CTE

Final Report

Probabilistic Evaluation of Mobile Source Air Pollution: Volume 1, Probabilistic Modeling of Exhaust Emissions from Light Duty Gasoline Vehicles

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North Carolina State University

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16. Abstract

Emission factors for light duty gasoline vehicles (LDGV) are typically developed based upon laboratory testing of vehicles for prescribed driving cycles. The U.S. Environmental Protection Agency has developed the Mobile series of emission factors models, which provides point estimates of emission factors. In this project, selected LDGV data sets and modeling assumptions used to develop Mobile5a were revisited. Probabilistic estimates of the inter-vehicle variability in emissions and the uncertainty in fleet average emissions for selected vehicle types and driving cycles were made. Case studies focused upon probabilistic analysis of base emission rate and speed correction estimates used in Mobile5a for throttle body and port fuel injected vehicles. Based upon inter-vehicle variability in the data sets, and a probabilistic model in which the standard error terms of regression models employed in Mobile5a are also considered, the uncertainty was estimated for average emission factors for the selected fleets of light duty gasoline vehicles. The 90 percent confidence interval for the average emission factor varied in range with pollutant and driving cycle. The 90 percent confidence interval for the mean emission factors were plus or minus 20 to 40 percent for hydrocarbon emissions, 20 to 40 percent for carbon monoxide (CO) emissions, and 25 to 55 percent for nitrogen oxides (NO_x) emissions. Furthermore, the mean values of emission factors obtained from the probabilistic estimate were typically larger than the corresponding point estimates that underlie the Mobile5a models. These latter results suggest that failure to quantitatively consider variability and uncertainty during model development can lead to potentially biased estimates of emission factors. The estimates of random and systematic error in this study are useful for quantifying uncertainty in emissions inventories. A methodology was proposed for weighting multiple driving cycles to obtain more accurate representations of traffic network emissions than current link-based emission inventory approaches. Additional work is needed to estimate uncertainty for other LDGV technology groups, other vehicle classes, and other components of the Mobile models, such as other correction factors

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Preface

This is Volume 1 of a two volume final report. The report title is "Probabilistic Evaluation of Mobile Source Air Pollution." Volume 1 is titled "Probabilistic Modeling of Exhaust Emissions from Light Duty Gasoline Vehicles." Volume 1 deals with quantification of variability and uncertainty in emission factors for light duty gasoline vehicles.

Volume 2 of the report is titled "Probabilistic Emissions Inventories For Highway Vehicles and Probabilistic Air Quality Modeling." Volume 2 deals with the use of the probabilistic emission factors described in Volume 1 in the preparation of emissions inventories. Uncertainty in the emissions inventories are quantified for highway vehicles and for seven road classifications. The quantification of uncertainty in the mobile source emission inventory is based upon probabilistic emission factors and analysis of vehicle activity data for selected road classifications. The probabilistic emission inventory is used as an input to a trajectory-based air quality model, OZIPP, for the purpose of evaluating the implications of uncertainty in highway vehicle emissions with respect to the development of emissions control strategies.

Abstract

Emission factors for light duty gasoline vehicles (LDGV) are typically developed based upon laboratory testing of vehicles for prescribed driving cycles. The U.S. Environmental Protection Agency has developed the Mobile series of emission factors models, which enable users to obtain point estimates of emission factors. In this project, we revisited some of the LDGV data sets and modeling assumptions used to develop Mobile5a. The data were used to develop probabilistic estimates of the inter-vehicle variability in emissions and the uncertainty in fleet average emissions for selected vehicle types and driving cycles. Probabilistic model development and case studies focused upon the base emission rate and speed correction estimates used within the Mobile5a model for throttle body and port fuel injected vehicles. Based upon inter-vehicle variability in the data sets, and a probabilistic model in which the standard error terms of regression models employed in Mobile5a are also considered, we estimated the uncertainty in the ability to predict average emission factors for the selected fleets of light duty gasoline vehicles. The 90 percent confidence interval for the average emission factor varies in range with pollutant and driving cycle. The 90 percent confidence interval for the mean emission factors are plus or minus 20 to 40 percent for hydrocarbon emissions, 20 to 40 percent for carbon monoxide (CO) emissions, and 25 to 55 percent for nitrogen oxides (NO_x) emissions. Furthermore, the mean values of emission factors obtained from the probabilistic estimate were typically larger than the corresponding point estimates that underlie the Mobile5a models. These latter results suggest that failure to quantitatively consider variability and uncertainty during model development can lead to potentially biased estimates of emission factors. The estimates of random and systematic error in this study are useful for quantifying uncertainty in emissions inventories. Additional work is needed to estimate uncertainty for other LDGV technology groups, other vehicle classes, and other components of the Mobile models, such as other correction factors.

Executive Summary

Estimates of emissions from highway mobile sources are typically developed using a deterministic point-estimate approach. This approach involves the use of emission factor models such as Mobile5a, developed by the U.S. Environmental Protection Agency, to make estimates of vehicle emission factors for hydrocarbons (HCs), carbon monoxide (CO) and nitrogen oxides (NO_x). The development of these estimates requires many assumptions that are subject to considerable variability and uncertainty. For example, even for a single vehicle category such as light duty gasoline vehicles (LDGVs), there is substantial variability in the emissions under the standard Federal Test Procedure (FTP) test conditions. Additional uncertainty exists because the FTP and other standard driving cycles that underlie the Mobile5a model may not be representative of on-road driving behavior. The driving cycles underlying Mobile5a are complete trip based speed profiles. However, no individual cycle may adequately represent area-wide emissions for a typical geographic region.

To address the need for more representative uses of driving cycle data, a probabilistic analysis of driving cycle emissions was carried out using Monte Carlo simulation features of a probabilistic environment called Analytica. To better predict area-wide emissions, a new methodology is presented by which data from multiple trip-based driving cycles can be combined to represent any arbitrary frequency distribution for speed. This method can be applied to the standard driving cycles used in the vehicle testing programs by EPA to better simulate on-road driving patterns and represent observed variations in speeds. Two case studies for vehicles on I-40 were done to demonstrate the working of this new methodology. The methodology can be extended to consider other factors affecting emissions, such as acceleration. However, currently, most routinely deployed traffic detection devices are not capable of recording such information.

As a bottoms-up approach to the development of an alternative probabilistic version of Mobile5a, demonstrative model development and case studies were carried out. The emission factor estimates for light duty gasoline vehicles are based upon data obtained from laboratory testing of vehicles for selected driving cycles, supplemented with additional data obtained from inspection and maintenance testing using the IM240 driving cycle. The U.S. EPA developed a regression model to convert IM240 data to an equivalent FTP basis. Additional data were collected based upon laboratory testing of selected cohorts of vehicles for the purpose of developing speed correction ratios. These data sets for selected LDGV technology groups were obtained and reanalyzed for the purpose of developing probabilistic estimates of the base emission rate, deterioriation rate, and speed correction ratios. The probabilistic estimates enable quantification of inter-vehicle variability in emissions and uncertainty in fleet average emissions. As part of data analysis, alternative approaches to the development of regression models to describe emissions as a function of vehicle odometer reading were considered. Because the residual error from linear regression models, such as those used by EPA, is typically not normally distributed, we employed log-linear models instead.

The probabilistic emission factor model was employed in case studies to develop probabilistic representations of emission factors for individual driving cycles and selected technology groups. The results of the case studies provide insights into the variability in vehicle emissions; the uncertainty in the mean fleet average and the confidence range on the mean emissions. The confidence interval analysis shows that the random error on the mean CO and HC emissions, based on a 90 percent probability range, is approximately 20 to 40 percent. The random error on the mean NO_x emissions is approximately 25 to 55 percent. The results also indicate that the point estimates underlying the Mobile5a model are systematically lower than the mean values obtained from the probabilistic estimates. The probabilistic methods described here enable better usage of emissions test data that has been collected at considerable expense. Recommendations regarding the incorporation of a log-linear base emission rate model; a new speed correction factor model; and the use of probababilistic methods in general will enable development of more realistic emission factors and inventories.

The probabilistic methodology applied in this study is illustrated via case studies involving a limited number of vehicle technology groups and only one of the emissions correction factors used in the Mobile emission factor model. However, the approach is generalizable, and it should be applied to other components of the Mobile model to obtain a more complete characterization of uncertainty in highway vehicle emission factors.

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1.0 INTRODUCTION

Highway vehicle emissions comprise a substantial portion of the US national emission inventory of ozone precursors and carbon monoxide. They are estimated to contribute 40 percent of US emissions of anthropogenic volatile organic compounds (VOCs) and nitrogen oxides (NO_x) and 60 percent of the carbon monoxide (CO) emissions (NRC, 1992). However, these numbers may be misestimated due to uncertainties associated with emissions inventories (Seinfeld, 1988; Gertler and Pierson, 1991; Ingalls, 1989; Guensler, 1993).

Motor vehicle emission inventories are estimated by quantifying emission producing activities and coupling these activities with activity specific emission rates. For example, vehicle travel is an emission producing activity quantified in terms of vehicle miles traveled (VMT). The activity-specific emission rates for vehicles are expressed in terms of grams of pollutant emitted per mile of vehicle travel (Seinfeld, 1988; Guensler, 1993).

Emission estimates from mobile source activities are summed to develop the total mobile source emission inventory that is used in air quality planning. The motor vehicle emissions modeling process consists of:

(1) Quantifying emission producing vehicle activities by using traffic count data, a travel demand model, or other means of estimation;

(2) Providing data on vehicle, fuel, operating and environmental characteristics to an emission factor model (e.g., Mobile5a or EMFAC);

(3) Running the emission factor model to predict activity-specific emission rates for a given set of assumptions regarding vehicle technology, fuel, and operating characteristics;

(4) Multiplying each activity estimate by its appropriate activity specific emission rate;

(5) Summing the estimated emissions for all emission producing activities.

1.1 BACKGROUND

Motor vehicle emission rates are a function of how, and under what conditions, vehicles are operated. Current mobile source emission factor models create matrices of emission rates depending on values of user specified inputs. A number of studies which compared modeled vehicle emissions to measured pollutant concentrations (e.g., tunnel studies, on-board instrumentation, etc.) have indicated that the mobile source emissions models appear to significantly misestimate on-road emissions (Lawson, et *al.,* 1990; Ingalls, 1989). The speed-related emission rate corrections employed in the federal emission factor model called Mobile5a, have been identified as one of the possible sources of emission prediction error (Guensler, 1993; NCHRP, 1995).

Emissions data are collected by the Environmental Protection Agency (EPA) and others during vehicle test programs. In these programs, vehicles are tested over standard driving cycles. A driving cycle provides a specific pattern of activity (e.g., acceleration, speed profiles, trip duration etc.). A significant source of inaccuracies in motor vehicle emission predictions is related to nonrepresentative driving cycle tests used in measuring vehicle emissions and in developing the existing emission models (CARB, 1992). No single driving cycle can address the shortcomings of the emission factor model estimates. Variations in actual driving cycles lead to additional variability in emissions. Furthermore, there is substantial variability in emissions for any population of vehicles even if they are operated under similar conditions.

The Federal Test Procedure (FTP) has been the basis for emissions inventory estimation for over 20 years (Gammareillo and Lòng, 1993). The frequency distributions of speeds and accelerations that underlie the FTP may not be representative of actual on-road driving behavior. For example, the FTP test does not include speeds over 57 mph or sharp accelerations (i.e., greater than 3.3 mph/s). Some of these "off - cycle" events are likely to result in conditions that lead to high emission rates. Failure to account for these and other sources of variability can lead to systematic and random errors in estimating emission factors.

Previous studies have indicated a number of problems with the current deterministic emission factor models. The variability and uncertainty in measurements used to develop the emission factors are often suppressed and/or ignored when data obtained from limited sampling of emission sources are averaged to develop an emission factor. Therefore, there is a need to identify and investigate methodologies for using a probabilistic framework in lieu of the currently employed deterministic approach for developing the emission factors. This thesis discusses a probabilistic approach which is based upon quantification of key inputs to EPA's emission factor model Mobile5a, the development of a probabilistic model and its application to estimate frequency distributions for emissions. The frequency distributions for emissions are compared to the emissions estimates that would be made in absence of the probabilistic approach. A probabilistic framework can provide answers to the following questions:

(1) What is the expected value (mean) of emission factors, and how do these means compare to the point-estimates currently used?

(2) What is the magnitude of variation in the emissions from one vehicle to another, for a given set of operating conditions?

(3) What is the 90 percent confidence range associated with each emission factor?

(4) How can the emissions data collected by EPA and others in the annual test programs be better used to estimate on-road emissions?

By using a probabilistic approach, the uncertainty and variability in the emission estimates can be displayed. This approach will help improve emission estimates. This in turn will help regulators take informed decisions about the efficacy of the selected emissions control strategy in achieving compliance with the National Ambient Air Quality Standards (NAAQS).

1.2 Overview

An overview of the current and future emission standards and regulations for mobile source emissions has been included in Chapter 2. The emission factor, activity and air quality models used to date in many major research efforts are reviewed in Chapter 3. Features and limitations of these models have been identified. A detailed description of EPA's emission factor model Mobile5a is provided in Chapter 4. The primary components of the model have been described. Two key components of the model, the base emission rates (BERs) and speed correction factors (SCFs), have been the focus of analysis in this thesis. The dataset which underlie the speed correction factors are described in Chapter 4 while a detailed analysis of the BERs is described in Chapter 8. Various approaches to estimating mobile source emissions are discussed in Chapter 5. These include tunnel studies, remote sensing, representative driving cycle and on-board instrumentation. The implications of these on-road studies with respect to identifying potential sources of systematic and random error in emissions factors are discussed. Chapter 6 describes the basic concepts of uncertainty and variability. The major sources of uncertainty and variability in mobile source emissions are identified. Chapter 7 focuses on the probabilistic modeling of the SCF data that underlies the Mobile5a model. This chapter first describes a new probabilistic version of Mobile5a. A new procedure for probabilistic analysis of the driving cycles emissions data used to develop the SCFs in Mobile5a model is discussed. A case study describing the application of the new methodology is included. To gain insight into uncertainty in the fleet average emission factors and the inter-vehicle variability in the emissions, each of the individual driving cycles that underlie Mobile5a were analyzed using alternative probabilistic models. Chapter 8 describes this probabilistic analysis of emission factors. The results indicate that there are significant sources of systematic and random errors in estimating emission factors that are not properly captured by current approaches. The implications of the true results for the development and use of emission inventories are discussed in Chapter 9.

2.0 EMISSION STANDARDS AND REGULATIONS

In the mid 1950s, California established the first state agency to control motor vehicle emissions. Motor vehicles are one of the key sources of CO, NO_x and VOC emissions. Complex chemical interactions between NO_x and VOCs result in photochemical smog and tropospheric ozone. CO is a pollutant with localized impacts. Brief exposures to CO can impair vision, physical co-ordination and result in significant interference with essential cardiovascular-respiratory functions. Concern with air quality, including ground level ozone and CO, increased from the 1960s and led to federal and state motor vehicle standards for emissions of HCs, CO and NO_x. California and the federal government set ambient air quality standards for ozone, CO, NO_x, etc. By 1988, emissions per VMT for new cars and light trucks had been decreased by roughly 90 percent from the uncontrolled level. Total VMT, however, increased 2.3 percent annually during the 1970s and 1980s, thereby offsetting some of the improvement (Atkinson *et al.*, 1990).

2.1 Clean Air Act

The Clean Air Act was signed in 1963. Major amendments were made to it in 1970, 1977, and 1990. The act establishes the federal-state relationship that requires the EPA to develop the NAAQS and empowers the states to implement and enforce regulations to attain them. EPA established NAAQS for each of six criteria pollutants: sulfur dioxide, particulate matter, nitrogen dioxide, carbon monoxide, ozone, and lead. The NAAQS are threshold concentrations based on a detailed review of the scientific information contained in the criteria documents prepared by EPA. Pollutant concentrations below the NAAQS are expected to have no adverse effects on the environment or human health. For each criteria pollutant, the NAAQS are comprised of a primary standard, which is intended to protect public health with a margin of safety, and a secondary standard, which is intended to protect the public welfare as measured by the effects of the pollutants on vegetation, materials and visibility (NRC, 1992). Table 1 shows the most recent (1990) NAAQS for the criteria pollutants.

In the Clean Air Act Amendments (CAAA) of 1970, the Congress set 1975 as the deadline for meeting the NAAQS. The 1977 CAAA delayed compliance with the ozone and CO NAAQS until 1982. Areas that demonstrated that they could not meet the 1982 deadline were given extensions until 1987. In 1990, there were 96 areas in the US which were not in attainment of the ozone NAAQS (EPA, 1990). The 1990 amendments classify non-attainment areas according to the degree of noncompliance with the NAAQS. The classifications are extreme, severe, serious, moderate, or marginal, depending on the percentage by which the ambient concentration of pollutants is greater than the NAAQS (NCHRP, 1995). Table 2 shows the classification of the levels of non-attainment and the corresponding deadlines for meeting the ozone and CO NAAQS.

