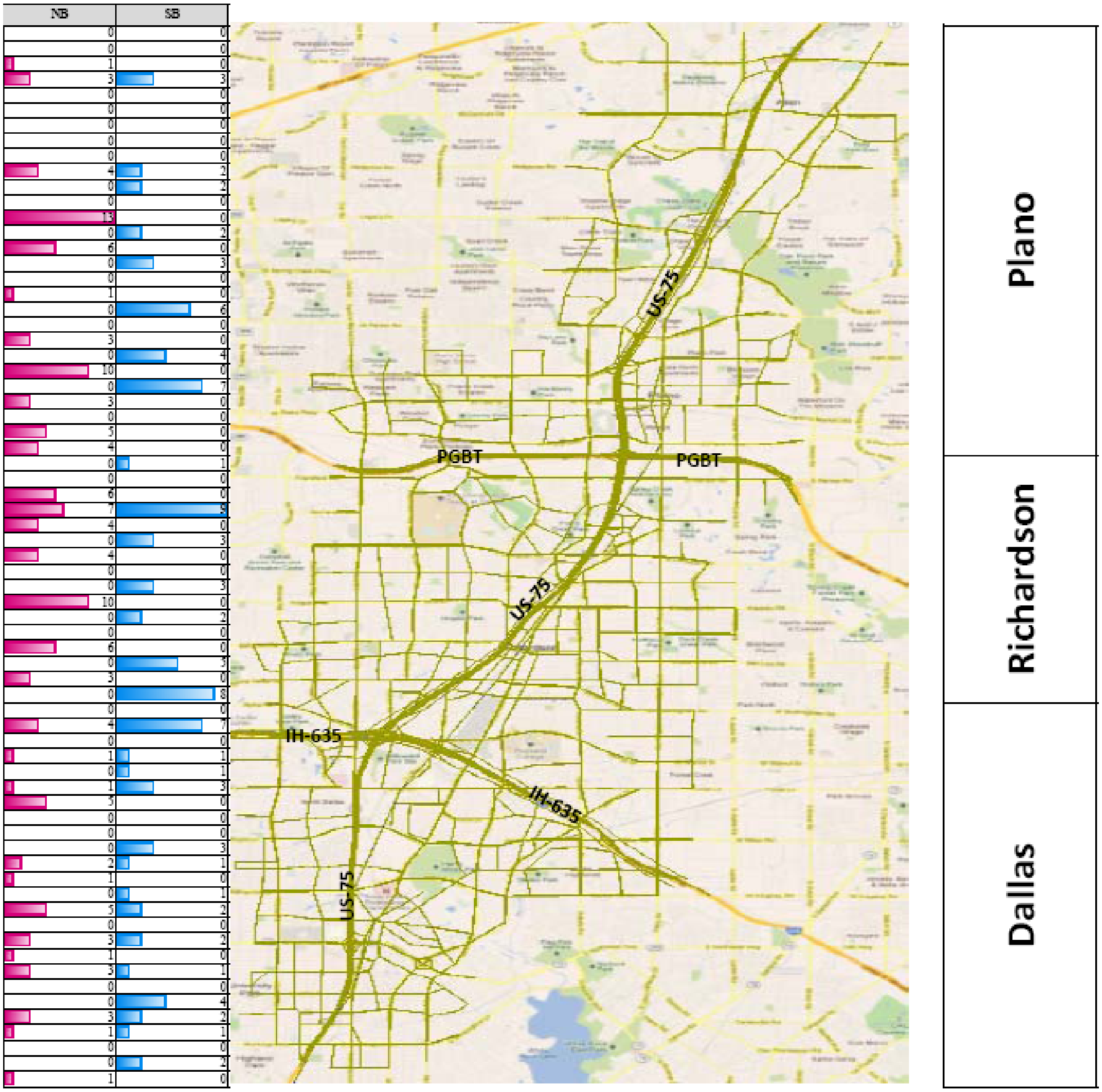


Figure B-18: Distribution of Incidents along US 75 Northbound and Southbound [Source: SMU]

Figure B-19 and Figure B-20 shows the distribution of the incident duration during the AM and PM peak periods for both directions. In general, about 90% of the incidents have duration less than one hour, and about 40% of the incidents have duration less than 30 minutes.

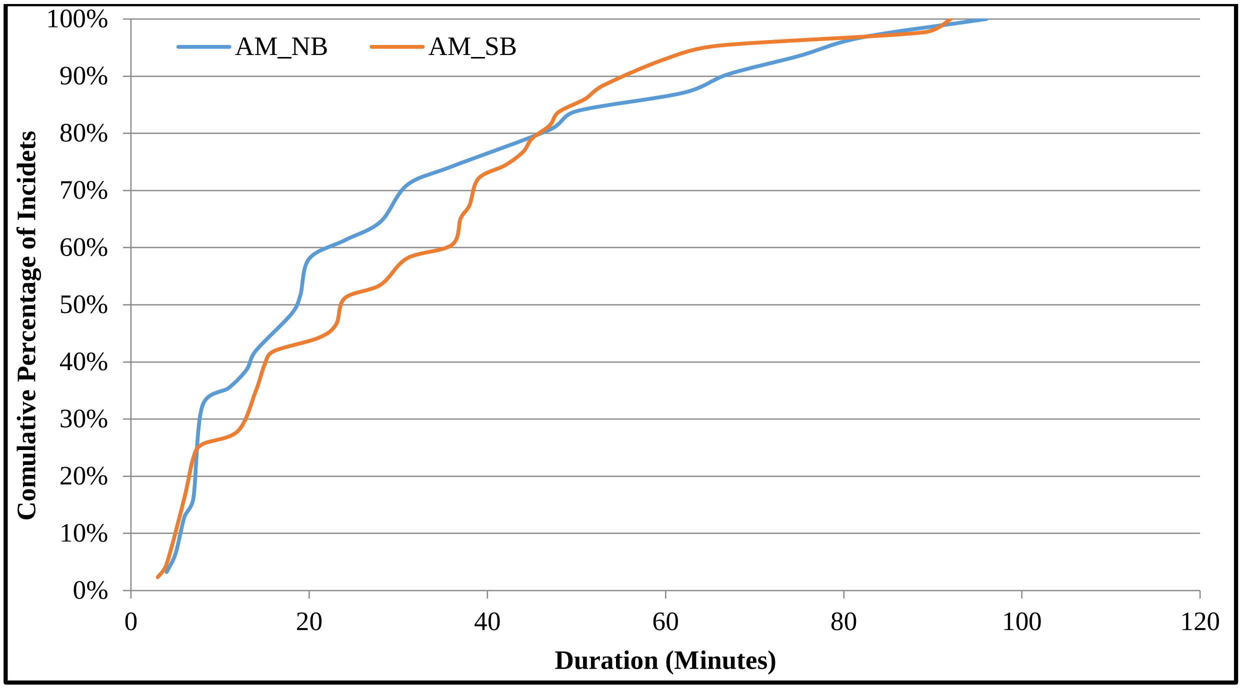


Figure B-19: Distribution of Incident Durations during AM Peak Period [Source: SMU]

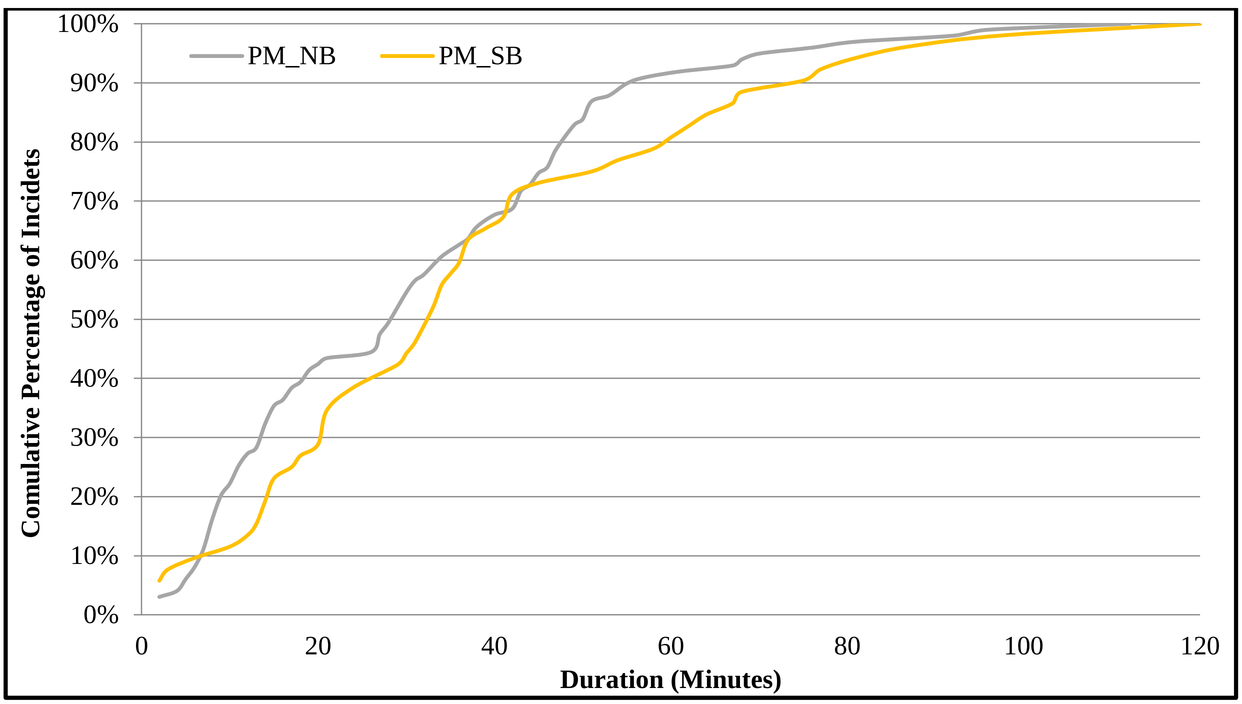


Figure B-20: Distribution of Incident Durations during PM Peak Period [Source: SMU]

Data Assembly

Traffic data was obtained for both directions (NB and SB) of the US 75 freeway during the AM peak period (6:00 AM - 9:00 AM) and PM peak period (4:00-7:00 pm) for 124 days in the year 2013. This data includes flows and speeds (travel times) from loop detector data and incident record data as archived and processed in the DalTrans Database system. As mentioned earlier, the weather data is obtained from the national weather service website. A summary of this data is provided in Table B-3.

The Demand data is presented in the form of the VMT ratio for each peak period. As described earlier, the VMT ratio is defined as the ratio between the VMT during the peak period and the average VMT for the data collection horizon. The incident data is presented in terms of their severity. In this analysis, the multiplication of number of closed lanes and their closure time is used to define the severity of the incident. The amount of precipitations is given for each peak period. For each peak period, the average travel time for each direction is also recorded.

The data for each of the 124 days for both directions (NB and SB) was classified into three traffic demand levels (low, medium, and high), three incident types (no incident, low/moderate severity, and high severity incident, and two weather types (dry and rain). For the demand data, the range of the VMT ratio is divided into approximately three equal intervals. For example, for the AM peak period, the VMT ratio ranges from 0.1 to 1.4. Low demand category is assumed for all periods with VMT ratio less than 0.5. The medium demand category is assumed for periods with VMT ration greater than 0.50 and less than 0.90. The high demand category is assumed for periods with VMT ratio greater than 0.9. For the PM peak period, the range of the VMT ratio is from 0.30 to 1.20. Accordingly, low demand category is assumed for all peak periods with VMT ration less 0.70. The medium demand category is assumed for periods with VMT ratio greater than 0.6 and less than 0.95. The high demand category is assumed for periods with VMT ratio greater than 0.95.

The incident severity is defined as the total lane-minute closure for each incident. As shown in Table B-2, incidents with less than 30 lane-minutes closure are categorized as low severity incidents. Otherwise, the incident is considered as a severe incident. Finally, peak periods are classified into dry and wet. If any level of precipitation is observed during a peak period, this peak period is classified as a wet period.

Table B-2: Categorization of Incident Based on Severity Level

Closure Index	*Category*
≤ 30 minutes	Low/moderate Severity
> 30 minutes	High Severity
0	No Incident

Table B-3: Data Assembly for Cluster Analysis for US 75

Day	AM_NB				AM_SB				PM_NB				PM_SB			
	Demand (VMT Ratio)	Severity (Seconds)	Precipitation (mm)	Travel Time (Minutes)	Demand (VMT Ratio)	Severity (Seconds)	Precipitation (mm)	Travel Time (Minutes)	Demand (VMT Ratio)	Severity (Seconds)	Precipitation (mm)	Travel Time (Minutes)	Demand (VMT Ratio)	Severity (Seconds)	Precipitation (mm)	Travel Time (Minutes)
20130723	1.17	0	0	21.99	1.22	0	0	23.45	1.05	1320	0	30.60	1.00	0	0	22.60
20130724	1.15	600	0	22.44	1.24	0	0	23.79	1.00	480	0	34.09	0.92	0	0	29.24
20130725	1.19	480	0	22.02	1.25	900	0	23.48	1.05	120	0	31.01	1.03	1980	0	22.62
20130726	1.05	480	0	23.23	1.11	900	0	25.32	1.02	120	2.8	30.59	0.96	1980	2.8	22.76
20130727	0.69	0	2.3	21.19	0.55	0	2.3	19.72	0.88	0	0	21.98	0.99	0	0	21.79
20130728	0.34	0	0	20.75	0.35	0	0	19.69	0.76	0	0	20.94	0.82	0	0	20.61
20130729	1.14	3360	0	21.70	1.23	0	0	24.73	1.04	0	0	31.36	0.94	0	0	22.42
20130730	1.15	0	0	21.93	1.22	0	0	25.35	1.00	0	0	31.54	0.89	2040	0	28.61
20130731	1.12	0	0	21.90	1.18	2700	0	24.57	0.94	4320	0	38.83	0.88	5640	0	32.85
20130803	0.71	0	0	20.78	0.56	0	0	19.96	0.75	0	0	21.37	0.81	0	0	21.06
20130804	0.36	0	0	20.38	0.35	0	0	19.74	0.82	0	0	20.87	0.82	360	0	20.51
20130805	1.17	0	0	21.61	1.11	10680	0	32.72	1.03	0	0	32.29	0.95	0	0	22.20
20130806	1.15	0	0	21.88	1.06	0	0	33.45	0.99	3060	0	37.43	0.94	1800	0	26.08
20130807	1.16	0	0	21.86	1.16	0	0	29.61	1.00	6480	0	34.49	0.98	0	0	22.12
20130808	1.23	0	0	21.72	1.19	2700	0	26.92	0.95	0	0	29.78	0.88	0	0	24.39
20130809	1.03	0	0	21.66	1.07	0	0	21.68	1.04	0	0	31.76	0.98	0	0	23.40
20130811	0.36	1440	0	20.42	0.33	0	0	19.68	0.82	0	0	21.00	0.86	0	0	20.59
20130812	1.20	0	0	21.71	1.25	0	0	24.71	1.03	0	0	32.30	0.95	0	0	22.67
20130813	1.22	0	0	21.84	1.19	0	0	27.76	0.94	4800	0	37.78	0.93	0	0	26.99
20130814	1.21	0	26.90	21.83	1.25	0	26.90	23.03	1.06	0	0	30.30	0.94	0	0	30.46
20130815	1.19	2580	18.5	23.36	1.27	0	18.5	23.33	1.06	0	0	32.66	1.00	120	0	26.42
20130816	1.16	0	0	23.17	1.13	3600	0	30.54	1.10	0	0.5	32.00	1.01	0	0.5	29.23
20130817	0.73	0	2.5	20.83	0.58	0	2.5	19.86	0.93	2040	0	21.88	1.03	0	0	21.47
20130818	0.37	0	0	20.35	0.36	0	0	19.64	0.84	0	0	20.79	0.88	0	0	20.42
20130819	1.13	0	0	21.55	1.18	0	0	25.77	1.05	0	0	31.56	0.97	960	0	22.51
20130820	1.21	0	0	22.21	1.23	0	0	27.16	1.00	660	0	37.67	0.98	0	0	23.87
20130821	1.04	0	0	21.94	0.97	1980	0	31.60	1.06	300	0	32.48	1.01	780	0	23.65
20130822	1.19	2160	0	21.89	1.15	2220	0	30.30	1.05	2940	0	37.82	1.00	0	0	25.76
20130823	1.21	0	0	21.78	1.21	960	0	24.73	1.00	120	0	34.27	0.96	3060	0	28.26
20130824	0.73	0	0	21.21	0.56	2880	0	20.17	0.92	0	0	22.32	0.97	360	0	21.54