2.2 Regulations for Tailpipe Exhaust Emissions

The CAAA of 1990 contains many features, with seven separate titles covering different regulatory programs. Title II impose more stringent regulations on automotive emissions with the intention of reducing the ambient ground-level ozone and CO concentrations in areas of the United States that did not meet the ambient air quality standards. Specific measures required under the new regulations are more stringent controls on automotive emissions, alternative clean fuels, and others.

Title II established stringent tailpipe emissions standards for non methane hydrocarbons (NHMC), CO, NO_x, and particulate matter for passenger cars and light trucks of 6000 pounds gross vehicle weight (GVW) rating or less (NRC, 1993). The

CAAA of 1990 provide for two tiers of emission standards. The first set of requirements (Tier I) are to be phased in beginning with the model year (MY) 1994, and 100 percent compliance is to be achieved by MY 1996. The Tier I standards call for a 35 percent reduction in tailpipe HC and a 60 percent reduction in NOx compared to MY 93 standards. For example, the NO_x standard would be reduced from 1.0 grams/mile (g/mi) to 0.4 g/mi by MY1996. The Tier I CO remains unchanged from the 1993 level.

The emission standards (both evaporative and tailpipe) from 1968 through 1993 motivated many technological innovations. Amongst these were: positive crankcase ventilation; ignition timing controls; exhaust gas recirculation; catalytic converter systems; fuel injection systems; activated charcoal canisters; computer-based sensors; and engine controls (Black 1991). Compliance with the Tier I standards can be achieved with full implementation of these technological innovations.

The Tier II standards would cut the Tier I standards for HC, CO and NO_x in half. By the end of 1999, the EPA will determine the need, cost, and feasibility of Tier II standards for vehicles produced for MY 2004 and thereafter. The Tier II standards may be implemented if the EPA concludes that there is a need for further mobile source emission reductions (Ross et *al.,* 1995). Table 3 gives the current and planned Passenger Car Emission Standards.

Compliance with the emission standards is determined by measuring the emissions performance of cars under highly controlled conditions specified in the FTP. Details of the FTP are published in the Code of Federal Regulations (40 CFR 86) and have remained unchanged since 1975. As part of the FTP, cars are driven on a chassis dynamometer using a prescribed speed-time sequence, which is referred to as a driving cycle. The speed-time profile of the FTP cycle is shown in Figure 1. The associated exhaust emissions are captured sequentially in three bags. Bag 1 is the cold start bag and is intended to measure the elevated tailpipe emissions that occur during the first several minutes of driving after start-up following an overnight rest or "soak", when the vehicle engine and the catalytic converter have cooled to ambient temperatures of around 70° F. Bag 2 captures the emissions from the warmed-up or hot stabilized driving, during which the emissions control system is fully functional. Bag 3 determines the emissions level during the several minutes following start-up after the vehicle has soaked for only 10 minutes (Ross et *al.*, 1995).

The manufacturers measure and report to the EPA the FTP emissions for CO, HC and NO_x and compare these to the standards.. The CAAA of 1990 directed the EPA to revise the FTP as necessary to more accurately reflect the manner and conditions under which the cars are actually driven. In February 1995, the EPA published a notice to revise the FTP. The revisions to the FTP are referred to as the Supplemental FTP (SFTP). The SFTP includes three additional bags which measure emissions from five kinds of driving behavior not represented in the original FTP. They are: aggressive driving episodes and rapid speed fluctuations (Bag 4); driving behavior immediately following start-up (Bag 5); and driving with the air conditioner on and intermediate duration soaks of an hour (Bag 6) (USEPA, 1995). Emissions can be much higher for speeds and accelerations outside the range of the current FTP (NRC, 1992). The use of the SFTP as a certification standard instead of the FTP is likely to lead to an increase in the measured emissions from vehicles tested on the SFTP. This in turn will require an increase in the percentage of emission reduction required if the regulatory emission limits are unchanged. Therefore, the new emission standards based upon the SFTP would be more stringent than the current ones.

2.3 California Standards

California has established emission standards that are more stringent than the federal standards. California's standards impose emission levels for five categories of vehicles: (1) conventional vehicles (CVs); (2) transitional low-emission vehicles (TLEVs); (3) low-emission vehicles (LEVs); (4) ultra-low emission vehicles (ULEVs); and (5) zero-emission vehicles (ZEVs).[1] Table 4 shows California's Passenger-Car Emissions Standards. Given the problems with marketing cars with different standards in different states, all automobiles may be designed to meet the more stringent emissions standards if they become widely accepted, even though air quality conditions differ from region to region (NRC, 1993). This could mean that regulations in California may drive research and development of new control technologies which could be used nationally.

2.4 Conformity

Conformity analysis is required for federally funded transportation plans, programs and projects. Conformity analysis involves demonstrating a net improvement in air quality as a result of implementation of a proposed transportation project. The EPA published a final rule in the November 24, 1993 Federal Register (58 FR 62188) that finalized the procedures to be followed by the US Department of Transportation in determining conformity. The conformity regulations require that nonattainment and maintenance areas prepare analyses for Baseline and Action scenarios. "Baseline" scenarios contain current or existing transportation plans. "Action" scenarios include Transportation Improvement Programs (TIPs) that are proposed to be completed in a future year. Conformity criteria requires that the emissions from the Action scenario should be less than the emissions for

[1] Note that ZEVs, such as electric cars, are misnamed and cause shifts of emissions from mobile sources to stationary sources (e.g., power plants).

the Baseline scenario for the same year (NCHRP, 1995). An important source of information for conformity analysis is highway vehicle emission factors. Errors in these factors may lead to potentially misleading results regarding whether an improvement may occur as a result of a TIP.

2.5 Discussion

Accurate emissions data are needed to predict ambient pollutant concentrations (wrt NAAQS) and to evaluate the benefits of transportation projects. Errors in the data lead to wrong conclusions. For example, a TIP may have no significant impact on air quality even though models used to predict those impacts say that it does. To understand the air quality modeling process, the currently used models for mobile source emissions are described in the next chapter.

Table 1. National Ambient Air Quality Standards.

Source: Seinfeld, 1986.

Pollutant	Primary Standard	Secondary Standard
O_3	240 $\mu g/m^3$ over 1 hour average.	240 $\mu g/m^3$ over 1 hour average
CO	10 mg/m^3 on an 8 hour average.	40 mg/m^3 over 1 hour average
NO_x	100 $\mu g/m^3$ maximum mean annual concentration.	100 $\mu g/m^3$ maximum mean annual concentration.
SO_2	80 $\mu g/m^3$ maximum mean annual concentration or 365 $\mu g/m^3$ on a 24 hour average.	1300 $\mu g/m^3$ on a 3 hour average.
Particulate Matter (PM 10)	75 $\mu g/m^3$ maximum mean annual concentration or 260 $\mu g/m^3$ on a 24 hour average.	60 $\mu g/m^3$ maximum mean annual concentration or 150 $\mu g/m^3$ on a 24 hour average
Lead	1.5 $\mu g/m^3$ on a quarterly average.	1.5 $\mu g/m^3$ on a quarterly average

Table 2. Classification of Level of Non Attainment of NAAQS for Ozone and CO.

Source: (NCHRP, 1995)

Pollutant	Classification	Design Value (ppm)	Attainment Deadline
Ozone	Marginal	0.121 up to 0.138	11/15/1993
	Moderate	0.138 up to 0.160	11/15/1996
	Serious	0.160 up to 0.18	11/15/1999
	Severe 1	0.18 up to 0.19	11/15/2005
	Severe 2	0.19 up to 0.28	11/15/2007
	Extreme	0.28 and above	11/15/2010
CO	Moderate	9.1 up to 12.7	12/31/1995
	Marginal	12.8 up to 16.4	12/31/1995
	Serious	16.5 and above	12/31/2000

Table 3. Passenger-Car Emission Standards, CAAA (1990)

Source: (NRC, 1993)

	Gasoline Engines			Diesel Engines	
Standard	NMHC (g/mi)	CO (g/mi)	NO_x (g/mi)	PM (g/mi)	NO_x (g/mi)
Current (1991)	0.41T	3.4	1.0	0.2	1.0
Tier I	0.25 (0.31)	3.4 (4.2)	0.4 (0.6)	0.08 (0.1)	1 (1.25)
Tier II	(0.125)	(1.7)	(0.2)	(0.08)	(0.2)

Note: NHMC - nonmethane hydrocarbons, T = total hydrocarbons,
Standards are for 5 years/50000 miles and for up to 3750 pounds loaded vehicle weight. Tier I standards are to be achieved by MY 1996 and Tier II would apply to MY 2000 and beyond, if it is imposed. Standards for 10 years/100000 miles are shown in parenthesis.

Table 4. California's Passenger Car Emission Standards

Source: (NRC, 1993)

Engines	Gasoline Engines		Diesel	
VEHICLE CLASS	NMOG (g/mi)	CO (g/mi)	NO_x (g/mi)	PM (g/mi)
93 base	0.25 (0.31)	3.4 (4.2)	0.4	(0.08)
TLEV	0.125 (0.166)	3.4 (4.2)	0.4 (0.6)	(0.08)
LEV	0.075 (0.090)	3.4 (4.2)	0.2 (0.3)	(0.08)
ULEV	0.040 (0.055)	1.7 (2.1)	0.2 (0.3)	(0.04)
ZEV	0	0	0	0

Note : NMOG = nonmethane organic gases; TLEV = transitional low-emission vehicle; LEV = low-emission vehicle; ULEV = ultra low-emission vehicle; ZEV = zero-emission vehicle. Standards are for 5 years/ 50000 miles. Standards for 10 years/100000 miles are shown in parenthesis. These standards are for up to 3750 pounds loaded vehicle weight (curb weight plus 300 pounds). For 1993 base, NMOG = nonmethane hydrocarbons only.

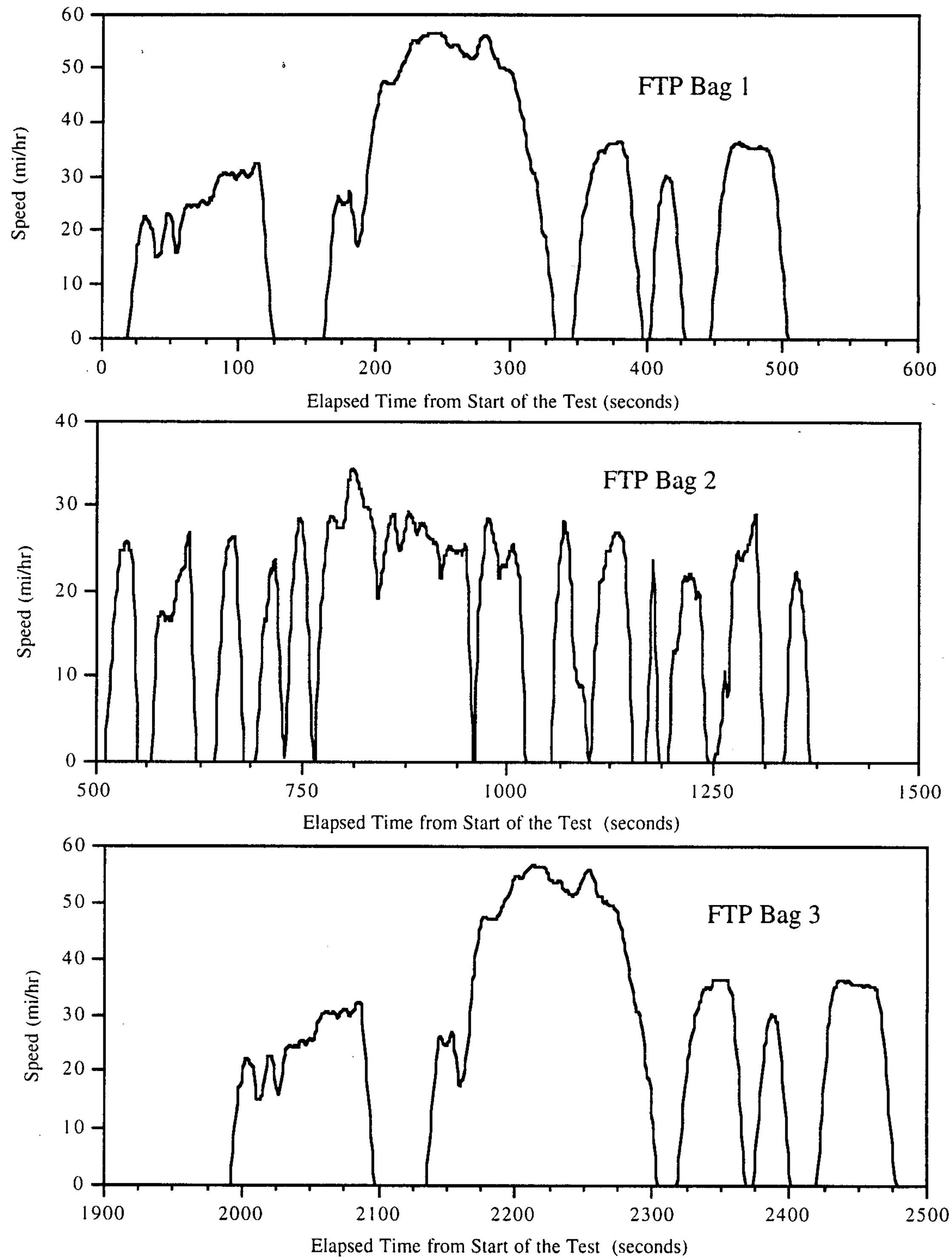


Figure 1. Speed Versus Time Profile of the FTP Driving Cycle

3.0 REVIEW OF EXISTING MODELS FOR MOBILE SOURCE EMISSIONS

Air quality studies and state implementation plans require accurate information on emissions of ozone precursors so that the causes of air pollution can be understood and effective plans can be developed for future air quality improvement. The prediction of changes in peak pollutant concentrations with changes in mobile source emission is essential to be able to assess if a region is in compliance with the air quality standard at some future date. Motor vehicle emissions result not only from tailpipe exhausts but also from evaporation of fuel from the "fuel tank- engine system" and running losses. Also, the total emissions from mobile sources depends critically upon the mode of operation of the vehicle, the ambient conditions (e.g., ambient temperature, etc.) and the state of repair and maintenance of that vehicle. Therefore for predicting the air quality impacts of mobile sources, models for mobile emission inventories (e.g., Mobile5a, EMFAC7F, PART5) are used in conjunction with air quality models (e.g., CALINE4, CAL3QHC, PALS, UAM, EKMA) and activity models (e.g., TRANPLAN, BURDEN7F). A more complete review of emission mechanisms and the control systems is given in Appendix C. The focus in this report is on tailpipe emissions of gaseous pollutants.

3.1 Mobile Source Emission Factor Models

Emission factor models, such as Mobile5a and EMFAC7F, estimate the rate at which different pollutants such as CO, NO_x and VOCs are emitted in grams per VMT for various class of vehicles. The vehicle classes are described in Table 5. The emission factor models are based upon data from tests of vehicle emissions. For example, Mobile5a uses measured emission rates from a sample of vehicles tested in laboratories. These vehicles were tested on the FTP and other driving cycles. In some tests, selected test parameters (e.g., temperature, fuel properties) were varied to evaluate the sensitivity of emissions to such changes. The data were used to develop base emission rates and emission correction factors in the emission model. While the emissions data underlying the models is based upon laboratory or other tests, the models are often used to make estimates of emissions for on-road vehicles. Therefore, the model attempts to account for on-road conditions such as the operating mode of vehicles (e.g., cold start, hot transient or hot stabilized); average speed of vehicles; the environmental conditions (e.g., ambient temperature), implementation of inspection and maintenance (I/M) programs and others. Emission factor models also incorporate information on the age distribution, the annual mileage accrued by each vehicle type and the percent of VMT mix attributed to each vehicle class in order to calculate the final emission factors (NCHRP, 1995; Sierra 1994; SAI, 1994; CEPA, 1993a).

Emission factors are typically defined for two broad categories of emissions: exhaust emissions; and evaporative emissions. The exhaust emissions are often further subdivided in to three processes which are: cold start; stabilized running (hot stabilized); and hot start. The evaporative emissions are subdivided in to four processes including hot soak emissions, diurnal emissions; resting losses; and evaporative running losses (NRC, 1992).

A detailed description of EPA's emission factor model, Mobile5a, and a new probabilistic version of the model, is given in Chapters 4 and 7 respectively. The emission factor model used by the California Air Resources Board (CARB) is called EMFAC. PART5 is an EPA approved model that is used to calculate fugitive dust emission factors. A brief description of EMFAC and PART5 is given below.

3.1.1 EMFAC

EMFAC was developed by the CARB for estimating on-road motor vehicle emissions. The data that provides the basis for EMFAC are obtained from extensive testing of motor vehicles conducted by the CARB and the EPA. Testing is performed using standardized test cycle conditions as well as non-standardized conditions. These latter tests are used to develop correction factors to the standardized test cycle results such that on-road conditions of operating mode, speed, and temperature can be approximated.