20130825	0.35	0	0	20.70	0.34	0	0	19.85	0.78	1440	0	21.37	0.79	0	0	20.62
20130826	1.17	0	0	22.19	1.09	0	0	27.89	1.04	0	0	32.64	0.90	0	0	25.33
20130827	1.23	0	0	22.10	1.18	0	0	34.21	1.05	6180	0	35.58	0.99	2340	0	24.70
20130828	1.19	0	0	22.13	1.11	0	0	35.73	0.92	4380	0	44.93	0.97	900	0	24.67
20130829	1.22	0	0	23.27	1.15	5880	0	35.76	0.92	19080	0	46.84	0.97	1260	0	30.13
20130830	1.17	4500	0	21.91	1.10	6120	0	32.82	0.95	0	0	30.08	0.90	1140	0	36.25
20130831	0.66	5100	0	21.26	0.55	0	0	20.01	0.90	1560	0	21.51	0.94	0	0	21.84
20130901	0.34	0	0	20.32	0.33	2160	0	19.87	0.77	0	0	20.87	0.79	4560	0	20.59
20130902	0.38	0	6	21.45	0.32	0	6	20.45	0.77	0	4.9	20.71	0.80	600	4.9	20.43
20130906	1.18	0	0	22.02	1.16	0	0	29.50	1.03	0	0	34.20	0.99	0	0	23.15
20130907	0.73	0	0	20.81	0.60	0	0	20.06	0.88	4080	0	22.28	0.98	1740	0	21.06
20130908	0.35	0	0	20.42	0.35	0	0	19.78	0.79	0	0	20.83	0.83	0	0	20.41
20130909	1.17	0	0	22.28	1.12	2940	0	36.86	1.04	1920	0	34.61	0.96	0	0	25.24
20130910	1.22	0	0	22.04	1.13	0	0	36.71	0.95	2400	0	41.02	0.90	0	0	31.27
20130911	1.26	0	0	22.23	1.17	2040	0	34.61	1.04	0	0	36.29	0.92	8880	0	31.47
20130912	1.21	0	0	22.00	1.14	0	0	35.13	1.04	420	0	37.19	0.97	0	0	27.21
20130913	1.24	0	0	22.06	1.22	0	0	26.63	1.01	0	0	30.57	0.88	8040	0	41.68
20130914	0.74	0	0	20.94	0.59	0	0	19.94	0.89	0	0	21.18	1.00	0	0	21.78
20130915	0.30	0	0	20.53	0.30	0	0	20.37	0.73	0	0	20.63	0.78	0	0	20.85
20130916	0.80	0	0	21.81	0.84	0	0	31.61	1.04	1740	0	32.67	0.97	2700	0	21.97
20130917	1.36	0	0	22.39	1.35	0	0	33.70	1.18	720	0	32.83	1.16	0	0	23.20
20130918	1.39	0	0	22.12	1.35	0	0	33.96	1.12	0	0	33.88	1.05	2400	0	33.11
20130919	1.37	0	0	22.02	1.35	0	0	33.78	1.16	0	0	33.57	1.19	0	0	22.92
20130920	1.12	0	101.7	25.78	1.22	0	101.7	34.22	1.15	1860	18.9	32.02	1.08	0	18.9	30.04
20130921	0.75	0	37.1	20.87	0.70	0	37.1	19.65	1.08	1680	0	24.86	1.12	1980	0	21.28
20130922	0.40	0	0	20.27	0.42	0	0	19.49	0.96	0	0	20.89	1.00	0	0	20.30
20130923	1.16	4920	0	30.91	1.34	0	0	32.72	1.13	0	0	33.30	1.09	0	0	23.47
20130924	1.38	0	0	22.22	1.32	0	0	35.85	1.13	0	0	36.91	1.05	2520	0	28.15
20130925	1.32	1080	0	25.76	1.33	840	0	35.28	1.10	0	0	38.05	1.11	0	0	24.77
20130927	1.36	0	0	22.12	1.34	1800	0	28.20	1.13	2280	0	32.64	1.08	0	0	31.28
20130929	0.37	0	7.9	20.46	0.41	0	7.9	19.52	0.91	0	0	20.79	0.96	0	0	20.15
20130930	1.29	0	0	22.73	1.35	0	0	33.27	1.17	0	0	32.86	1.12	0	0	21.64
20131001	1.18	16200	0	27.94	1.26	4560	0	36.60	1.10	6720	0	38.07	1.14	0	0	22.85
20131002	1.36	0	0	22.00	1.36	0	0	32.44	1.18	0	0	30.80	1.15	7320	0	23.47
20131003	1.36	0	0	22.20	1.37	0	0	31.05	1.13	1560	0	37.00	1.12	0	0	29.04
20131004	1.32	0	0	21.86	1.38	0	0	24.82	1.14	2640	0	32.29	1.10	0	0	29.79
20131005	0.78	0	0	20.77	0.70	0	0	20.03	1.06	0	0	23.49	1.18	1440	0	21.70
20131006	0.37	0	20.60	20.40	0.41	0	20.60	19.59	0.94	0	0	20.91	0.93	4200	0	21.16