EMFAC calculates hot and cold start emissions separately from hot stabilized emissions. EMFAC differs from Mobile5a because it uses California-specific emission rates. EMFAC contains air basin-specific assumption values for various inputs including IM, anti-tampering and vehicle mileage and age distribution data which are different from those used by Mobile5a.

The latest version of EMFAC is EMFAC7F. This version produces composite emission factors for the following six pollutants: total organic gases; carbon monoxide; oxides of nitrogen; exhaust particulate matter; particulate matter due to tire wear; and evaporative emissions (CEPA, 1993a).

3.1.2 PART5

Particulate matter with characteristic diameters less than or equal to 10 microns (PM_{10}) is a product of combustion, machinery and wear of tires and brake linings, and facility and road conditions. PART5 is an EPA model that calculates PM_{10} emission factors in grams per mile from automobiles, trucks and motorcycles for particle sizes up to ten micrometers. The PM_{10} emission factors include exhaust particles, brake wear, tire wear and re-entrained dust. All of these are required for PM_{10} inventories and analyses. This model supersedes previously used AP-42 emission factors. The inputs required by this model include: overall fleet average vehicle weight; overall fleet average number of wheels per vehicle; average vehicle speed; roadway silt loading characteristics; atmospheric and meteorological conditions; and VMT mix and mileage accumulation rates (NCHRP, 1995).

3.2 Activity Models

The activity data used to calculate the inventory estimates include VMT, vehicle populations, trips taken (with hot and cold starts distinguished), average vehicle speeds, and ambient temperature. The sources and development of these motor vehicle activity data are discussed in the following sections:

3.2.1 Vehicle Populations

The motor-vehicle registration department in each state and local jurisdiction maintain areawide aggregate data. Vehicle populations are estimated based on this data. Typically, this data contains registration distributions by age for different vehicle types, sales fractions by model year, the fraction of travel by each vehicle that is typical of urban areas, and the total fleet size by vehicle type (NCHRP, 1995; CEPA, 1993b).

3.2.2 Vehicle Miles Traveled (VMT)

There are two approaches to estimation of VMT that are acceptable to EPA for areawide emissions estimation. These are Highway Performance Monitoring System (HPMS) and network-based travel demand models (Harvey and Deakin, 1992). Typically, 24- or 48-hour traffic counts are taken on road segments once every three years. These counts are then adjusted, based upon day-of-week and season, to annual averages from a small number of traffic recorders such as loop detectors. "Axle correction factors" are also incorporated in this HPMS sample, to account for large trucks in traffic. Once the Base Year VMT is estimated, future year VMT are determined using growth rates based on trends in VMT in the past (NCHRP, 1995).

VMT estimates can also be obtained from transportation planning models. The aggregate VMT estimates that are produced from transportation planning models (e.g., TRANPLAN) must be consistent with HPMS estimates (NCHRP, 1995).

3.2.3 Vehicle Trips

Vehicle emissions are significantly higher, especially for HC and CO, when a cold engine is first started than after the vehicle is warmed up. Therefore, the determination of the operating modes is important in order to accurately predict fleet emissions. This is because the emissions control systems such as the catalytic converter do not provide full control until they reach operating temperature (Sierra, 1994).

Estimates of the percentage of each vehicle trip that is in cold start, hot stabilized and hot start mode is a complex task. Determination of operating mode (e.g., hot or cold starts) of a vehicle requires measurements of engine temperature, and such measurements are difficult to implement (NCHRP, 1995) In 1984, field data were collected as a part of a New Jersey study in which vehicles were stopped and roadside measurements of engine oil and coolant temperature were taken. Estimates of engine run time was obtained from the drivers. The data were analyzed to develop operating mode fractions (Brodtmen and Fuce, 1984). Extensive information for estimating the proportion of VMT occurring in cold start mode by time of the day, trip length and trip purpose is provided by Ellis *et al.*, (1978).

Another method of estimating the operating modes of vehicles is through the use of computer models for network analysis and traffic assignment. An example os such a model is the Traffic Assignment Program for Emission Studies (TAPES). This model simulates the elapsed time of interzonal trips as they are assigned on each link along their path of travel (Venigalla, 1994). The duration of the "cold start" portion of the FTP cycle (Bag 1) is 505 seconds. In the model, this is assumed to be representative of the cold start time for all vehicles. Based on the duration of the FTP Bag 1, the assigned volume on a link can be classified as transient or stabilized depending upon whether the elapsed time from the origin of the trip exceeds 505 seconds or not. Other travel modeling programs like MINUTP and EMME/2 also have this capability but their use for the purpose of developing operating mode fractions has been limited. Venigalla *et al.* (1995) tested the TAPES software with travel and network data for Charlotte, NC and found that the estimated operating modes varied considerably by functional class of roadways (e.g., urban or rural interstate, primary arterial, minor arterial, federal collector street, etc.) location of roadway facility within an urban area, and the time of day of travel. In another study, Venigalla *et al.* (1995) analyzed data available from the Nationwide Personal Transportation Survey (NPTS) to develop operating mode fractions. As a result of the complexity involved in estimating the operating mode distributions, the state of practice is to use default values of operating mode fractions for all functional road classes. These default values of operating modes are: 20.6 percent for cold transient mode, 27.3 percent for the hot transient mode and 52.1 percent for the hot stabilized mode, based on the FTP driving cycle (NCHRP, 1995). However, the use of these operating fractions on interstates or primary arterials would be inappropriate.

3.2.4 Vehicle Speed Distribution

There are a wide variety of speed measures used by transportation engineers for different purposes. Spot speeds represent the instantaneous speed as a vehicle passes a given point on the roadway. Running speeds measure the average speed over a section of roadway, while the vehicles are in motion. Average travel speeds along a route segment represents the overall speed including delays. Mobile5a is calibrated based on average speed values of deriving cycles used for exhaust emission rates (NCHRP, 1995).

A standard practice in planning work is to estimate the speed on a link using a speed-flow curve such as the Bureau of Public Roads (BPR) curve. Chapter 11 of the 1985 Highway Capacity Manual contains a method for determining average speeds on the basis of free flow speeds, intersection spacing, signal timing and functional class (HCM, 1985).

Vehicle travel speed can also be computed by the analytical process described in traffic simulation models such as the HPMS. The HPMS estimates average travel speeds in miles per hour for various vehicle types, classes of roads and geographic areas, and other strata by incorporating several factors such as speed change and stop cycles, idle time, pavement and geometric characteristics.

Other methods of calculating speeds include empirical observations, using spot speeds, running speeds, video surveillance and loop detectors. Spot speeds represent the instantaneous speeds as a vehicle passes a given point on the roadway. Running speeds measure the average speed over a section of a roadway, excluding events in which vehicles are stationary. The method for calculating speeds varies among relevant state transportation departments (NCHRP, 1995).

3.3 Air Quality Models

Air Quality models are mathematical descriptions of atmospheric transport and chemical reaction of pollutants. They operate on sets of input data characterizing the emissions, topography and meteorology of a region. A practical model typically consists of four structural levels (Seinfeld, 1986):

(1) A set of assumptions and approximations that reduce the actual physical problem to an idealized one that retains the most important features of the actual problem. This involves the conceptual formulation of the model.

(2) The basic mathematical relations that describe the idealized physical system.

(3) The computational schemes that are used to solve the basic equations.

(4) The computer program that actually performs the calculations.

The term “model” can be used to apply collectively or separately to all four functional levels. Models that focus on a group of interacting processes are called "modules."

Air quality models can be classified as prognostic or diagnostic. The models which are based on the fundamental physiochemical principles governing air pollution are called prognostic models while those which involve statistical description of observed air quality data are called as diagnostic models(Seinfeld, 1988).

Prognostic models can be further classified as Eulerian or Lagrangian. Eulerian models use what is called a “moving coordinate” approach to describe pollutant transport. In Eulerian models, the reference point of the coordinate system moves with the moving air mass. In contrast Lagrangian models use a fixed coordinate approach to describe pollutant transport. A Gaussian Plume model is an example of a Lagrangian model. In these models, air masses move with respect to the coordinate system. Lagrangian models based upon numerical simulations of the physics and chemistry within user specified cube of air are called Grid models.

Gaussian Plume models such as Caline4, CAL3QHC and PALS are used in mobile-source related CO analyses. These models calculate how pollutants are dispersed by representing the relationships between various meteorological, transportation, emission and other site specific information, in the form of mathematical equations (Seinfeld, 1988; NCHRP, 1995). Plume models are appropriate for short range transport of relatively unreactive pollutants. More complex grid-based models are needed to simulate the photochemistry of ozone formation.

Photochemical air quality models are used in determining the emission controls needed to attain the ozone NAAQS. EPA guidelines identify two photochemical models: a trajectory model called EKMA and a grid-based model called UAM. All of these air quality models are described in the following sections.

3.3.1 Caline4 and CAL3QHC

CAL3QHC is the EPA-required dispersion model that is to be used in modeling emissions at intersections. Caline4 is a line source dispersion model, designed by the California Department of Transportation (CDOT), to predict the air pollutant concentrations near highways and arterial streets due to emissions from motor vehicles operating under free flow conditions. Both of the models are based on the Gaussian diffusion equation and employ a mixing zone concept to characterize pollutant dispersion over the roadway (Benson, 1989; USEPA, 1992).

CAL3QHC works by considering a roadway intersection as a series of links, on which vehicles are in different modes of operation. The model calculates average queue lengths over the specified time interval. In the accepted procedure, different emission factors from the Mobile model are then applied, based upon whether vehicles are in idling (queued) or free flow mode. However, this procedure represents an incorrect use of Mobile5a. This is because Mobile5a provides trip-based average emission factors.

3.3.2 PALS

The Point, Area, Line, Source (PALS) model is recommended for modeling CO emissions in parking areas including multilevel parking garages. Each level in a multi-level parking deck can be treated as an individual elevated area source as long as the cumulative effect of the emissions at levels closer to the entrance and exit levels are taken in to account.

3.3.3 EKMA and UAM

The Urban Airshed Model (UAM) and the empirical kinetic modeling approach (EKMA) are the EPA-recommended photochemical models for estimating attainment with the NAAQS for ozone. The three dimensional, grid-based air quality models such as UAM are used for ozone non-attainment areas designated as extreme, serious or severe (EPA, 1991). The region to be modeled is bounded on the bottom by the ground and on the top by an inversion base or some other height that characterizes the maximum extent of vertical mixing. The space being modeled is subdivided in to a three dimensional array of grid cells. The horizontal dimensions of each cell are usually a few kilometers for urban applications. Older grid-based models assumed only a single, well mixed vertical cell extending from the ground to the inversion base. Current models subdivide the region in to layers (Seinfeld, 1988).

EKMA, which is also used to demonstrate ozone NAAQS attainment, simulates urban ozone formation in a hypothetical box of air that is transported from a region of most intense source emissions to a downwind point of maximum ozone accumulation. Emissions of VOCs and NO_x are assumed to be well-mixed in the box. The height of the box can be varied to represent changes in the height of atmospheric mixing. Ozone formation is simulated using a photochemical mechanism. By simulating an air mass as a box of air over its trajectory for a large number of combinations of initial VOC and NO_x concentrations, EKMA generates ozone isopleths (lines of constant value) specific to particular cities. Once the maximum ozone concentration in the city is identified, VOC and NO_x reductions needed to achieve NAAQS are determined from the distance along the VOC and NO_x axes to the isopleth that represents 120 ppb peak ozone concentration mandated by the NAAQS (NRC, 1992).

The use of models described above to predict ambient pollutant concentrations is summarized in the next section..

3.4 General Procedure for Air Quality Modeling

As described in NCHRP (1995), the procedures employed in the development of pollution estimates using the emission factor, activity and the air quality models are:

(1) Determine the level of spatial and temporal resolution required (e.g., for dispersion models, information must be provided on an hourly, gridded basis);

(2) Determine total VMT by functional class of roadway;

(3) Develop growth factors and predict future-year VMT;

(4) Develop emission factors based on the rates at which different pollutants are emitted per VMT by various types of vehicles in various operating modes;

(5) Multiply these emission factors by calculated VMT to determine total mobile-source emissions for the non-attainment region;

(6) Determine emissions from area sources and point sources to calculate the total emissions for the non attainment region;

(7) Determine meteorological, boundary and terrain data that are used as inputs, together with the total emissions, by dispersion models;

(8) Determine the ambient pollutant concentrations.

The accuracy of the final emissions estimates is linked strongly to the methodologies and algorithms employed by the emissions-factor models such as Mobile5a. Any error in the input assumptions of the analysis is propagated from the start of the modeling procedure to the final emission estimates (NCHRP, 1995). Therefore, it is important to revisit the data used for developing the model and to carry out analyses to determine the nature of uncertainty and variability in the emission factor models like Mobile5a. The next chapter addresses the basic concepts in uncertainty and variability and discusses those issues in relation to mobile source emission estimates.

Table 5. Model Year and Technology Groupings for Speed Factor Development

Source (EEA, 1991)

Tech Group No.	Model Year	Fuel Metering [a]	Fuel Control [b]	Catalyst Type [c]
1	1981+	Carbureted	OL	3W+O , O
2	1981+	Carbureted	CL	3W
3	1981-82	PFI, TBI	CL	3W, 3W+O
4	1981-82	Carbureted	CL	3W+O
5	1983 +	Carbureted	CL	3W+O
6	1983-86	TBI	CL	3W
7	1983-86	TBI	CL	3W+O
8	1987+	TBI	CL	3W
9	1987+	TBI	CL	3W+O
10	1983-86	PFI	CL	3W
11	1983-86	PFI	CL	3W+O
12	1987+	PFI	CL	3W
13	1987+	PFI	CL	3W+O

a PFI = Port Fuel Injection, TBI = Throttle body Fuel Injection.
b OL = Open Loop, CL = Closed Loop.
c 3W = three-way catalyst, 3W+O = Dual Bed Catalyst, O = oxidation catalyst.

4.0 EPA's EMISSION FACTOR MODEL: Mobile5a

Mobile5a calculates emission factors for HC, CO, and NO_x from eight separate classes of on-road motor vehicles. These vehicle classes are listed in Table 6. The emission factor estimates are typically generated for the entire on-road fleet of vehicles in a metropolitan area, and the results are used to prepare emission inventories, evaluate control measure effectiveness, and to determine compliance with federal regulations (Heirigs and Dulla, 1994; Sierra, 1994; SAI, 1994).

4.1 Basic Structure of Mobile5a

Mobile5a calculates emission rates for each vehicle class in gram/miles by determining the emission rate of each model year making up the vehicle class, weighting the model-year specific emission rate by fractional usage (i.e., VMT or travel fraction), and summing over all model years that comprise the vehicle class. In addition, a variety of corrections are applied to the BERs to account for conditions not included in the standard test procedures used to develop the base emission rates. For example, exhaust emission rates can be adjusted for nonstandard driving cycle average speeds using SCFs, and evaporative emissions can be corrected for differing fuel volatility and temperature using temperature correction factors (TCFs) (Heirigs and Dulla, 1994; Sierra, 1994; SAI, 1994).

The Mobile5a model calculations can be summarized by the following equation:

$$EF_{j,k} = \sum_{m=1}^{n} \{f_{VMT,m} \bullet (BER_{j,k,m} \bullet \prod_{l=1}^{L} CF_{j,k,l,m})\} \qquad (1)$$

where

j = pollutant (e.g., CO, HC, NO_x);

k	=	emissions process (i.e., exhaust, evaporative);
l	=	correction factor (e.g., speed, temperature, deterioration rate);
L	=	total number of correction factors.
m	=	model year;
n	=	total number of model years;
$EF_{j,k}$	=	fleet-average emission factor for pollutant *j*, and process *k*;
$f_{VMT,m}$	=	fractional VMT attributed to model year *m* (the sum of $f_{VMT,m}$ over all model years *n* is unity);
$BER_{j,k,m}$	=	base emission rate for pollutant *j*, process *k*, and model year *m*.
$\prod Cf_{j,k,m,l}$	=	product of correction factor(s) for pollutant *j*, process *k*, and model year *m*; over index *l*.

The sum is carried out over the number of model years, *n*, making up the vehicle class (e.g., typically 25 model years for light duty gasoline vehicles (LDGV) in Mobile5a). The process is repeated for all eight vehicle classes, and the results are weighted by the travel fraction associated with each class and summed over all classes to develop a fleet-average emission rate (Heirigs and Dulla, 1994; SAI, 1994; Sierra, 1994). Typical inputs used include tampering rates, average vehicle speed, the daily temperature profile, typical vehicle operating modes, the distribution of vehicle ages and the types and nature of any applicable inspection programs (USEPA, 1992).