20131007	1.34	0	0	22.04	1.39	0	0	28.30	1.03	0	0	42.97	1.04	7200	0	27.34
20131008	1.31	2820	0	22.85	1.26	0	0	35.79	1.04	21060	0	39.93	1.08	0	0	29.67
20131009	1.27	6540	0	23.24	1.33	0	0	32.53	1.15	0	0	32.86	1.04	4440	0	33.93
20131010	1.35	0	0	22.05	1.31	0	0	34.43	1.09	2640	0	40.84	1.10	2460	0	28.04
20131012	0.77	0	0	21.05	0.79	0	0	20.06	1.07	6300	0	27.47	1.12	0	0	22.03
20131013	0.38	0	0	20.68	0.42	0	0	19.71	0.97	0	0	21.07	0.98	0	0	20.25
20131014	1.09	0	4.1	25.04	1.20	0	4.1	33.32	1.12	0	12	29.56	1.00	2520	12	27.60
20131015	1.25	0	19.6	22.70	1.35	4560	19.6	31.42	1.04	0	0.6	43.47	1.03	1860	0.6	26.34
20131016	1.26	1200	42.6	23.60	1.35	2820	42.6	33.39	1.21	0	0.3	29.40	1.18	0	0.3	21.82
20131017	1.27	2280	6.1	24.90	1.36	0	6.1	28.96	1.09	1860	0	38.20	1.08	0	0	33.43
20131018	1.31	2940	0	23.06	1.37	0	0	22.91	1.07	6300	0	34.74	1.06	0	0	36.84
20131019	0.81	0	1	21.14	0.73	0	1	19.92	1.06	0	0	24.30	1.10	3240	0	28.13
20131020	0.39	0	0	20.36	0.40	0	0	19.77	1.01	3420	0	24.61	1.03	0	0	20.85
20131021	1.04	0	0	21.82	1.07	0	0	29.86	1.18	0	0	30.98	1.11	0	0	22.92
20131022	1.32	0	0	22.59	1.30	0	0	34.05	1.08	1620	0	38.13	1.10	0	0	25.00
20131023	1.30	300	0	22.92	1.36	0	0	31.49	1.14	0	0	34.10	1.14	0	0	25.34
20131024	1.34	0	0	22.86	1.35	0	0	31.48	1.06	5940	0	40.95	1.13	2220	0	26.45
20131025	1.31	0	0	22.96	1.35	0	0	26.29	1.05	2580	0	42.37	1.02	4500	0	40.11
20131026	0.82	0	0	21.36	0.67	480	0	20.15	1.00	0	0	21.32	1.18	0	0	21.51
20131027	0.38	0	40.2	20.55	0.38	0	40.2	19.80	0.81	3420	0	21.76	0.88	0	0	20.27
20131028	1.25	0	0	22.54	1.31	0	0	29.64	1.17	3420	0	30.42	1.11	0	0	23.24
20131029	1.32	0	0	22.93	1.34	0	0	34.10	1.20	0	0	30.57	1.16	1620	0	23.15
20131030	1.19	0	0.6	24.00	1.24	0	0.6	39.74	1.10	1920	1.1	36.67	1.05	1260	1.1	28.78
20131031	1.32	0	1.5	22.20	1.33	720	1.5	33.49	1.06	0	0	41.32	1.07	0	0	24.39
20131101	1.33	0	0.3	22.03	1.35	3060	0.3	27.67	1.14	0	0	31.06	1.16	0	0	25.79
20131102	0.78	0	0	21.13	0.65	360	0	19.96	1.00	1620	0	25.60	1.11	0	0	24.89
20131103	0.21	0	0	20.22	0.24	960	0	19.64	1.00	0	0	21.48	1.02	0	0	21.07
20131104	1.33	0	0	21.81	1.35	0	0	36.70	1.06	900	0.6	39.78	1.00	0	0.6	32.56
20131105	1.28	0	38.30	23.30	1.37	0	38.30	35.83	1.05	420	0	41.66	1.05	0	0	27.51
20131107	1.36	0	4.8	22.37	1.36	840	4.8	31.64	1.11	120	0	38.77	1.16	0	0	28.51
20131108	1.35	0	0	22.57	1.43	0	0	24.41	1.02	3660	0	44.04	1.06	360	0	37.85
20131109	0.83	0	0	20.97	0.70	0	0	20.49	1.03	0	0	26.09	1.17	0	0	25.77
20131110	0.40	0	0	20.39	0.41	0	0	19.71	0.96	0	0	22.38	1.00	0	0	20.92
20131111	1.29	0	0	22.47	1.35	7680	0	30.82	0.99	3660	0	48.24	1.12	0	0	25.75
20131112	1.36	0	0	22.58	1.35	0	0	38.38	1.00	0	0	45.17	1.02	0	0	36.94
20131113	1.31	0	0	22.57	1.38	0	0	34.32	0.97	8040	0	49.57	1.11	0	0	30.83
20131114	1.30	0	0	22.50	1.39	0	0	34.21	1.06	2640	0	41.78	1.14	0	0	30.55
20131115	1.39	0	0	22.05	1.42	840	0	27.98	1.01	660	0	42.21	0.91	4140	0	55.32

20131116	0.83	0	0	20.82	0.73	0	0	20.16	1.03	3120	0	23.56	1.19	480	0	24.88
20131117	0.40	0	0	20.29	0.43	0	0	19.82	0.94	0	0	21.51	1.00	0	0	21.59
20131118	1.33	0	0	22.76	1.38	0	0	33.94	1.05	5640	0	42.08	1.12	0	0	27.63
20131119	1.36	0	0	22.39	1.38	0	0	34.49	1.01	4080	0	46.23	1.09	4440	0	30.81
20131120	1.37	0	0	22.49	1.41	0	0	33.88	1.07	0	0	39.98	1.09	120	0	36.77
20131121	1.36	0	0	22.59	1.34	0	0	35.48	1.05	660	0.6	43.76	1.09	0	0.6	36.06
20131122	1.23	840	1.5	24.46	1.29	1680	1.5	30.67	0.95	0	0.8	49.77	0.94	0	0.8	43.87
20131123	0.66	0	6.1	21.50	0.59	4680	6.1	19.99	0.99	1440	1.60	23.42	1.12	0	1.60	21.29
20131124	0.34	0	1	20.63	0.36	0	1	19.99	0.62	0	0	20.81	0.64	0	0	20.25
20131125	1.05	0	11.70	23.37	1.18	0	11.70	25.96	1.17	0	2.5	27.37	1.03	0	2.5	21.37
20131126	1.23	1800	16.8	22.42	1.33	2640	16.8	23.66	1.00	9420	0	42.28	0.96	0	0	44.16
20131127	1.21	0	0	21.45	1.25	0	0	20.65	1.01	2340	0	34.47	0.99	0	0	35.88
20131128	0.38	0	0	20.53	0.43	0	0	19.75	0.68	0	0	20.53	0.74	0	0	20.73
20131129	0.71	0	0	20.52	0.63	0	0	19.86	0.99	0	0	22.31	1.07	0	0	24.06
20131130	0.58	0	0	20.37	0.50	0	0	19.70	1.01	0	0	21.55	1.07	0	0	23.25
20131201	0.38	0	0	20.20	0.42	0	0	19.65	0.94	0	0	21.67	1.01	0	0	21.01
20131207	0.24	3960	23.6	31.02	0.21	0	23.6	27.01	0.31	4560	0	34.04	0.33	0	0	29.07
20131208	0.14	0	0	27.11	0.13	0	0	26.82	0.52	0	0	25.87	0.54	0	0	26.18

APPENDIX C. Cluster Analysis Approach

Once the data is assembled, cluster analysis is performed to determine the dominant operational conditions for the morning and evening peak periods. Cluster Analysis techniques help to partition peak periods into groups/clusters to minimize the variance within each cluster (so peak periods within each cluster are similar) and maximize the variance between clusters (so peak periods in different clusters are dissimilar). As such, clusters with similar operating conditions can be combined into one scenario. The outcome of this analysis is a number of baseline scenarios that are used in this study.

The following are steps for Cluster Analysis:

1. Identify data to represent underlying phenomena. In this analysis, end-to-end freeway VMT, amount of precipitation, and incident severity measured in terms of total lane-minute closure are used to describe the underlying phenomena variables.
2. Identify data to represent system outcomes. In this analysis, the average peak period travel time, end-to-end, by direction is used.
3. Normalize underlying phenomena data and system outcomes data as follows:

   Normalize values X’ = MinX + (X – MinMin) * (MaxX-MinX) /(MaxMax – MinMin)

   X': normalized value
   X: attribute value
   MinMin: the smallest value recorded for the attribute
   MaxMax: the largest value recorded for the attribute
   MinX: The lower bound of the normalized values
   MaxX: The upper bound of the normalized values

4. For a pre-specified number of clusters (e.g., n=3), group the peak periods into clusters so as to minimize the sum of the differences between the peak period values and the mean for each cluster.
5. Report the results of each cluster which includes:
   - Sum of the Squared Error (SSE)
   - The coefficient of variation (CV) for each variable for all clusters
   - The list of peak periods in each cluster
6. Repeat steps 4 and 5 after incrementing the number of clusters by 1 (i.e., number of clusters = n+1)
7. Stop if the number of clusters n reaches a certain pre-specified maximum number. The maximum number of clusters is a function of number of data records. In this analysis, the procedure stops when the number of clusters n is equal to 14 (the maximum possible number of clusters that might be considered for the simulation analysis).
8. Analyze the result of each clustering pattern to determine

The analysis is performed separately for the morning and evening peak periods. The next section represents the results of this analysis.

APPENDIX D. Cluster Analysis Results

Morning Peak Period

The results for the cluster analysis for the morning peak period are presented in Table D-1 and Table D-2, and Figure D-1 to Figure D-3. Table D-1 gives the results for different clustering patterns in which the number of clusters is varied from 3 to 14. For each case, the total sum of squared errors (SSE), the minimum and maximum numbers of peak periods in each cluster, the coefficient of variations for the different variables, and the normalized indices that describe the overall performance of the clustering patterns are given.

As shown in the first row of Table D-1 and Figure D-1, increasing the number of clusters systematically reduces the SSE. For example, a total SEE for 7.04 is recorded when the number of clusters is set at 3. The SEE is reduced to 1.87 when the number of clusters is increased to 14. These results indicate that more homogeneous clusters (i.e., less variation within each cluster) can be obtained by increasing the number of clusters. However, increasing the number of clusters could result in clusters with few data records. As presented in the table, as the number of clusters increased to 7, a cluster with only three data records is obtained as part of this clustering pattern.

Table D-1 also gives the maximum and minimum CV for the four analyzed variables (VMT, incident severity, and precipitation level and travel time). The maximum CVs for travel time and VMT are recorded to be less than 0.50. For instance, for the case in which six clusters are considered, the maximum travel time CV recorded for any of these six clusters is 0.10, while the minimum travel time CV recorded for these clusters is 0.01. Nonetheless, the CVs for the precipitation level variable and the incident severity variable are relatively higher. This could be contributed to the nature of these two variables which are characterized by high level of variability.

The last row in Figure D-1 gives the values of a clustering index which is computed by multiplying the (0-1) normalized value of the SSE by the (1-2) normalized number of clusters. This index is used to determine a clustering pattern that is characterized by having small number of clusters while still provide distinct clusters with a reasonable level of homogeneity within each cluster. Figure D-2 shows the values of this index for the different clustering patterns considered in the analysis. The values of this index tends to form a convex pattern with the smallest values of the index are generally obtained when the number of clusters is in the range of 6 to 8 clusters.

As mentioned above, using a clustering pattern with number of clusters greater than seven result in a pattern in which a cluster with very few observations is obtained. To avoid this undesirable property and considering the closeness of the clustering index values for the patterns with six, seven and eight clusters, the clustering pattern with six clusters is used to describe the main operational conditions for the morning peak period. To further investigate the properties of these clusters, the average time-varying travel time for the US 75 freeway in the SB direction is obtained for each cluster. The time-varying travel time pattern for these six clusters is shown in Figure D-3. With the exceptions of Clusters 1 and 2, all clusters are shown to have distinct time-varying travel time implying that they represent distinct operational conditions.

Table D-2 provides a description of these six clusters. The table gives the number of peak periods and the average value for each variable used in the analysis. Comparing the values of these variables against the average values for all data records, meaningful description of these six clusters can be obtained. For example, comparing the VMT level of these six clusters with the average value, it can be suggested that Clusters 1 and 2 represent low demand operational conditions. Clusters 3, 4 and 5 could be described as medium-high demand level. Finally, Cluster 6 represents the high demand level. For the incident severity level, one can describe Cluster 5 as the major incident cluster. In this cluster, the total lane closure is recorded at about 90 minutes. All other clusters are characterized by lower incident severity. The level of precipitation recorded for these clusters is low (less than 7 mm) suggesting that they represent dry operational conditions.

Based on this analysis, the following four operational scenarios are proposed to represent the main operational conditions in the morning peak period.

- Scenario 1: High Demand + Minor Incident + Dry Conditions (Cluster 6)
- Scenario 2: Medium-High Demand + Major Incident + Dry Conditions (Cluster 5)
- Scenario 3: Medium-High Demand + Minor Incident + Dry Conditions (Clusters 3-4)
- Scenario 4: Low Demand + Minor Incident + Dry Conditions (Clusters 1-2)

Table D-1: Summary of the Clustering Analysis for the AM Peak Period

No. of Clusters	3	4	5	6	7	8	9	10	11	12	13	14
Total SSE	7.04	5.27	4.79	4.30	3.27	3.20	2.83	3.41	3.11	2.18	2.20	1.87
Min no. of elements in Cluster	34	8	9	9	3	3	3	3	2	3	2	2
Max no. of elements in Cluster	49	41	39	35	35	35	34	24	24	21	21	21
Max CV - VMT	0.33	0.33	0.21	0.21	0.21	0.21	0.44	0.44	0.30	0.42	0.44	0.30
Max CV- Incident	3.19	3.19	3.49	3.49	3.49	3.49	3.32	3.32	3.32	4.24	3.24	3.32
Max CV - Rain	3.73	3.66	4.35	4.15	3.36	3.36	3.31	3.46	3.46	3.46	3.46	3.74
Max CV- Travel Time	0.09	0.10	0.10	0.10	0.10	0.10	0.14	0.14	0.06	0.15	0.14	0.07
Min CV - VMT	0.08	0.08	0.08	0.07	0.05	0.04	0.05	0.03	0.03	0.03	0.03	0.03
Min CV- Incident	1.92	0.41	0.44	0.44	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Min CV – Rain	2.59	2.59	2.03	2.03	0.48	0.48	0.00	0.00	0.00	0.00	0.00	0.00
Min CV- Travel Time	0.06	0.06	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00
AVG CV for VMT	0.17	0.15	0.12	0.11	0.11	0.09	0.13	0.12	0.12	0.13	0.11	0.11
AVG CV for Travel Time	0.08	0.07	0.07	0.06	0.05	0.05	0.05	0.05	0.03	0.05	0.04	0.03
AVG CV for all attributes	1.39	1.27	1.32	1.30	1.15	1.02	0.98	0.97	0.87	0.95	0.74	0.83
No of clusters * SSE	21.12	21.06	23.94	25.79	22.91	25.60	25.50	34.14	34.25	26.21	28.62	26.13
No of clusters * AVG CV	4.18	5.08	6.58	7.78	8.07	8.19	8.80	9.69	9.61	11.45	9.67	11.62
No of clusters * AVG CV Travel Time	0.23	0.30	0.33	0.34	0.37	0.38	0.47	0.52	0.37	0.63	0.52	0.44
Normalizing Cluster Numbers (0,1)	0.00	0.09	0.18	0.27	0.36	0.45	0.55	0.64	0.73	0.82	0.91	1.00
Normalizing SSE (0,1)	1.00	0.66	0.56	0.47	0.27	0.26	0.19	0.30	0.24	0.06	0.06	0.00
Normalizing Cluster Numbers (1,2)	1.00	1.09	1.18	1.27	1.36	1.45	1.55	1.64	1.73	1.82	1.91	2.00
Normalizing SSE (1,2)	2.00	1.66	1.56	1.47	1.27	1.26	1.19	1.30	1.24	1.06	1.06	1.00
Clustering Index Nor(No.Clusters)xNor(SSE)	2.00	1.81	1.85	1.87	1.73	1.83	1.83	2.13	2.14	1.93	2.03	2.00

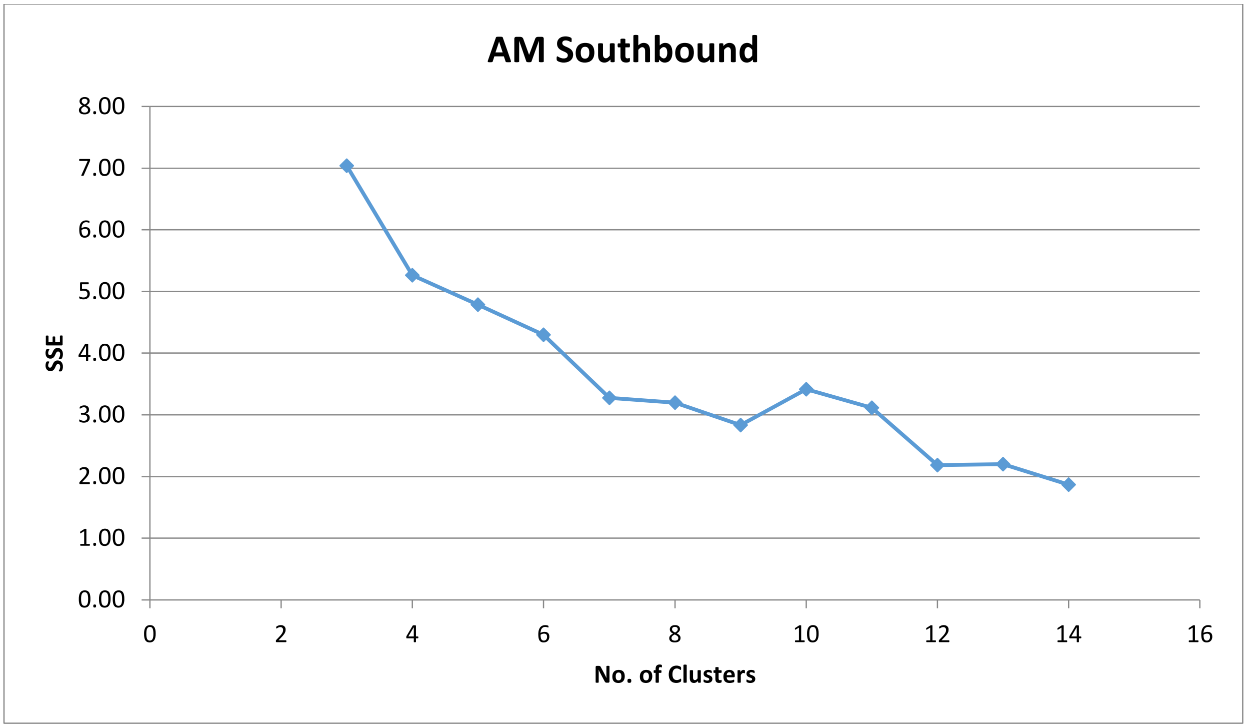


Figure D-1: Sum-Squared Error for Different Clustering Patterns for the AM Peak Period [Source: SMU]