4.2 The Mobile Exhaust Base Emission Rates

In the previous versions of the MOBILE model, data used for BERs were collected by surveillance testing wherein the vehicle owners were randomly contacted and asked to give up their cars for a week of testing. However, the EPA felt that the vehicles from the surveillance testing were not representative of the in-use fleet. Specifically there was concern regarding under-representation of poorly maintained, high emitting vehicles. The survey of vehicles used to develop some components of the Mobile5a model may have suffered from self-selection bias. For example, the vehicle owners of poorly maintained, high emitting vehicles may not have volunteered to submit their vehicles for testing in proportion to their numbers in the general population. To overcome this sample bias, EPA used IM240 emissions data collected during the initial two years of a mandatory I/M program in Hammond, IN, to develop the exhaust BER equations for Mobile5a.

The Mobile5a model is primarily based upon the FTP cycle. All of the correction factors in the model are based upon the FTP cycle. Thus, the BERs in Mobile5a are also required to be based on the FTP. The IM240 cycle consist of Bag 2 and Bag 3 portions from the FTP cycle (Heirigs and Dulla, 1994). Therefore, for obtaining the BERs in Mobile5a, the IM240 data were converted to an equivalent FTP basis using regression models. Data for these models was developed by testing approximately 646 vehicles on both the FTP and IM240 cycles. For HC and CO, the emissions data were log transformed because the emissions varied by more than an order of magnitude. Thus, a log-log regression was done to develop a relationship between the average IM240 and FTP emissions. The NO_x regressions were based on a linear model because NO_x emissions did not display as much variation as did HC and CO emissions.

The IM240 does not include a cold start as represented by Bag 1 of the FTP. Thus, the IM240 test is conducted with vehicles in a warm stabilized condition. Therefore, the regression models developed for HC and CO include a "cold start offset." The cold start offset is intended to be the difference between the cold start emissions and the average of Bags 2 and 3. Cold starts do not have a discernible effect on the NO_x emissions.

Therefore the regression model for NO_x does not include a cold start offset. The HC and CO transformations from IM240 to FTP were developed according to the following log-log regression equation:

$$\text{Log (FTP-X)} = b + m \bullet \text{Log (IM240)} \qquad (2)$$

where

X = The cold start offset in the FTP cycle (g/mi)

b = the intercept from the regression analysis

m = the slope from the regression analysis

In Mobile5a, the BERs are expressed in the form of linear equations which relate the emissions rate to the "mileage accumulation." The latter is the odometer reading of the tested vehicles. The linear equations include a zero mile level (ZML) and one or two deterioration rates (DR),or slopes, which represent the expected increase in emissions per 10,000 miles of accumulated mileage. The baseline emission factors by model year in Mobile5a are estimated by a companion program called TECH5. As in Mobile5a, the emissions data are classified in TECH5 by emission standard and technology groups. The technology groups include closed-loop carbureted (CARB/CL), closed-loop multiport fuel-injection (MPFI/CL), closed-loop throttle-body injection (TBI/CL), and open loop. The data are then aggregated in to four basic emitter groups or regimes. The four emitter groups are:

- Normal: $\leq 2 \times$ HC Std. <u>and</u> $\leq 3 \times$ CO Std.
- High : $> 2 \times$ HC Std. <u>or</u> $> 3 \times$ CO Std.

- Very High : > 4 × HC Std. <u>or</u> > 4 × CO Std.
- Super : > 10 gm/mile HC <u>or</u> > 150 gm/mile CO

Thus, vehicles having HC emissions less than or equal to 2 times the applicable standards (see Table 3) and CO emissions less than 3 times the applicable standard are classified as normal emitters. For NO_x, the model classifies vehicles in only two emitter categories viz. normal (< 2 gm/mile) and high (>2 gm/mile).

The BERs as a function of vehicle mileage are determined by multiplying the emission rate of each emitter category by the fraction of each category making up the fleet at the corresponding mileage intervals. Both the emitter category emission rates and growth functions (i.e., change in the mix of normals, highs, very highs and supers with mileage) for Mobile5a were developed from the data collected in the Hammond program. BERs for each model year are generated by weighting the technology-specific emission rates by the fraction of each technology in the fleet. Thus, each model year base emission rate equation is a combination of up to four technologies (i.e., MPFI/CL, TBI/CL, CARB/CL, and open loop) and four emitter categories (i.e., normals, high, very high, and supers) (Heirigs and Dulla, 1994; SAI, 1994; Sierra, 1994). The functional form of the BERs in Mobile5a is

$$\mathrm{BER} = \begin{cases} \mathrm{ZML} + \mathrm{DR1} \bullet \mathrm{MA}; & \mathrm{MA} \le 50{,}000\ \text{miles} \\ \mathrm{ZML} + \mathrm{DR1} \bullet 50{,}000 + \mathrm{DR2} \bullet (\mathrm{MA} - 50{,}000); & \mathrm{MA} \ge 50{,}000\ \text{miles} \end{cases} \tag{3}$$

where:

BER = Base Emission Rate (g/mi.)

ZML = Zero mile Level (g/mi.) obtained as the Y- intercept of the mileage accumulation regression equations used to develop the BERs.

DR1 = Deterioration Rates (g/mi/10,000 mi) obtained as the slope of the mileage accumulation regression equations for mileage accumulation less than 50,000 miles.

DR2 = Deterioration Rates (g/mi/10,000 mi)obtained as the slope of the mileage accumulation regression equations for mileage accumulation greater than 50,000 miles.

MA = Mileage Accumulation (10,000 mi)

4.3 Correction Factors

The BERs in Mobile5a are adjusted to deal with differences in driving cycles, temperature and vehicle characteristics compared to the standard FTP. In some cases, the correction factors are developed by comparing the measured emission factors for the same vehicles operating under alternative conditions. In other cases where the same vehicle was not available for tests under alternative conditions, the correction factors are developed based upon comparison of similar groups of vehicles. In these cases, the ratio of the average emissions under the alternative conditions to the average emissions for the standard conditions is used to correct the BERs. For example, if vehicles tested on the FTP at 105 $^{\circ}$F had average HC emissions twice that of the same group of vehicles tested at 75 $^{\circ}$F, then the temperature correction ratio would be 2. To estimate emission factors at 105^{0} F, the BER for that subgroup of the fleet would be multiplied by a correction factor of 2 (SAI, 1994).

Previous studies have indicated that there is a significant uncertainty associated with the SCFs in Mobile5a (Guensler, 1993, NCHRP, 1995). This motivates a need for re-analyzing the SCF used in Mobile5a. Therefore, this report has focused on analyzing SCFs in Mobile5a. The next section describes the SCF in Mobile5a. A detailed analyses of the SCF data is described in Chapters 7 and 8.

4.4 Speed Correction Factors

Speed correction factors in Mobile5a adjust motor vehicle emissions as a function of average speed of a driving cycle. The FTP cycle, with an average speed of 19.6 miles per hour, is used as the base estimate.

The emissions data used in EPA's speed correction analysis were collected by the EPA in their periodic LDGV emissions testing programs. The speed correction data files contained emissions information on vehicles tested on eleven different driving cycles. A speed versus time profile of each of the driving cycles is given in Appendix A. A selected group of 371 LDGVs were tested over five driving cycles with average speeds between seven and 48 miles per hour. EPA augmented the five driving cycles with three additional low speed cycles with average speeds between 2.45 and 4.02 miles per hour. To obtain more emissions data that represented city driving conditions, a different set of 302 vehicles were tested across the eight driving cycles (EEA, 1991). In addition, data for the three high speed cycles, which were intended to be more representative of freeway and interstate driving, were obtained by EPA from CARB. The data set for the three high speed cycles were obtained from tests carried out on a different population of vehicles compared to the other eight driving cycles. All of the eleven driving cycles are in hot stabilized mode. A vehicle is considered to be in the hot stabilized mode after the engine warm-up has occurred, and after the engine and emission control systems have reached full operating temperatures (Sierra, 1994). Table 7 describes the characteristics of the eleven driving cycles used in Mobile5a.

A total of 13 LDGV technology groups were tested to develop the SCFs. These groups are based upon model year, fuel metering system, and emissions control technology. Emission controls consist of a fuel control system and a catalyst type. Fuel control systems are open loop (OL) and closed loop (CL). Open loop systems utilize oxidation catalyst. Closed loop systems use either a three-way catalyst or three-way plus oxidation catalyst. Three types of fuel metering systems are carbureted, port fuel injected (PFI) and throttle body injected (TBI) (EEA, 1991).

An EPA contractor, EEA, Inc., examined the driving cycle emissions data to determine if there existed any vehicles within a particular group whose emissions were such that they would bias the analysis of emissions as a function of speed. EEA reported that the log (base 10) of the HC, CO and NO_x emissions were essentially normally distributed, although the distributions of CO at low speed were more uniformly distributed. However EEA does not cite any criteria by which the shapes of the distributions were evaluated (EEA, 1991).

EEA defined outlier vehicles as those vehicles whose logarithm of emissions at a speed cycle were more than two standard deviations from the mean logarithm of emissions of similar vehicles for the same speed cycle. These outliers represented vehicles with extremely high or low emissions. Vehicles which were outliers at three or more speeds were removed from the sample analyzed by EEA. No rational was cited for this approach, which appears to be arbitrary. The driving cycle emissions, which are based on hot stabilized operation modes, were then normalized to the Bag 2 emissions of the FTP, since these emissions are also for hot stabilized mode. The data were then used to estimate the parameters for an assumed SCF model:

$$SCF = \left\{\frac{A}{E}\right\} \bullet \left\{\frac{1}{S}\right\} + \left\{\frac{B}{E}\right\} \qquad (4)$$

where

A = Slope of the regression model used for speed correction (g/mi)

B = Technology specific constant (g/mi)

E = gram per mile emissions at 16.1 mph (Bag 2)

S = average cycle speed (mph)

This equation was used only for the low and medium speed cycles with speeds between 2.5 to 48 mph. For the high speed cycles with average speeds between 50.9 mph and 64.3 mph, Mobile5a uses a linear function.

The speed correction factor coefficients used as inputs to Mobile5a differ from those reported by EEA. Documentation regarding the coefficients actually used by the model is not available. The coefficients were weighted based upon the fraction of each technology group comprising total sales in each year, and based upon normal versus high emitters, to obtain model year specific coefficients which are used in the speed correction equations in Mobile5a.

The next section describes the inputs and outputs required by Mobile5a to calculate the emission factors.

4.5 Parameters of the Mobile5a Model

The Mobile5a model has the capability of using an interactive mode or a batch file mode for accepting inputs from a user and generating emission factor outputs. In the batch file mode, the user has to enter a batch file containing the input and output file names. The input file contains the specific details for which the user wants emission factors. Mobile5a writes the results to the user specified output file. The key user inputs to the Mobile5a model are:

1. Average speed(s)
2. Ambient temperature
3. Operating mode fractions: These fractions represent the percentage of time of a driving cycle associated with cold starts, hot stabilized driving and hot starts.
4. VMT mix
5. Annual mileage accumulation rate and registration distributions by age
6. Basic exhaust emission rates: Although default values are included in the model and are commonly used, Mobile5a allows the user to use an alternative set of BERs.
7. I/M program(s): Mobile5a has the capability of modeling the effects of I/M programs. The inputs for modeling I/M programs are described in section 4.5.7.
8. Air conditioning (A/C) usage, extra loading, trailer towing, and humidity corrections
9. Tampering rate: User can input locally derived tampering rates.
10. Anti-tampering program (ATP): Mobile5a models programs which are intended to assure that vehicle owners have not disabled or tampered with the emission control system components.
11. Refueling emission: Refueling emissions occur when a fuel tank is filled. These emissions result due to vapor space displacement and spillage.
12. Local area parameters (LAP): A number of local conditions are required by Mobile5a that describe the ambient conditions (e.g., temperature variations) and fuel parameters (e.g., fuel volatility, oxygenate content etc.)
13. Trip length distribution: In Mobile5a the trip length refers to the duration of the trip (how long a vehicle has traveled) and not to the distance traveled in the trip.

4.5.1 Average Speed

Average speeds are used to represent different trip-based driving cycles. Emission factors may vary considerably with the average speed assumed. The Mobile5a input for speed can have a significant effect on the resulting emission factors for exhaust and running loss emissions. As an example, the sensitivity of the HC, CO and NO_x emission rates as function of average speed is shown in Figure 2. For HC and CO, the figure displays high emissions at low speeds, with emissions decreasing sharply at first and then gradually as average speed increases until minimum emissions are reached at about 48 mph. In Mobile5a, the same emissions are assumed for all speeds from 48 to 55 mph for HC and CO. For NO_x, the emission rates are high at low speed. The emissions gradually decrease as average speed increases until minimum emissions are reached at 19.6 mph. Beyond 19.6 mph, the NO_x emission rate is predicted to increase with increases in average speed (Sierra, 1994; SAI, 1994; Heirigs and Dulla, 1994).

In Mobile5a, average speed emissions analysis can be carried for all vehicle classes at one average speed or for each individual vehicle class at different average speeds. The user is requested to input the type of speed analysis (e.g., one speed for all vehicle classes or different speed for each vehicle class), the class of vehicles on which the analysis is to be performed and the range of speeds for which the user wants to carry out the analysis (USEPA, 1992).

4.5.2 Ambient Temperature

Changes in ambient temperature can have a significant effect on evaporative emissions. The emissions from the fuel storage and delivery system are called evaporative emissions. Evaporative emissions can be categorized as: hot soak; diurnal; running losses;

resting losses; and refueling losses. When a hot engine is turned off, fuel exposed to the engine (e.g., in fuel injectors) may evaporate and escape to the atmosphere. These are called "hot soak" emissions. The escape of fuel vapors from the vent of a fuel tank due to fluctuations in daily temperature are called as "diurnal" emissions. Running losses result from vapor generated in the fuel tanks during engine operation. Resting losses are emissions resulting from vapors permeating parts of the evaporative emission control system (e.g., rubber vapor routing hoses), migrating out of the carbon canister, or evaporating liquid fuel leaks.

The minimum and maximum daily temperatures are directly used in Mobile5a in calculating the diurnal portion of evaporative HC emissions, and in estimating the temperature of the dispensed fuel for use in calculation of refueling emissions. The temperatures used in calculating the temperature corrections to exhaust HC, CO, and NO_x emissions, the hot-soak portion of the evaporative emissions, and resting and running loss HC emissions are calculated on the basis of minimum and maximum temperature unless overridden by the user. The input temperature value must be between 0^0 F and 100^0 F.

Diurnal emissions are most frequently measured for the FTP temperature range of 60^0 F to 84^0 F. The BERs for HC, CO and NO_x are based on a standard temperature of 75^0 F. Mobile5a calculates an average temperature over the course of the day based on input minimum and maximum daily temperature and adjusts the emission factors for temperature accordingly.

4.5.3 Operating Mode Fraction

EPA's emission factors are based on testing over the FTP cycle, which is divided in to three segments called the cold start (Bag 1), the stabilized part (Bag 2) and the hot start (Bag 3). Each of these bags represent an operating modes. Emissions are typically highest for Bag 1. During cold starts, the vehicle, the engine and the emission control equipment are all at ambient temperature. The catalytic emissions control system does not provide full control until it reaches a "light-off" temperature of several hundred degrees Fahrenheit. In addition, the exhaust gas composition must be maintained within a narrow range of acceptable oxygen concentration in order for the catalyst to operate effectively. During engine warm-up a richer fuel-air mixture must be provided to the cylinders to achieve satisfactory engine performance. Thus the exhaust gas composition is outside the range for catalyst operation and uncontrolled emissions of CO and HC are high. Emissions are somewhat lower in the hot start mode. Emissions are typically lowest for the stabilized mode, when the vehicle has been in operation long enough for all the systems to have attained relatively stable, fully warmed up operating temperatures as long as the vehicle operates within a narrow range of fuel-to-air ratio for proper catalyst function (Sierra, 1994; SAI, 1994).

4.5.4 VMT mix

The VMT mix specifies the fraction of the total highway VMT that is accumulated by each of the eight vehicle classes. This parameter is used in Mobile5a only to calculate the composite fleetwide emission factor for a given scenario on the basis of the eight vehicle class-specific emission factors.

As a default, Mobile5a calculates the VMT mix based upon national data characterizing registration distributions and annual mileage accumulation rates by age for each vehicle type, diesel sales fractions by model year (for LDVs and LDTs only), total HDDV registrations and annual mileage accumulations by weight class, the fraction of travel of each vehicle type that is typical of urban areas, and total vehicle counts by vehicle type. Thus VMT mix calculation is highly dependent on annual mileage accumulation rates and registration distributions by age (Sierra, 1994; SAI, 1994).

4.5.5 Annual Mileage Accumulation Rate and Registration Distributions by Age

Mobile5a's emission factor calculations use travel fractions for vehicles of specified ages and types. The travel fractions are the percentages of total miles traveled by a vehicle type in each model year. Thus in Mobile5a, the sum of travel fractions for each vehicle type over 25 model years is unity. The travel fractions are based upon estimates of average annual mileage accumulation by age (1 - 25 years of operation). The model also uses registration distributions by age (1 - 25 years) for each vehicle type, except motorcycles, for which annual mileage accumulation rates and registration distributions are for the first 12 years of operation. Registration distributions include the percentage of a vehicle type registered in each model year. Like travel fractions, the sum of registration distributions for a vehicle type over 25 model years is unity.