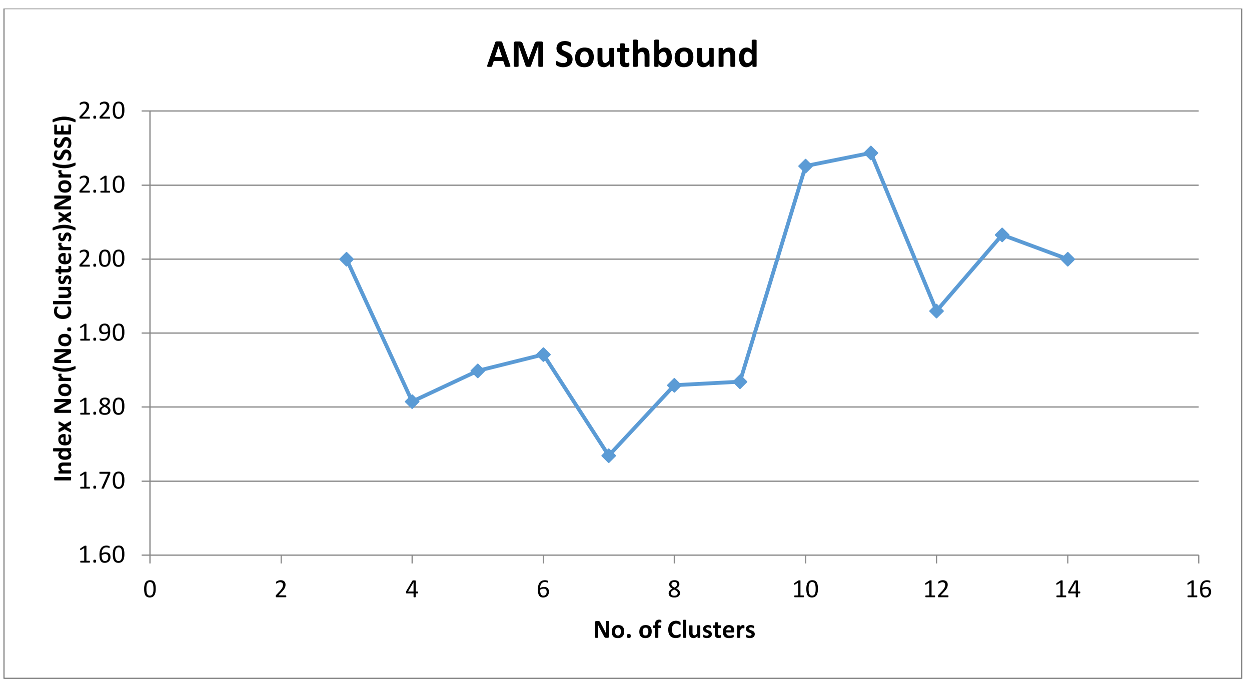


Figure D-2: Clustering Index for the AM Peak Period [Source: SMU]

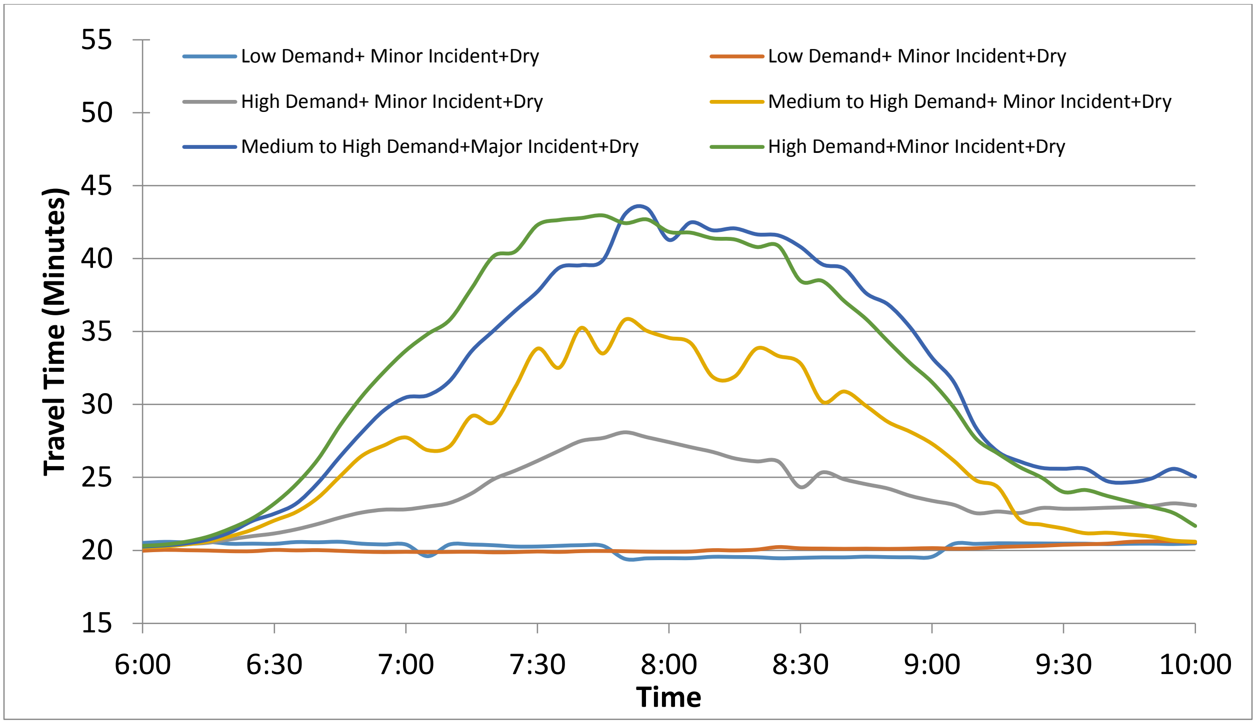


Figure D-3: Time-Varying Travel Time for the Six Clusters during the AM Peak Period [Source: SMU]

Table D-2: Description of the Six Cluster Patterns Obtained for the AM Peak Period

Variables	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
No. Records	124	23	18	21	18	9	35
Records (%)	100%	19%	15%	17%	15%	7%	28%
Cluster Description		Low Demand + Minor Incident + Dry	Low Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	Medium to High Demand + Major Incident + Dry	High Demand + Minor Incident + Dry
VMT (vehicle miles)	278,304	97,860	176,172	347,133	338,595	338,045	361,739
Incident severity (min.)	11.72	2.26	7.78	6.43	13.22	90.44	2.11
Level of precipitation (mm)	4	4	3	4	0	7	4
Travel Time (min)	27	20	20	24	29	33	34

Evening Peak Period

The cluster analysis is also conducted for the evening peak periods. The results for this analysis are presented in Table D-3 and Table D-4, and Figure D-4 to Figure D-6. Table D-3 gives the results for different clustering patterns in which the number of clusters is varied from 3 to 14. For each case, the total sum of squared errors (SSE), the minimum and maximum numbers of peak periods in each cluster, the coefficient of variations for the different variables, and the normalized indices that describe the overall performance of the clustering patterns are given.