For all eight classes of vehicles, Mobile5a uses national average values for the annual mileage accumulation rate and registration distributions, if the user does not provide any alternative mileage accumulation rate and/or registration distributions. The annual mileage rates are based on analyses of information developed over a long period of time and the registration distributions are based on analysis of calendar year 1990 registration data (Sierra, 1994; Heirigs and Dulla, 1994).

To calculate the effect of the annual mileage accumulation or the registration distributions, the user is expected to enter the age of the vehicle (between 1 and 25 years) and the average range of mileage accumulation (USEPA, 1992).

4.5.6 Basic Exhaust Emission Rates

Default BERs are contained in Mobile5a as described in Section 4.2. However, it is possible for the user to override these values. Specifically, the BERs can be modified by model year in the input file by using the appropriate input file flag number (e.g., if the user desires to use the Mobile5a BERs, the flag value for this parameter can be set to 1). Typically no changes to these equations are warranted for use in developing emission factors or inventories for SIP purposes. However, if the user wants to use alternative BERs, then the information that needs to be supplied includes: the number of alternate BER equations that are to be entered, the region (low or high altitude) to which these BERs apply, the vehicle types affected, the first and last model years to which the alternate equations apply, and the ZML (g/mi.) and the deterioration rates (g/mi. per 10k mi.) (Sierra, 1994; Heirigs and Dulla, 1994; USEPA, 1992).

4.5.7 Inspection/Maintenance Program(s)

This I/M flag allows the option of having Mobile5a include the emissions benefits of operating the I/M programs on the emission factors. The user has the option of assuming that no I/M program is in effect for any year, or of modeling the effect of one or two I/M programs. To model an I/M program the information required is: calendar year that the I/M program starts, stringency level, first and last model years of vehicles subject to the I/M program, waiver rates, compliance rate, program type, frequency of inspection, test type, and cutpoints for HC, CO and NO_x if defaults are not used (USEPA, 1992).

4.5.8 Air Conditioning (A/C) Usage Extra Loading, Trailer Towing, and Humidity Corrections

Mobile5a can adjust exhaust emission factors to account for air conditioning usage, extra loading, trailer towing, and humidity. These corrections apply only to light-duty gasoline-fueled vehicle types with the exception that the humidity correction affects only NO_x emission factors and is also applied to motor cycle emissions (USEPA, 1992).

4.5.9 Tampering Rates

Tampering refers to any disabling of the emission control systems of motor vehicles, whether willful or not, not caused by defect or normal wear. A tampering rate is the portion of the vehicle fleet subject to such tampering.

Eight types of tampering modeled by Mobile5a include: air pump disablement; catalyst removal; fuel inlet restrictor disablement; overall misfueling; Exhaust Gas Recirculation (EGR) system disablement; evaporative control system disablement; Positive Crankcase Ventilation (PCV) system disablement; and missing gas caps.

To quantify the effect of tampering on emissions, "emission impact rates" are used in the model. The BERs for the different technology group of vehicles in Mobile5a are combined with the corresponding fraction of vehicles equipped with the given control technology and the emissions impact rates to obtain the tampering "offsets". These offsets are later added to the non-tampered emission factors (USEPA, 1992; SAI, 1994; Sierra, 1994).

4.5.10 Anti-Tampering Program (ATP)

The ATP parameter allows the user to include the benefits of an anti-tampering program in the emission factor calculations. The user specifies an ATP, its start year, the earliest and most recent model years of vehicles subject to the program, frequency of inspection (annual or biennial), compliance rate and the inspections performed (air system, catalyst, fuel inlet restrictor, tailpipe lead deposit test, EGR system, evaporative system, PCV, gas cap) (USEPA, 1992).

4.5.11 Refueling Emission

This parameter controls how Mobile5a represents refueling emissions from gasoline fueled vehicles. Refueling results in the displacement of fuel vapor from the fuel tank to the atmosphere. There are two basic approaches to the control of vehicle refueling emissions, generally referred to as the "Stage II" (at the pump) and "on board" (on the vehicle) vapor recovery system (VRS). Mobile5a has the ability to model uncontrolled levels of refueling emissions as well as the impacts of the implementation of either or both of the major types of VRS.

To model the effect of a Stage II VRS, the user must provide four inputs: the start year (calendar year in which the requirement takes effect), number of years for the Stage II VRS installation to be completed and the system efficiency at controlling refueling emissions. For modeling on-board effects, the user needs to provide only the starting model year and the type of vehicle subject to the requirement (Sierra, 1994; SAI, 1994).

4.5.12 Local Area Parameters

This record contains seven to ten fields: scenario name, ASTM fuel volatility class, minimum and maximum daily temperatures, period 1 RVP, period 2 RVP, period 2 RVP start year and optional values to indicate if the user is inputting data on oxygenated fuel program, alternate diesel sale fractions by model year and the use of reformulated gasoline (USEPA, 1992).

4.5.13 Trip Length Distribution

For any given set of conditions, running loss emissions increase significantly as the duration of the trip is extended and the fuel tank and the engine become heated.

Temperature and fuel volatility is used by Mobile5a for each combination of vehicle type and trip length category for calculating the running loss emissions at the standard test speed. This information if supplied by the user is used in weighting these factors together to derive the average emission factor which is then corrected for average speed (USEPA, 1992).

The next chapter describes other measurement techniques and approaches that have been used to estimate on-road mobile source emissions.

Table 6. Vehicle Classes Modeled By the Mobile5a Emission Factor Model. Source (Heirigs and Dulla, 1994)

Symbol	DESCRIPTION
LDGV	Light-Duty Gasoline Vehicles
LDGT1	Light-Duty Gasoline Trucks under 6000 pounds. gross vehicle weight
LDGT2	Light-Duty Gasoline Trucks from 6,000 to 8,500 pounds. gross vehicle weight
HDGV	Heavy - Duty Gasoline Vehicles
LDDV	Light-Duty Diesel Vehicles
LDDT	Light-Duty Diesel Trucks
HDDV	Heavy - Duty Diesel Vehicles
MC	Motorcycles

Table 7. Driving Cycle Characteristics.

Source (EEA, 1991; Guensler; 1993)

Cycle	Average Speed	Duration	Distance	Percent of Time By Mode			
	mph	sec	mi.	Idle	Acceleration	Cruise	Deceleration
LSP1	2.45	617	0.42	45.9	16.2	23.2	15.2
LSP2	3.63	638	0.64	36.4	23.4	17.7	22.6
LSP3	4.02	625	0.70	34.1	24.2	19.2	22.6
NYCC	7.10	599	1.18	31.9	23.9	21.4	22.7
SCC12	12.10	349	1.17	25.5	26.1	27.8	2.6
FTP Bag 2	16.10	867	3.89	17.4	27.2	36.9	18.5
FTP Bag 3	25.52	505	3.59	19.0	22.7	39.1	19.2
SCC-36	35.85	966	9.90	6.3	18.9	61.6	13.2
HFET	48.40	766	10.20	1.2	14.2	75.5	9.1
HSP1	50.90	480	6.80				
HSP2	57.6	486	7.80				
HSP3	64.3	492	8.80				

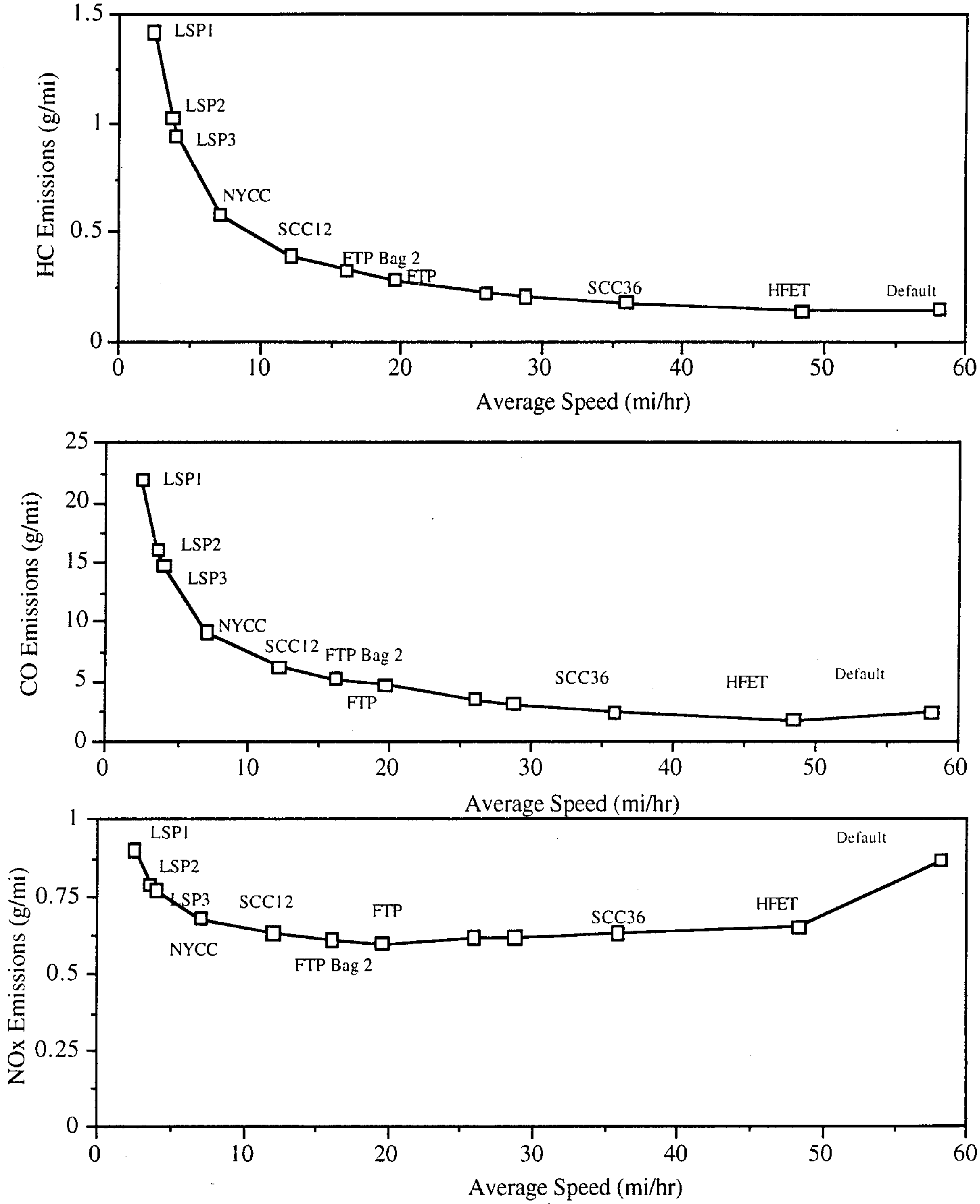


Figure 2. Variation in Emissions Predicted by Mobile5a Across the Average Speeds of Different Driving Cycles

5.0 APPROACHES TO ESTIMATING MOBILE SOURCE EMISSIONS

The EPA uses Mobile5a to develop area-wide estimates of highway mobile source emissions. Unfortunately few attempts have been made to validate the model.

A number of techniques exist for measuring emissions of on-road vehicles. Comparisons of measured versus modeled emissions provide some insight into possible sources of systematic and random error that are not accounted for in Mobile5a. In the case of mobile source emissions, it is difficult to obtain a meaningful datum for actual on-road emissions, due to the substantial variability in emissions across a population of vehicles and the limitations of measurement techniques. These limitations typically include small sample size, lack of representativeness, or inability to directly measure the quantity that is of interest. For example, remote sensing provides measurements of pollutant concentrations rather than mass emission rates. The latter is more useful for emission inventory development. However, inspite of the limitations, the various types of on-road measurements are the best data available for comparison to emission factor estimates (Frey et *al.*, 1996; Guensler, 1994; Gertler and Pierson, 1991).

Examples of measurement techniques and approaches include: (1) tunnel studies; (2) remote sensing; and (3) on-board instrumentation. Instrumented vehicles have also been used to better characterize driving cycles. In this section we briefly review work in these areas.

5.1 Tunnel Studies

Emissions of on-road vehicles have been measured in studies at the Fort McHenry, Tuscarora and Van Nuys tunnels. In the tunnel studies, mass emissions exiting the mouth of the tunnel, after accounting for winds and total air flow, were measured. By counting the number and types of vehicles that passed through the tunnel during each sampling period, gram per mile emissions of HC, CO and NO_x were derived (Ingals, 1989). The Mobile5a model was applied to attempt to predict emissions in the tunnel and the model estimate was compared to the tunnel study measurements. Mobile5a overpredicted mobile source HC and CO emissions observed at the Tuscarora and Fort McHenry tunnels by a factor of two. In contrast to this, Mobile5a underpredicted HC and CO emissions observed during the 1987 Van Nuys tunnel experiment by factors of two or more. There was no significant difference in the predicted and measured NO_x emissions (Gertler et al., 1995).

Possible explanations for differences between the measured and the modeled emissions may include: (1) differences in the tunnel versus the modeled fleet; and (2) differences in speed variability in some tunnels.

The Desert Research Institute (DRI) has reported substantial variability in speed in the Van Nuys tunnel experiment. In contrast, comparatively little variability in speed was reported for the Fort McHenry and Tuscarora tunnel studies (Ingals, 1989; Lawson, 1990 and Pierson et al., 1995). In the Van Nuys tunnel, the variability in speed may be higher than for the driving cycles associated with the same average speed in Mobile5a. Similarly, Mobile5a does not have the capability to model steady speeds typical of the Tuscarora tunnel. Furthemore, Mobile5a is not intended to be used for link based emission estimates, since it is based upon complete driving cycles. Therefore, Mobile5a model results cannot be directly compared to the observations from the tunnel studies. The driving cycles embedded in Mobile5a are not representative of the speed variations observed in these tunnel studies.

5.2 Remote Sensing

Remote sensing technology provides a means to measure ratios of CO to CO_2 and HC to CO_2. From these ratios, the concentrations of CO and HC in the exhaust plume of on-road vehicles can be inferred by making assumptions regarding fuel composition and the air-to-fuel ratio. NO_x emissions are not included in the present remote sensing studies because a reliable NO_x measuring instrument is not yet available. Remote sensing studies have shown considerable variability in the emissions of the in-use vehicles (Bishop, 1994). For example, the concentration of CO typically varies by three orders-of-magnitude on a percent volume basis, while HC concentrations typically vary by two orders-of-magnitude. Dual remote sensing measurements conducted by CARB have shown that in-use vehicles have considerable variability on repeat measurements for percent CO. Comparison of CO emissions data from the two remote sensors showed high variability as evidenced by a coefficient of determination (R^2) value of 0.52 (Cadle, Gorse, Carlock et *al.*, 1994). Thus, emissions may change significantly on a second-by-second basis. However it must be noted that remote sensing emission measurements are inherently more variable than those from traditional dynamometer tests. This is because remote sensors measure instantaneous emissions, whereas dynamometer tests are used to measure the emissions over a specified driving cycle. Remote sensing measurements are also sensitive to driving modes (e.g., cruise, acceleration).

5.3 On-Board Instrumentation

In order to evaluate the emissions under real-world driving conditions, vehicles with on-board instrumentation have been used to measure the emissions of HC and CO (Pablo and Long, 1995, Kelly and Groblicki, 1993). At CARB, calibration of the on-board instrumentation was performed by parallel sampling on a dynamometer. The calibration phase consisted of different driving cycles. The on-board collected data generally had higher emission rates as compared to the dynamometer data because of the effect of road grades. These effects are further exacerbated when air conditioning is operating or a fully occupied vehicle is used (Pablo and Long, 1995).

In addition to providing insights in to the possible systematic errors in the emission factors, on-board instrumentation studies carried out by CARB have indicated that there is substantial variability in the CO and HC emissions. These emissions varied by a factor of about four depending on the speeds and routes on which an instrumented vehicle was driven (Kelly and Groblicki, 1993). This implies that emissions are sensitive to the difference in the driving cycles.

5.4 Representative Driving Cycle

To enhance the representation of contemporary driving patterns in the South Coast Air Basin (SCAB), a driving cycle called the Unified cycle was developed by Sierra Research (Austin et al, 1993). This cycle was developed by using an instrumented "chase car" in the SCAB to characterize typical driving patterns. The Unified cycle has an average speed of 24.6 mph with peak velocity of 67.2 mph and maximum acceleration of 6.9 mph/s. However there are many high speed and acceleration events which are not represented by even the Unified Cycle (Gammeriello and Long, 1993).

The CARB tested 56 vehicles from the 1983-1992 model years, on both the Unified and FTP driving cycles. According to CARB, the predicted HC, CO and NO_x emissions were higher by 27 percent, 68 percent, and 17 percent respectively, for the Unified cycle (Gammeriello and Long, 1993). If the Unified cycle better represents typical driving patterns than the FTP, this would imply a systematic underestimation of emissions by the

Mobile5a model. However, no individual driving cycle can be representative of all vehicle trips.

5.5 Implications of the On-Road measurements for Emission Factors

The results of the tunnel studies, remote sensing and on-board instrumentation studies indicate that no single cycle can address the shortcomings of the emission factor model estimates. There is substantial variability in emissions for any population of vehicles even if they are operated under similar conditions. Variations in actual driving cycles lead to additional variability in emissions. Failure to account for these and other sources of variability can lead to systematic and random errors in estimating emission factors. Emission factor models are typically intended to estimate "average" emission factors with respect to vehicle population. The application of "average" emission factors to a specific vehicle activity does not represent the diversity of the vehicle activity (Guensler, Sperling and Jovanis, 1991).

EPA's Mobile5a model is based on a deterministic approach, utilizing average or point estimates as inputs. Many of these input parameters are more appropriately represented as distributions. The emissions data which underlies the Mobile5a model has substantial variability even for similar vehicles tested on the FTP. Also, uncertainty exists because the FTP and other standard driving cycles used in the formulation of the Mobile5a model may not be representative of the on-road driving behavior.

The degree of variability and uncertainty in the emissions estimates can be better explained using a probabilistic version of Mobile5a. The probabilistic analysis would help quantify the uncertainty and variability associated with the emission factor estimates calculated by Mobile5a. Chapters 7 describes a probabilistic version of Mobile5a . A new methodology for probabilistic analysis of emission data from different driving cycles is described. A demonstrative case study describing the application of the new methodology to the SCF data underlying is also included.

6.0 THE NATURE AND SOURCES OF UNCERTAINTY AND VARIABILITY

Emissions of ozone precursors from mobile sources are estimated from emission factors and activity data. Emission factors for mobile sources are developed based on limited sampling of emission sources within a given category under certain operating conditions. The variability and uncertainty in the measurements used to develop emission factors are not fully quantified. There is a tendency to place too much confidence in estimates which may be highly uncertain.

In this chapter the basic concepts of uncertainty and variability and their implications in mobile source emission predictions are discussed. Sources of uncertainty which are described here include measurement errors for model inputs and the approximation errors in a model itself. For mobile sources, the uncertainty in fleet average due to inter-vehicle variability and the differences in operating conditions of vehicles in lab tests versus the real world applications is discussed. Sources of variability described include vehicle activity and the emission factors. A description of various types of probability distributions that can be used to characterize uncertainty and variability is also included.

6.1 Uncertainty

In this section, sources of uncertainty related to measurement errors for model inputs and for the models themselves are reviewed.

6.1.1 Measurement Error

Uncertainty results due to lack of complete and accurate information regarding the true value of a quantity. Uncertainty is introduced because of measurement errors and because of simplifications introduced while analyzing information.

Uncertainty can be characterized in terms of accuracy and precision for measured quantities. The accuracy of an estimate is related to bias. Any sampling procedure that produces inferences that consistently underestimate or consistently overestimate some characteristic of the population (e.g., emissions of CO, NO_x, HC from mobile sources) is said to be biased. Accuracy implies a lack of bias. Lack of accuracy is denoted by the difference between the actual value of a quantity and the average estimated value (Gschwandtner, 1993).

6.1.1.1 Systematic Error

Systematic errors arise from biases in the measuring apparatus and the experimental procedures. They may be due to imprecise calibration, faulty reading of the scale and inaccuracies in assumptions used to infer the actual quantity from the observed data. Careful design and calibration of measurement apparatus and procedure and careful analysis of the assumptions will help to reduce this error. However, there will be an irreducible residual systematic error. Even if all known sources of bias are adjusted, the sources of error which are unknown or merely suspected are difficult to estimate and require a large element of subjective judgment (Morgan and Henrion, 1990).

As an example to illustrate how bias in a model may be identified, Table 8 shows a comparison of the highest 25 predicted and observed 1-hour concentrations of CO (ppm) at an intersection in suburban Chicago, Illinois. The average observed value was 35 ppm while the average concentration predicted by the emission model (CAL3QHC) was 24 ppm. Thus the systematic error in the estimate was 11 ppm, or 46 percent higher than the true value.

Table 8. Predicted and Observed hourly concentrations of CO at an Intersection in Chicago, Illinois.

(Source - Schewe, 1991)

Observed PPM	**Predicted** PPM	**Observed** PPM	**Predicted** PPM	**Observed** PPM	**Predicted** PPM
43.7	38.0	41.2	35.5	38.5	34.3
38.0	29.6	37.5	26.7	37.2	24.0
36.0	24.0	35.5	23.1	35.3	22.9
35.0	22.8	35.0	22.6	34.0	22.6
34.0	22.1	33.3	21.5	33.3	21.3
33.3	21.3	33.0	20.5	33.0	19.8
32.0	19.4	31.7	19.3	31.5	19.1

6.1.1.2 Random Error

Precision is the proximity of the estimated value to that of the model or target value. Precision implies a lack of dispersion of measured values. Precision is defined as the inverse of the standard deviation of a set of measurements. Thus measurements with a large random error are imprecise. Highly precise values can be inaccurate and vice versa. Uncertainty can be viewed as a combination of precision and estimated accuracy (Gschwandtner, 1993).

The distinction between precision and accuracy is important for understanding the errors associated with any set of measurements or estimates. Ideally estimates should be both accurate and precise. However it is very difficult to obtain the "true value" of any phenomenon. For example, in case of mobile sources, it is very difficult to obtain data on on-road emissions to compare to lab data.

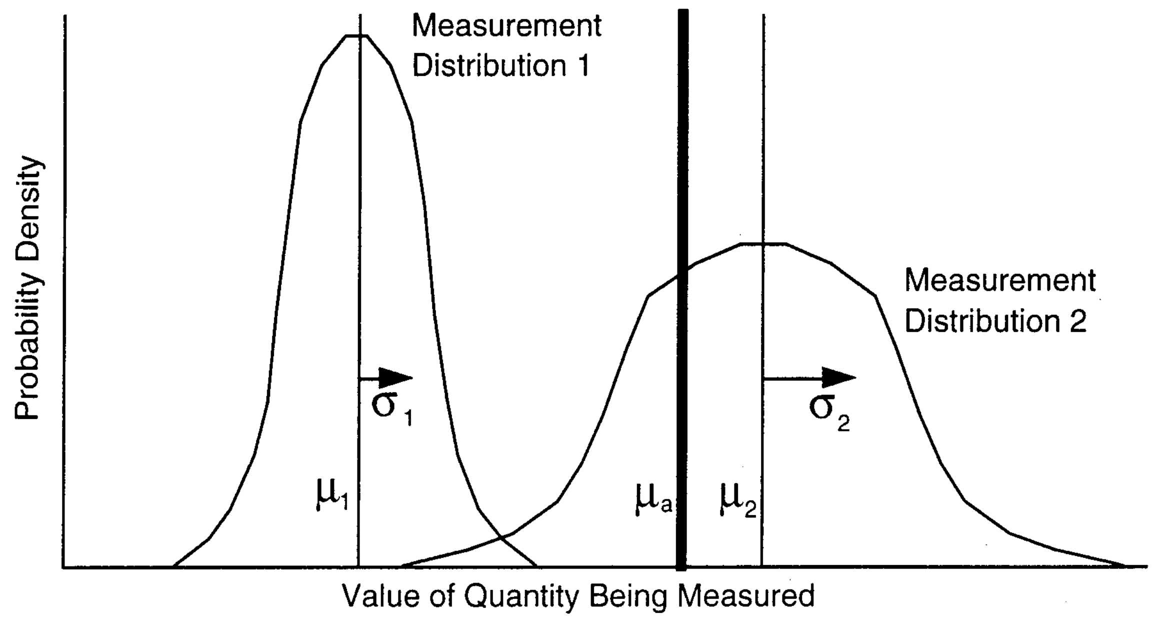


Figure 3. Hypothetical Distribution of Measurements Illustrating Precision and Accuracy

μ_1 = mean of distribution 1
μ_a = actual value
μ_2 = mean of distribution 2

Figure 3 is a schematic depicting different combinations of accuracy and precision. In one case, measurement distribution 1, an inaccurate but precise measurement is obtained In the second case, measurement distribution 2 an accurate but imprecise measurement is obtained.

The uncertainty in emission estimates due to errors in measurement of input parameters depends upon the range of variations between the observations and the number of observations taken. Uncertainty can be quantified in many ways. One of the most useful ways is to use probability distributions (Morgan and Henrion, 1990).

6.1.1.3 Probability Distributions

Probability distributions can be expressed in terms of probability density functions (PDFs) and cumulative distribution function (CDFs) or both. The PDF is a graphical means of representing the relative likelihood or frequency with which values of a variable may be obtained. The PDF also illustrates whether a probability distribution is skewed or symmetric. In a symmetric unimodal distribution the mean, median and the mode coincide. In a positively skewed distribution (e.g., Lognormal), the mean is greater than the mode. An alternate way to represent a probability distribution is the CDF. The CDF shows probability fractiles on the y-axis and the value of the distribution associated with each fractile on the x- axis (Morgan and Henrion, 1990; Frey, 1992). The CDF is and the integral of PDF.

$$F(x) = \int_{-\infty}^{x} f(x)\, dx \tag{5}$$

where:

F(x) = Cumulative Distribution Function

f(x) = Probability Density Function

also $P(X \leq x) = F(x)$

Figure 4 show the PDFs and CDFs of some of the probability distributions that will be used in the analyses done for the purpose of this report.

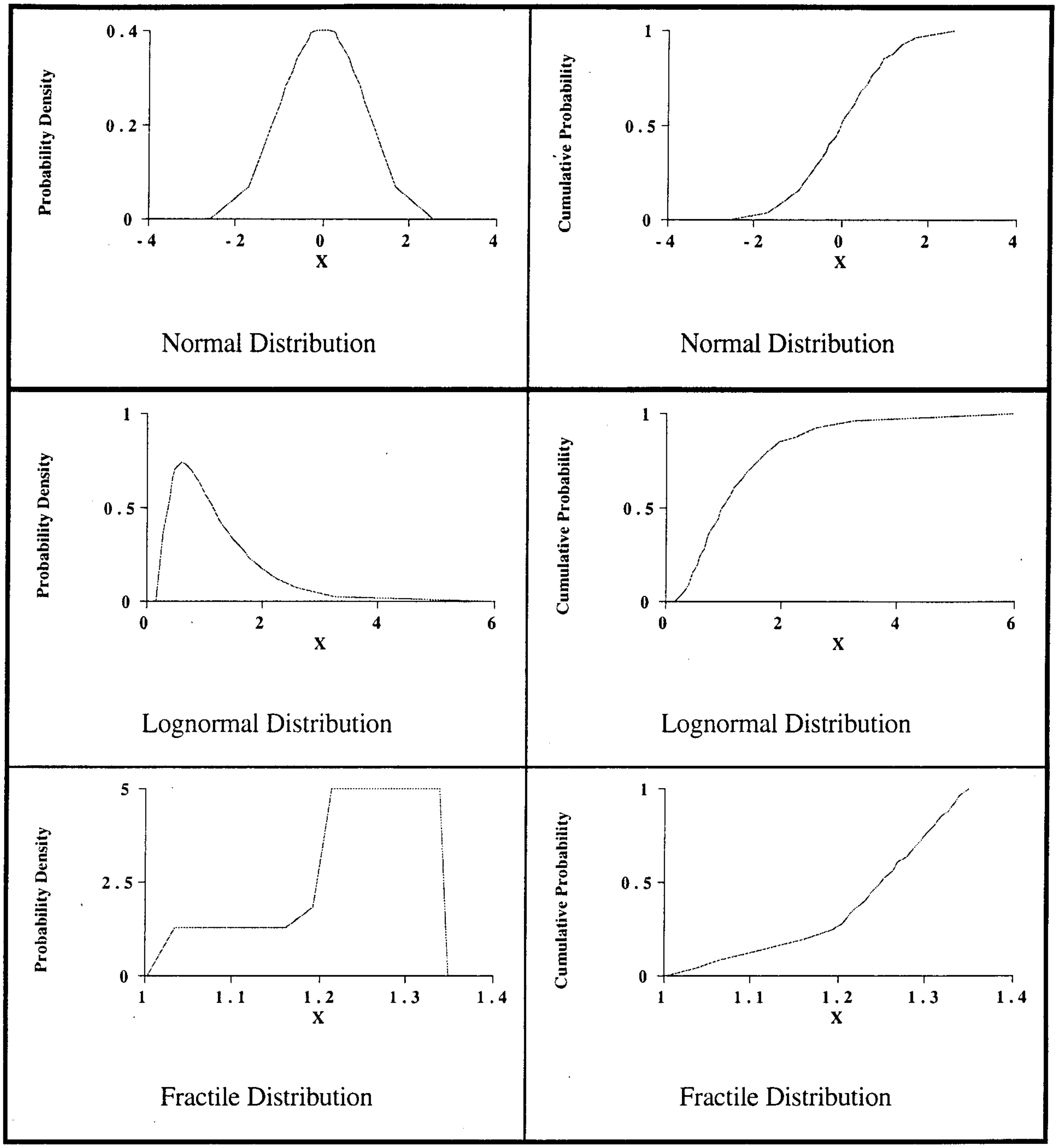


Figure 4. Probability Density Functions and Cumulative Distribution Functions of Selected Probability Distributions.

6.1.2 Approximations (Model Uncertainty)

In addition to uncertainties due to the limitations of measurements, uncertainty is also introduced by the model itself. The structure of mathematical models employed to represent the real world scenarios may be a key source of uncertainty. Models are only representative portrayals of real world systems. Significant approximations are an inherent part of the assumptions upon which models are built. Different sources of model uncertainties, as listed by Frey (1992), are given below.

6.1.2.1 Model structure

Model "structure" is composed of algorithms based upon a specific set of assumptions regarding relationships among model inputs in determining the model output. Alternative scientific or technical assumptions for the development of the model can alter the model structure. A model with an altered structure would make different predictions for the same set of input values. The implications of these alternative foundations can be evaluated by comparing the results from each alternative model. A difference in the results may call upon the subjective judgment of the analyst to choose the most plausible option for the given problem. For example, in the Mobile5a model, the BERs have been calculated using a linear model where the independent input variable is "mileage accumulation". Thus, the BER is dependent on the miles accumulated by a vehicle. The parameters of the BER were estimated as using a linear least squares regression. However, since emissions vary over orders-of- magnitude, a log-linear model is an alternative structure for the BER model. The implications of using a log-linear model are discussed in Chapter 8, where the Mobile5a emission factors are analyzed as a function of BERs and SCFs.

6.1.2.2 Model Detail

Models are often simplified for tractability by making some simplifying assumptions. Simplified models are also developed due to lack of confidence or knowledge about the actual structure of the model. In Mobile5a, there are significant simplifying assumptions. For example, the SCFs do not explicitly account for modal operations such as acceleration and deceleration (Guensler et *al.*, 1993; Guensler and Geraghty, 1991).

6.1.2.3 Validation

Validation is a process by which model predictions of a quantity are verified by comparison to observed values of the same quantity. Precision and accuracy of model predictions can be quantified by comparing model predictions to actual values of the same quantity. In case of Mobile5a, the validation process should involve a detailed re-analysis of the data used to develop the model algorithms along with confidence interval analysis. This can help practitioners identify the model components contributing to the greatest uncertainty to emission estimates (Guensler, 1993).

6.1.2.4 Extrapolation

Extrapolation is a key source of uncertainty. Models which are validated for one portion of the parameter space may be completely inappropriate for making predictions in other regions of the space. The SCFs in the Mobile model extrapolate between average speeds of standard driving cycles described in Chapter 4. However, the differences between the driving cycles can not be solely explained by average speed. Thus it is a misuse of data to "interpolate" between driving cycles (Frey *et al.*, 1996).

6.1.2.5 Scenario Reasonableness

Before using a model a scenario for the problem of interest must be developed. A scenario is a set of assumptions about the nature of the problem to be analyzed. Scenarios can be constructed to represent an actual environmental problem or they may be constructed based on policy motivations. For example, in case of mobile source emission models, a scenario would involve specifications of the following: average speed, vehicle mix, I/M programs, and other factors. The Mobile5a model is used to make predictions for specified scenarios. However, if the scenario is improperly specified (e.g., a link based average speed instead of a trip based average speed) then the model may be misapplied, in turn leading to meaningless predictions. Furthermore, even if a qualitatively correct scenario is constructed, if errors are made in specifying the values for the model inputs, then the model predictions would be in error compared to the actual "real-world" scenario.

6.1.2.6 Dependence

It is essential to consider the dependence between the input variables in a model. However, in simplified models, dependence between input variables is often ignored for convenience or because of lack of sufficient information to develop a more detailed model. Failure to account for dependence can lead to uncertainty in the model predictions.