Similar to the AM peak period case, increasing the number of clusters systematically reduces the SSE, as shown in the first row of Table D-3 and Figure D-4. For example, a total SEE for 6.27 is recorded when the number of clusters is set at 3. The SEE is reduced to 1.23 when the number of clusters is increased to 14. These results indicate that more homogeneous clusters (i.e., less variation within each cluster) can be obtained by increasing the number of clusters. However, increasing the number of clusters could result in clusters with few data records. As presented in the table, as the number of clusters increased to 6, a cluster with only two data records is obtained as part of this clustering pattern.

Table D-1 also gives the maximum and minimum CV for the four analyzed variables (VMT, incident severity, precipitation level, and travel time). The maximum CVs for travel time and VMT are recorded to be less than 0.25. For instance, for the case in which six clusters are considered, the maximum travel time CV recorded for any of these six clusters is 0.15, while the minimum travel time CV recorded for these clusters is 0.04. Nonetheless, the CVs for the precipitation level variable and the incident severity variable are relatively higher. This could be contributed to the nature of these two variables which are characterized by high level of variability.

Similar to the analysis performed for the AM peak period, the last row in Table D-1 gives the values of a clustering index which is computed by multiplying the (0-1) normalized value of the SSE by the (1-2) normalized number of clusters. This index is used to determine a clustering pattern that is characterized by having small number of clusters while still provide distinct clusters with a reasonable level of homogeneity within each cluster. Figure D-5 shows the values of this index for the different clustering patterns considered in the analysis. The values of this index tends to form a convex pattern with the smallest value of the index is at the pattern with six clusters.

As mentioned above, using a clustering pattern with six clusters results in a pattern in which a cluster with only two observations is obtained. The same problem is encountered when the pattern with five clusters is considered. In this pattern, a cluster with only four observations is obtained. Cluster analysis was performed for the pattern with five clusters after modifying the algorithm to constraint the minimum number of records in any of the obtained clusters to be greater than a certain value. In this analysis, the minimum size of the clusters was limited to 10 records (5% to 10% of the total number of records).

After obtaining this clustering pattern and to further investigate the properties of the resulting clusters, the average time-varying travel time for the US 75 freeway in the NB direction is obtained for each cluster. The time-varying travel time pattern for these five clusters is shown in Figure D-6. As shown in this figure, all five clusters are shown to have distinct time-varying travel time implying that they represent distinct operational conditions.

Table D-4 provides a description of these five clusters. The table gives the number of peak periods and the average value for each variable used in the analysis. Comparing the values of these variables against the average values for all data records, meaningful description of these five clusters can be obtained. For example, comparing the VMT level of these five clusters with the average VMT value, it can be suggested that Cluster 1 represents low demand operational conditions. Clusters 2 and 5 could be described as medium-high demand level. Finally, Clusters 3 and 4 represent the high demand level. For the incident severity level, one can describe Cluster 5 as the major incident cluster. In this cluster, the total lane closure is recorded at about 140 minutes. Clusters 1, 2 and 3 are characterized by lower incident severity. Cluster 4 could be characterized as medium severity incident. No precipitation is recorded for these clusters (except one cluster with average precipitation of 1.0 mm) suggesting that they represent dry operational conditions.

Based on this analysis, the following four operational scenarios are proposed to represent the main operational conditions in the evening peak period:

- Scenario 1: Medium-High Demand + High Severity Incident + Dry Conditions (Cluster 5)
- Scenario 2: High Demand + Medium Severity Incident + Dry Conditions (Cluster 4)
- Scenario 3: Medium-High Demand + Minor Severity Incident + Dry Conditions (Clusters 2)
- Scenario 4: High Demand + Minor Incident + Dry Conditions (Clusters 3)

Table D-3: Summary of the Clustering Analysis for the PM Peak Period

No. of Clusters	3	4	5	6	7	8	9	10	11	12	13	14
Total SSE	6.27	5.78	4.33	3.07	2.87	2.36	2.16	1.58	1.40	1.35	1.19	1.23
Min no. of elements in Cluster	35	24	4	2	2	2	2	2	2	2	2	2
Max no. of elements in Cluster	49	38	44	42	40	37	24	26	23	23	20	23
Max CV - VMT	0.18	0.18	0.19	0.19	0.20	0.20	0.20	0.25	0.25	0.25	0.25	0.25
Max CV- Incident	1.97	2.06	2.20	2.20	2.62	2.62	2.62	2.56	2.56	2.56	2.56	3.32
Max CV - Rain	4.91	4.51	4.90	4.90	4.92	3.65	4.36	5.00	4.58	4.58	4.36	4.58
Max CV- Travel Time	0.11	0.11	0.15	0.15	0.17	0.17	0.17	0.14	0.14	0.14	0.14	0.14
Min CV - VMT	0.05	0.05	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Min CV- Incident	1.15	1.13	0.40	0.40	0.40	0.05	0.05	0.05	0.05	0.05	0.05	0.00
Min CV – Rain	2.81	2.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Min CV- Travel Time	0.08	0.07	0.06	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.01
AVG CV for VMT	0.10	0.09	0.08	0.07	0.07	0.07	0.06	0.06	0.06	0.06	0.05	0.05
AVG CV for Travel Time	0.09	0.09	0.09	0.08	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.05
AVG CV for all attributes	1.44	1.38	1.16	1.02	0.86	0.86	0.92	0.87	0.75	0.78	0.81	0.61
No of clusters * SSE	18.80	23.13	21.63	18.43	20.12	18.84	19.43	15.82	15.38	16.20	15.45	17.18
No of clusters * AVG CV	4.32	5.51	5.81	6.14	6.01	6.89	8.31	8.67	8.25	9.34	10.53	8.61
No of clusters * AVG CV Travel Time	0.28	0.34	0.46	0.50	0.52	0.52	0.57	0.62	0.62	0.65	0.64	0.68
Normalizing Cluster Numbers (0,1)	0.00	0.09	0.18	0.27	0.36	0.45	0.55	0.64	0.73	0.82	0.91	1.00
Normalizing SSE (0,1)	1.00	0.90	0.62	0.37	0.33	0.23	0.19	0.08	0.04	0.03	0.00	0.01
Normalizing Cluster Numbers (1,2)	1.00	1.09	1.18	1.27	1.36	1.45	1.55	1.64	1.73	1.82	1.91	2.00
Normalizing SSE (1,2)	2.00	1.90	1.62	1.37	1.33	1.23	1.19	1.08	1.04	1.03	1.00	1.01
Clustering Index Nor(No.Clusters)xNor(SSE)	2.00	2.08	1.91	1.74	1.82	1.79	1.84	1.76	1.80	1.88	1.91	2.02