Whenever possible, it is better to explicitly model the dependence between two variables using a functional relationship based upon statistical specification of covariance. Modeling dependence explicitly involves the development of a more detailed model which captures the sources of dependence between two quantities. For example, in the Mobile5a model, the correction factors (viz., SCF, TCF etc.) are assumed to be independent of each. If the temperature testing had been undertaken on the test cycles used to develop the SCFs, then the relationship between the relative emissions, average speed and temperature would have been more certain, than the independent use of existing SCFs and TCFs.

6.2 Sources of Uncertainty in Mobile Source Emission Estimates

Uncertainties in emission estimates for vehicles can arise from errors in estimates of VMT, emission factor model inputs and the emission factor model itself. The driving cycle data which underlies the emission models (e.g., Mobile5a), may not be representative of real world driving conditions. Furthermore, neither variability in measurements for a given type of vehicle nor the uncertainty in estimation of the fleet average emission factors is quantified. Thus the level of variability associated with model predictions and their use in developing emission inventories is unknown.

Another source of uncertainty is the database used to establish the algorithms in the emission factor models. The algorithms may have been developed using incorrect assumptions or misapplied statistical techniques. The database may not be representative of the on-road fleet. For example, the data which underlie the SCF in Mobile5a were based upon voluntary testing of vehicles. Therefore, there may be an under-representation of the high emitting vehicles.

The Mobile5a model uses a point estimate approach. Thus, information regarding variability is not captured. Therefore, the model estimation gives a misleading sense of precision.

6.3 Variability

Variability implies heterogeneity in observations. It can be a heterogeneity within a population or a subset of the population under consideration. Thus variability indicates the range of distribution for a population.

Variability can characterized using a frequency distribution. The frequency distribution for a subset of the population under consideration reflects the true differences between the individual members. Knowledge of the frequency distribution helps to assess whether a population needs to be subdivided in to groups which are more nearly homogeneous.

Although the terms uncertainty and variability are sometimes used interchangeably, they are distinct. Uncertainty generally is considered to arise from errors of omission, specification, measurement, or extrapolation. Variability refers to spatial and temporal differences between individuals in a population or larger group. Frequency distributions for variability can be used to identify significant subpopulations which merit more focused studies. But uncertainty in the characteristics of specific members of the population results in uncertainty in the frequency distributions (Frey, 1992). Therefore, it is important to qualify and quantify the uncertainty and variability associated with specific inputs which contribute most significantly to uncertainty in final decision variables.

In case of mobile sources, emissions vary between individual vehicles when operated under the same conditions and for a given vehicle when operated over a range of conditions. Sources of variability in mobile source emissions are: activity data and emission factors.

6.3.1 Activity Data

Vehicle activity is conventionally defined in units of average daily VMT, which is the product of average daily traffic volume and roadway length. VMT can be calculated for each link or for an entire area, distributed over each functional road class. Therefore, VMT is distributed over a characteristic vehicle type mix and assigned a characteristic speed according to the road class (Keating *et al.*, 1995).

Thus the activity data for mobile source emission is spatially disaggregated and temporally variable. In other words many quantities associated with mobile emissions such as vehicle class and age, vehicle type, VMT, vehicle speed etc., are variable over time and space. For example, vehicles operate under varying speed, accelerations and operating modes (i.e., cold or hot starting and hot stabilized vehicle operations). Each of these can be described by frequency distributions.

6.3.2 Emission Factors

Emission factors are generated by using emission factor models such as Mobile5a. There is a significant variation in emission factors inherent within a class of vehicles due to equipment configurations, and location-specific factors such as temperature, speed, and fuel characteristics. For example, fuel volatility and composition, which affect both evaporative and tailpipe emissions, may vary seasonally and with location. The in-use fleet of vehicles is composed of several generations of vehicles and several control technology groups. The vehicle design, such as the type of emission control equipment and other engine components, affect emission levels. Emission factors are also affected by vehicle maintenance or reflected by deterioration in emissions control with increasing age and mileage accumulation. Also location specific characteristics such as temperature and vehicle speed have a profound effect on the emission factors. For a summer day, with temperature variations between 65 ^{0}F to 85 ^{0}F, the highway vehicle emission factors vary by a factor of 2 (Battye, 1993). From Figure 2 (Chapter 4) it can be seen that estimated emission factors can vary substantially with change in average speed of vehicles.

The deterministic emission factor models such as Mobile5a are intended to estimate "average" highway emission factors. However it is unlikely that the point estimates provided by the model correspond to an average in a rigorous statistical sense. This is because the model does not account for variability in emissions even for a given set of operating conditions of the in-use fleet. The models attempt to develop averages that account for a mix of technology groups, deterioration, maintenance and other factors. The variability and uncertainties in the mobile source emissions can be propagated through the model by representing the model inputs as frequency distributions. The next section describes simulation techniques that can be used to propagate inputs as distributions through a model.

6.4 Monte Carlo and Latin Hypercube Sampling (LHS)

The most classic sampling technique used for numerical simulation is Monte Carlo sampling. To illustrate how Monte Carlo methods work, consider the following conceptual approach. First, a probability distribution is specified for each model input. Each distribution can be represented as a CDF. The CDF can be inverted so that the value of a random variable is represented as a function of uniformly distributed cumulative probability. A random number generator then generates n random numbers from a uniform distribution on the interval [0,1], where n is the sample size. These random values are then transformed into the input variable, X, using the inverse CDF of X. In a general case of a model with m input variables, the n sample values from an input distribution, X_i are paired randomly with n values of a second input distribution. This process can be repeated for m number of variables to create "m-tuples" representing one random draw from each of the m variables. One m-tuple defines a scenario, which is propagated through a model to obtain one output value. This process is repeated n times so that n scenarios are propagated through the model resulting in a distribution of *n* output values (Morgan and Henrion, 1990).

One advantage of using Monte Carlo sampling is that with a sufficient sample size, it provides an excellent approximation of the output distribution. Also, since it is a random sampling technique, the resulting distribution of values can be analyzed using standard statistical methods (Morgan and Henrion, 1990).

The primary disadvantage of Monte Carlo technique is that even a minimum necessary sample size is often undesirable large. This is because a large sample size may be necessary in order for a sufficient number of samples to be taken from low probability events. As an alternative to random sampling, a stratified sampling technique can ensure that samples are taken from the entire range of distribution. Latin Hypercube Sampling (LHS) is one such sampling technique. In LHS, the range of each input distribution is divided into *n* intervals of equal marginal probability. One value of the random variable is selected from each interval. The sample taken from each interval may be selected at random from within the interval, or from the median of the interval. The former is referred to as a random LHS while the later is called median LHS. In both median and random LHS, the n values from each distribution are grouped into *n-m* tuples by the same method described for Monte Carlo sampling. The stratification of the input distributions into *n* equal probability intervals ensures that the sample size compared to random Monte Carlo sampling. However, since LHS is not a purely random sampling technique, the results may not be subject to analysis by standard statistics (Mckay et *al.*, 1979).

Deterministic mobile source emission factor models fail to quantify the variability and uncertainty for a given set of model input assumptions. Although, it is assumed that the emission factors generated by Mobile5a represent average values, there are sources of systematic error that lead to bias in the ability of the model to accurately reflect data (e.g., driving cycle emission data) that underlie the model. To account for all these short-comings of the deterministic model, a probabilistic version of Mobile5a was developed. This model makes use of simulation techniques described above to allow the user to represent inputs as probability distribution. Chapter 7 describes the probabilistic model in detail. A new methodology for analyzing driving cycle data in a probabilistic environment is discussed.

7.0 PROBABILISTIC MODELING OF MOBILE EMISSIONS USING A MIXTURE DISTRIBUTION

This chapter discusses the development of a probabilistic version of the Mobile5a model and describes a number of general capabilities of this new model. A detailed analysis of the driving cycle emissions that underlie the speed correction factors for LDGV in Mobile5a is discussed. A new methodology is presented by which data from multiple trip-based driving cycles can be combined to represent any arbitrary frequency distribution of vehicle speed. This method can be applied to the standard driving cycles used in the vehicle testing programs by the EPA, to better simulate on-road driving patterns and represent observed variations in speed. The method is based upon quantification of variability in key inputs to the emission factor model and the application of a probabilistic model to estimate frequency distributions for emissions. The frequency distributions for emissions are compared to the emissions estimates that would be made in absence of the probabilistic approach. By making use of: (1) existing data from several standard driving cycles; (2) a probabilistic representation of variability in emissions over a fleet of vehicles; and (3) the capabilities of a new area wide vehicle detection technology, the emission estimates predicted by the emission models can be improved. In the next chapter, the development of probabilistic estimates for each driving cycle will be considered in more detail.

7.1 Probabilistic Version of Mobile5a

The original Mobile5a model requires point estimates for each model input and calculates a point value for HC, CO and NO_x emission factors. The original code was implemented primarily for the purpose of single runs in a batch mode, and was not readily suitable for repeated runs in an iterative mode, as would be required in sensitivity and uncertainty analyses. To address these and other short comings, an interactive probabilistic version of the Mobile5a model was developed and implemented as a callable subroutine. This work was done at the North Carolina State University primarily by Sing-Yih Fu under the supervision of Dr Ranji Ranjithan. This allows for repeated execution of the emission factor estimation model through function calls. Figure 5 illiterates the modifications made to the deterministic version of Mobile5a.

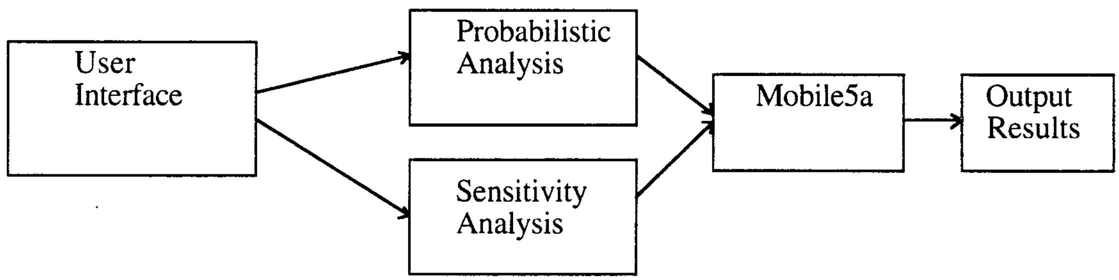


Figure 5. Probabilistic Version of Mobile5a.

The interactive probabilistic version of Mobile5a includes a sensitivity analysis capability. This procedure allows the users to select an input from a list, specify a range and interval for the input, and specify a set of output emission factors. This model is then executed repeatedly to evaluate the sensitivity of the emission factors with respect to the selected model inputs. Several procedures were also implemented to allow for uncertainty analysis. These include random Monte Carlo simulation and Latin Hypercube sampling (LHS) (Iman et *al.*, 1984). Both of these methods were reviewed in Section 6.4. These sampling procedures allow the users to specify a set of model inputs to be treated as stochastic variables, to select a probability distribution for each selected input, and to specify the parameters (e.g., mean, variance, upper or lower bound) for each distribution. Currently the following distributions are supported: normal, lognormal, uniform, loguniform, triangular, beta and a user-defined frequency distribution.

In order to identify the most significant input assumptions in a probabilistic analysis, a post processor framework is employed to compute partial correlation coefficients (PCC) and the standardized regression coefficients (SRC) (Iman et *al.*, 1985). Using PCC and SRC, the user can analyze and quantify the sensitivity between the stochastic input parameters and specified Mobile5a output variables. This software also has the capability to calculate these coefficients based on ranks, rather than sample values.

7.2 Probabilistic Analysis of Driving Cycle Emissions

The Mobile5a model accepts any average speed between 2.5 and 65 mph as an input. However, since there are 11 driving cycles for LDGVs, with 11 corresponding point estimates of emissions for average speed, the model will interpolate between driving cycles. Interpolation between driving cycles is actually a form of extrapolation. This is because driving cycles are not characterized only by average speed, but also by time-dependent speed and acceleration profiles. The differences among driving cycles can not be explained solely by average speed. Thus, it is a misuse of the data to "interpolate" between driving cycles. It is more appropriate to consider methods by which multiple driving cycles may be combined to develop more representative emission estimates.

The driving cycle emissions data sets were analyzed using both deterministic and probabilistic approaches. The probabilistic analysis is based on existing data from several driving cycles. A new approach based upon a mixture distribution for the driving cycle emissions is discussed. The mixture distribution for driving cycle emissions is based upon a mixture distribution for speed. This mixture distribution for speed depends upon the availability of empirical data regarding vehicle speeds. To demonstrate the application of this approach, two case studies based upon speed data from a segment of Interstate 40 (I-40) near Raleigh, NC, were carried out. In the next section, the methodology used for the analyses is described.

A first step is to characterize variation in emissions for each of the driving cycles. The analyses focus on hot stabilized exhaust emissions of LDGV of Technology Group 12 (TG12) for selected driving cycles. This group was selected because it is comprised mostly of recent model year vehicles. The Mobile5a deterministic estimate for a particular model year is based on a weighting of emissions across all technology groups. In this analysis the deterministic emission estimate of Mobile5a across all technology groups is compared to the mean of a probabilistic estimate obtained from the emissions distribution for TG12.

7.3 Data files for the Speed Correction Factors in Mobile5a

The data files used to develop the speed correction factors in Mobile5a were obtained from EPA and analyzed for this study. The data analyzed in this study included emissions of CO, HC and NO_X for eight of the eleven driving cycles with average speeds ranging from 2.45 mph (LSP1) to 48 mph (HFET). The driving cycle characteristics of all eight cycles are described in Table 7. The higher speed cycles data were not included in this analysis because these data were for a different population of vehicles. A unique feature of the data set analyzed in this study is that the same group of 673 vehicles were tested for five of these cycles, with 302 of these vehicles also tested on the three slowest average speed cycles. The driving cycle emissions for the set of 673 vehicles were classified into Technology Groups and analyzed. The exhaust emissions from LDGV of TG12 for each speed cycle were used for the probabilistic analysis.

7.3.1 Frequency Distribution for Speed

To characterize variability in speed for an actual highway, we obtained data collected by Nagui Rouphail and Steven Click of the Department of Civil Engineering at the North Carolina State University. As a part of a separate project, an advanced area-wide traffic detection device has been employed to measure micro and macro statistics for individual vehicles and overall traffic flow, respectively. The advanced traffic detector, called Mobilizer, is representative of a new generation of video based traffic detection systems. Traffic detectors such as Mobilizer offer an empirical basis for the development of input assumptions for emissions models. In fact, a key shortcoming of emission factor models is that their input requirements typically far exceed the information available regarding on-road vehicles. A key example is the estimation of average speed, which is a required input for Mobile5a. Conventional traffic detectors, such as loop detectors, measure vehicle counts and vehicle occupancy. Speed can not be directly measured with these commonly used systems. Furthermore, even if an average speed is known, it is quite likely that none of the driving cycles that underlie Mobile5a will correspond to the on-road conditions. However, by having the capability to measure a frequency distribution for speeds under real-world conditions, it is possible to optimize the use of emissions data from existing driving cycles.

Vehicles on westbound I-40 near Cary, NC were taped from the Reedy Creek road overpass on May 31, 1995 from 7:50 a.m. for about 80 minutes. Two lanes of Wade avenue merge with I-40 near the site where the video was recorded. The camera was placed a short distance beyond the point of the merging and vehicles in all four lanes were recorded. The speed data on individual vehicles were obtained from the video tape, by making use of Mobilizer.

Mobilizer has the ability to determine individual vehicle speed, vehicle density, vehicle headways, overall flow, and the percentage of trucks. The Mobilizer can display each of these statistics by lane and as an aggregated statistic depending upon the time interval specified by the user. The Mobilizer distinguishes the presence of a vehicle by a change in the background pixel color. Therefore if a vehicle is moving at very low speeds, the Mobilizer may not be able to monitor that vehicle. The Mobilizer also has difficulty tracking a vehicle if it changes lanes

7.3.2 Input Assumptions for Deterministic and Probabilistic Analysis of Emissions

The deterministic analysis was carried out for the entire LDGV fleet of the 1991 model year. The probabilistic analysis focused on LDGVs of TG12. For the probabilistic analysis, input assumptions to Mobile5a reflect only these vehicles for which we have performed a statistical analysis of the emissions data. Table 9 summarizes the input assumptions that were made in the input file for both the deterministic and probabilistic versions of Mobile5a.

7.4 Methodology For Probabilistic Analysis of Emissions

Frequency distributions of speeds were obtained from measurements of traffic on I-40. Distributions were available for each of four individual lanes, and also in aggregate for all lanes. The measured speeds ranged from three to 80 mph. Since the maximum speed contained in the eight driving cycles analyzed here is only 60 mph, the analysis of the speed data was only for those vehicles with speeds less than or equal to 60 mph. In order to compare with driving cycle data, the frequency distributions for speeds were weighted based upon the amount of time a vehicle would spend on any given length road, rather than based upon vehicle counts. Thus, the data for high speed vehicles received less weight than the data for low speed vehicles. The adjusted frequency distributions for measured speeds were then compared to the frequency distributions of speeds for each of the driving cycles.