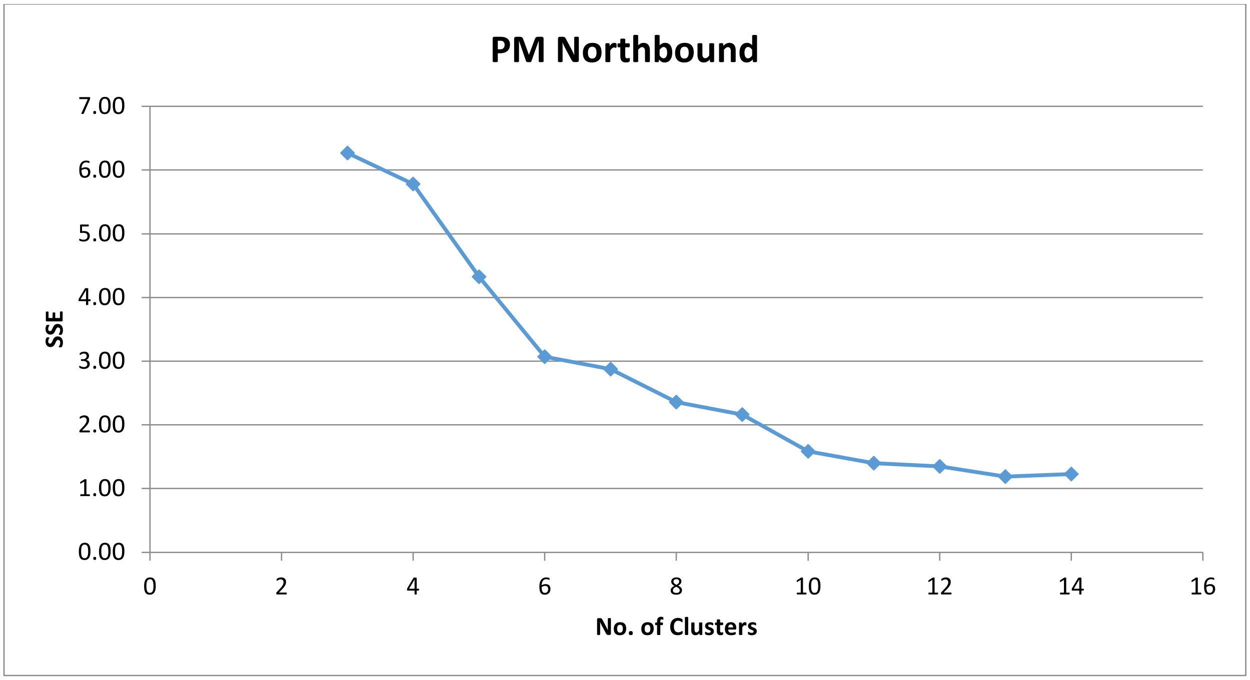


Figure D-4: Sum-Squared Error for Different Clustering Patterns for the PM Peak Period [Source: SMU]

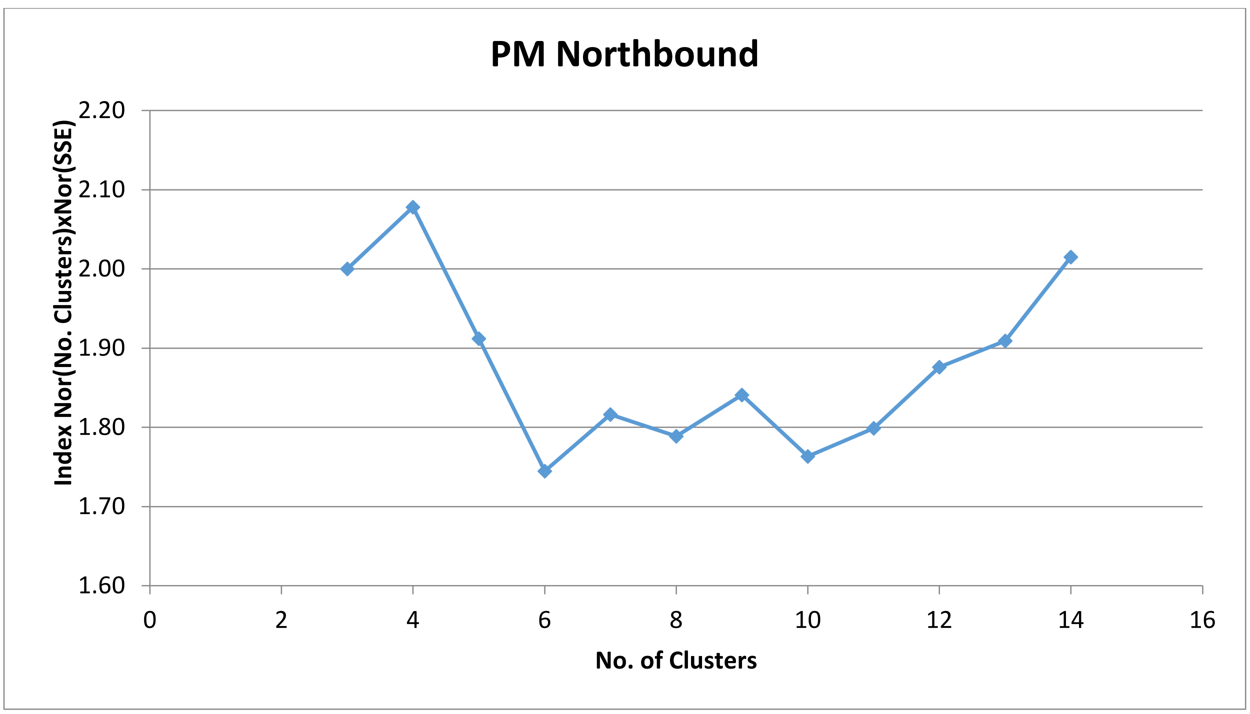


Figure D-5: Clustering Index for the PM Peak Period [Source: SMU]

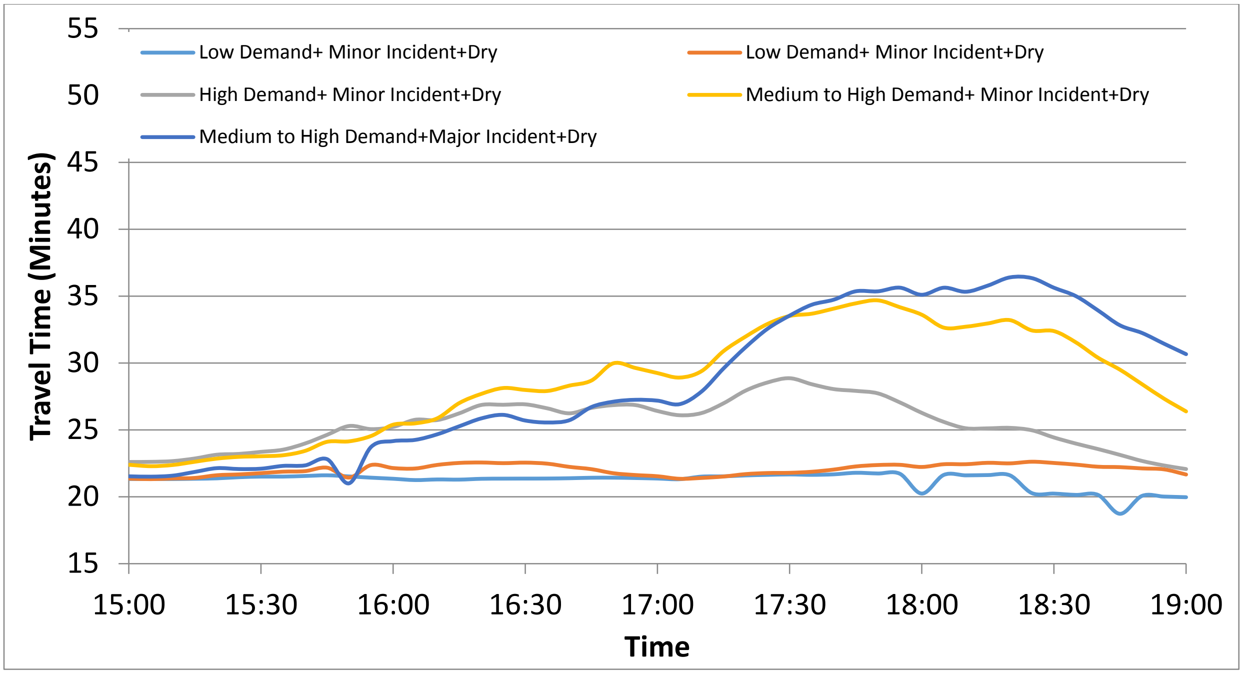


Figure D-6: Time-Varying Travel Time for the Five Main Clusters for PM Peak Period [Source: SMU]

Table D-4: Description of the Five Main Clusters for PM Peak Period

Variables	All	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
No. Records	124	15	25	42	32	10
Records (%)	100%	12%	20%	34%	26%	8%
Cluster Description		Low Demand + Minor Incident + Dry	Medium to High Demand + Minor Incident + Dry	High Demand + Minor Incident + Dry	High Demand + Medium Severity Incident + Dry	Medium to High Demand + High Severity Incident + Dry
VMT (vehicle miles)	334,175	239,333	324,504	362,694	349,158	332,891
Incident severity (min.)	27.0	10.5	12.6	10.2	32.2	141.6
Level of precipitation (mm)	0	0	0	1	0	0
Travel Time (min)	32	22	23	32	40	45

U.S. Department of Transportation
ITS Joint Program Office-HOIT
1200 New Jersey Avenue, SE
Washington, DC 20590

Toll-Free “Help Line” 866-367-7487
www.its.dot.gov

FHWA-JPO-16-373

U.S. Department of Transportation