A numerical simulation approach was used to determine which mixture of standard driving cycle speed distributions best fits the observed frequency distribution for speed. A probabilistic modeling environment called DEMOS was used to simulate the frequency distributions. Using the Monte Carlo analysis features of DEMOS, samples were selected from each of the standard driving cycle speed distributions based upon user-specified weighting factors. A mixture distribution of speed was thus created from multiple driving cycles. The weights were adjusted to minimize the sum of square errors in the comparison of the percentiles of the mixture versus measured distributions. The analysis focused on two cases, which yielded different mixture distributions. These cases were for Lane 2 only and All Lanes. Figure 6 shows a comparison of the CDFs for the mobilizer data and the resulting mixture distribution for speed. The mixture has a large share of vehicles at low speed or even at idle because all of the driving cycles contain significant portions of time spent in low speeds. This is because driving cycles are meant to represent vehicle trips from start to finish. The weighting factors obtained from this analysis were then employed in the probabilistic analyses of emissions.

Probabilistic analyses of the HC, CO and NO_x emissions for different driving cycles that were used to develop the SCFs for LDGVs of TG12 in Mobile5a, were carried out in another modeling environment called Analytica. Analytica is a probabilistic modeling environment developed by Lumina Decision Systems of Los Altos, CA. The emissions data for each driving cycle was sorted in ascending order. Using the Fractile distribution in Analytica, 1000 samples for emissions data across each of the driving cycles were generated. The Fractile distribution is used to represent an emperical dataset as a continuous CDF. The input to a fractile distribution is a set of $(n+1)$ numbers. Each element in the list must be greater than or equal to the previous element. The $(i+1)^{th}$ element specifies the $(1/i)^{th}$ fractile of the distribution. The probability density function bounded by each pair of adjacent fractiles is assumed to be uniform. Thus the probability of sampling betweeen any two adjacent fractiles is the same(Henrion et *al.*, 1996). As an example of how the Fractile distribution is employed, consider the following hypothetical dataset of emissions of three different vehicles across a driving cycle:

Vehicle Number	CO Emissions (g/mi.)
1	3.5
2	7.8
3	4.6

To obtain a fractile distribution for this dataset, the emissions are sorted in an ascending order. The matrix of the sorted data is the fractile distribution. In this example, fifty percent of the emissions would be uniformly distributed between 3.5 g/mi and 4.6 g/mi. The other fifty percent of the fractile distribution would be uniformly distributed between 4.6 g/mi. and 7.8 g/mi.

The use of an empirical Fractile distribution alleviates the need to fit a parametric distribution to the input data. Attempts were made at fitting the SCF emission dataset to lognormal and Beta distributions. First an attempt was made to fit a lognormal distribution with two parameters (viz the geometric mean and the standard deviation) to the frequency distribution of the SCF emissions data using the "fit-model" feature of the statistical package called JMP. This was followed by an attempt to fit a four parameter Beta Distribution to the frequency distributions of the SCF emissions data for each driving cycle. This analysis was also carried out in JMP. In most cases neither the lognormal nor the Beta distributional models enabled a good fit to the data set.

For carrying out case studies for the All Lanes and Lane 2 of I-40, a model was developed using the median LHS feature in Analytica. The weight factors obtained from the mixture distribution for speed were used to determine what sample from each cycle would be included in the predicted mixture distributions for emissions. For example, in the case study for All Lanes, weight assigned to the FTP Bag 2 driving cycle is 0.50. Thus 500 of the 1000 samples that were generated for this cycle were used in the mixture distribution. Similarly the weight assigned to the SCC36 cycle was 0.40 and the weight assigned to HFET cycle was 0.10. Thus 400 of the samples for the SCC36 cycle and 100 of the samples generated for the HFET cycle were assigned to the mixture distribution. In the case study for Lane 2 of I-40, samples were assigned to the mixture distribution from four driving cycles. The SCC12 driving cycle was assigned a weight of 0.20, the FTP Bag 2 and the SCC36 cycles were assigned weights of 0.35 each while the HFET cycle contributed the final ten percent of the samples in the mixture distribution.

In this case study, the emission rates for hot stabilized mode were used based upon vehicle test data for each cycle. This is not the way that Mobile5a was developed. Mobile5a estimates are based upon BERs which are then adjusted by a SCR. The BER is based upon a larger dataset obtained from IM240 tests. This dataset may include more high emitting vehicles than the SCR dataset. Therefore it should be expected that the point estimates from Mobile5a would be higher than the average results of this probabilistic case study.

7.5 Model Results

The deterministic version of the Mobile5a model was run for several cases to provide a basis for comparison with the results of the probabilistic model. The results obtained for the deterministic cases represent emission estimates for LDGV of all the thirteen technology groups. These cases include one each for: (1) the average speed of each of the eight driving cycles; (2) the average speed of the observed speed distributions for I-40; and (3) the speed of 58.1 mph, based on previous work of the state air quality agency. For urban interstate highways, a typical average speed of 58.1 mph has been used in developing emission inventories for ozone air quality modeling. The results for HC, CO, and NO_X emissions predicted from the deterministic runs of Mobile5a are shown in Table 10.

The probabilistic version of Mobile5a was run using different frequency distributions for HC, CO and NO_X emissions for eight driving cycles. Figure 7 to Figure 9 illustrate the variation in HC, CO and NO_X emissions respectively, for each cycle, for TG12. The point estimates obtained from the deterministic runs are also shown in the figures. The means of the probabilistic HC and CO emission estimates vary significantly from the point estimates in most cases. The means of the probabilistic NO_X emission estimates show relatively smaller variation in comparison to the point estimates.

In most cases, the mean value of the HC emission factors obtained from the 111 vehicle data points were lower than the Mobile5a point estimates for the eight driving cycles studied in this analysis. Of course, the deterministic analysis is based upon a weighted average of all technology groups while the dataset employed in this analysis is specific to TG12. Thus, a possible source of difference is due to the potentially higher HC emissions for the other technology groups that are included in the deterministic analysis. However, TG12, comprises the majority of new registered vehicles for the 1991 calendar year used in the analysis. Another source of difference can be accounted to the fact that the point estimates of Mobile5a are based upon BER which are not accounted for in this analysis. The variability in HC emissions typically spans more than an order of magnitude from the lowest to the highest emitter. The confidence interval varies from plus or minus 25 to 50 percent in most cases. Thus, there is considerable uncertainty in predicting the mean.

The differences in the deterministic and probabilistic estimate of CO emissions are more pronounced in most cases compared to the HC emissions. For example, although the SCF is highly sensitive to speed at low speeds, the data indicate no significant difference in emissions for the four lowest speed cycles. In most cases, the uncertainty in the mean values range from plus or minus 30 to 50 percent.

The confidence intervals of the mean values of the NO_x emissions data for the eight driving cycles, with few exceptions, enclose a value of 0.5 grams per mile. This implies that there may be relatively little variation in NO_x emissions as a function of the different driving cycles. The uncertainty in the mean is lower for NO_x emissions than either HC or CO, with a range of typically plus or minus 10 to 20 percent. The variability in emissions covers an order-of-magnitude or more in most cases.

An alternative probabilistic approach to emissions estimation is demonstrated to illustrate how the driving cycle data may be better utilized. The probabilistic version of Mobile5a was run using mixture distributions for driving cycle emissions that were developed based upon mixture distributions for speed, for both Lane 2 and All Lanes of I-40. These two cases were done to illustrate the variability in exhaust emissions based on alternative mixture distributions. A comparison of the deterministic and probabilistic modeling results for exhaust emissions based upon speed data for Lane 2 of I-40 is given in Figure 10. Figure 11 contains results based upon speed data for all four lanes of I-40. As described above, the point estimate is expected to be higher then the average results of this probabilistic case study. But in contrast to this expectation, the default point estimates for HC and CO for the Lane 2 case are lower than the mean estimate from the probabilistic analysis. This indicates that the BERs and/or the SCF used to calculate these point estimates are in error. Furthermore, uncertainty in the mean value of the emissions, due to the limited sample of vehicles used to develop the emissions data set, is significant, ranging from plus or minus 10 to 40 percent over the cases considered here. The confidence interval calculated here does not address uncertainty due to the potential lack of representativeness of the measured vehicle fleet or to systematic errors between driving cycle measurements and actual on-road emissions. Thus the confidence intervals represent a lower bound on the uncertainty of the emission factors

Two alternate point estimates were considered. One is a case using the I-40 measured average speed as the input to Mobile5a. In the cases of HC and CO, this led to an increase in the predicted emissions rate. In the case of NO_X, the point estimate for the average speed of the I-40 data sets yielded substantially lower estimates of emissions compared to the default value. In all cases, the measured average speed did not correspond to any driving cycle within Mobile5a; therefore, the model extrapolated using the speed correction factors. Another point estimate was developed by combining the point estimates for each driving cycle with the weighting factors developed from the mixture distribution analysis of speeds on I-40. This represents an approach in which no effort is made to interpolate or extrapolate from the driving cycles. However, due to the biases in the speed correction factors, this approach was not able to yield an accurate point estimate of emissions when compared to the means of the probabilistic analyses.

The probabilistic analysis of emissions based upon the measured speed distributions yielded broad estimates of variation in emissions even for a single technology group of vehicles. For all three pollutants and both probabilistic case studies, the emissions vary by one to three orders-of-magnitude.

7.6 Discussion

Since the mixture distributions are based upon emissions from individual driving cycle, the magnitude of variation observed in the mixture distribution is more than that of any single individual driving cycle. The ranges of uncertainties in the fleet average emissions, obtained using the mixture distributions for HC, CO and NO_x are shown in Table 11.

The current approach for predicting emission factors interpolates between average speed of driving cycles. The methodology described here does not require any interpolation. Besides, the methodological approach developed here can be extended to any driving cycle data set, although the analyses here are based upon driving cycles with known limitations. Furthermore the approach described here allows existing data which has been collected at considerable expense to be used in conjunction with the newer driving cycle data. Therefore, this approach is much improved in comparison to the conventional approach that is being employed to predict the emission factors.

While this analysis has focused on frequency distributions for speed, the approach can be extended to account for acceleration events by including acceleration as a criteria in developing weighting factors for the driving cycles. However acceleration data are not typically available from either conventional or advanced traffic detection devices.

There are, of course, a number of shortcomings inherent in the use of driving cycle data. Studies by CARB suggest that on-road conditions lead to higher emissions than those obtained in dynamometer testing. Thus, driving cycle emissions data may not be representative of the emissions from the on-road fleet. Chapter 8 describes an alternative approach for analyzing the uncertainty and variability in the predicted emission factors from individual driving cycles. In Chapter 8 the emission factors have been analyzed as a function of BERs and SCFs using alternative models.

Table 9. Key Input Assumptions to the Mobile5a Model.

Description	Value
Technology Group	12 (PFI 1987 and 3W catalyst)[a]
VMT Mix	LDGV = 0.993, all other classes =0.001[b]
Temperature	60-84 F
Calendar Year and Model Year	1991[a]
I/M Programs	None

[a] For Probabilistic Analysis Only

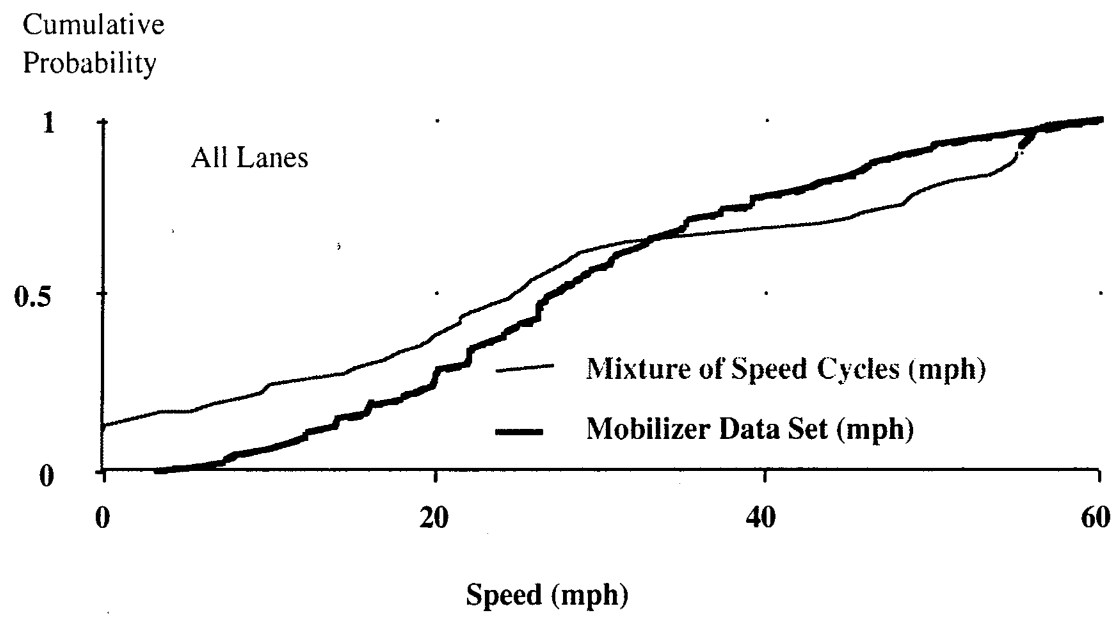
[b] Mobile5a requires that all vehicle classes be assigned a minimum fraction of 0.001

Table 10. Exhaust Emissions for Deterministic Analysis of Mobile5a.

Speed (mph)	HC (g/mi.)	CO (g/mi.)	NO_x (g/mi.)	Comment
2.45	1.41	22.00	0.90	Average Speed of LSP1 Cycle
3.63	1.03	16.10	0.79	Average Speed of LSP2 Cycle
4.02	0.94	14.73	0.77	Average Speed of LSP3 Cycle
7.10	0.58	9.24	0.68	Average Speed of NYCC Cycle
12.10	0.39	6.29	0.63	Average Speed of SCC12 Cycle
16.10	0.32	5.26	0.61	Average Speed of FTP Bag 2
19.60	0.28	4.71	0.60	Average Speed of FTP Cycle
26.00	0.22	3.49	0.62	Average Speed for Lane 2 of I-40
28.80	0.20	3.12	0.62	Average Speed for All Lanes of I-40
35.90	0.17	2.45	0.63	Average Speed of SCC36 Cycle
48.40	0.14	1.78	0.65	Average Speed of HFET Cycle
58.10	0.15	2.44	0.87	Default Speed for Urban Interstate

Table 11 Uncertainties in the Mean of the Fleet Emissions Obtained from Mixture Distribution of Emissions for I-40.

Pollutant	Random Error on Mean based on a 95% Confidence Interval
HC	30 to 40 percent
CO	25 to 40 percent
NO_x	10 to 15 percent



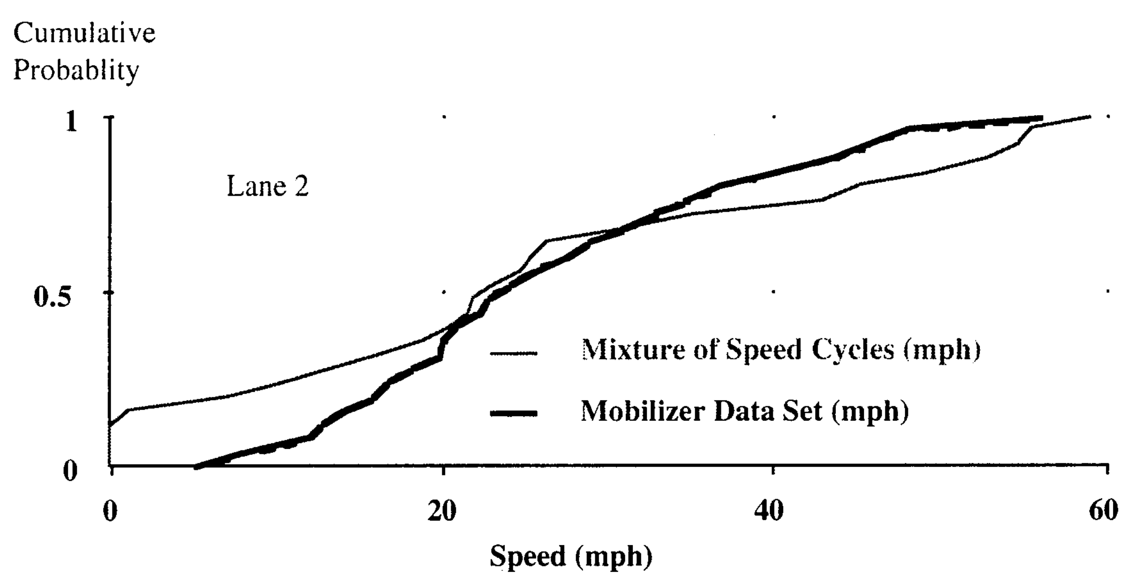
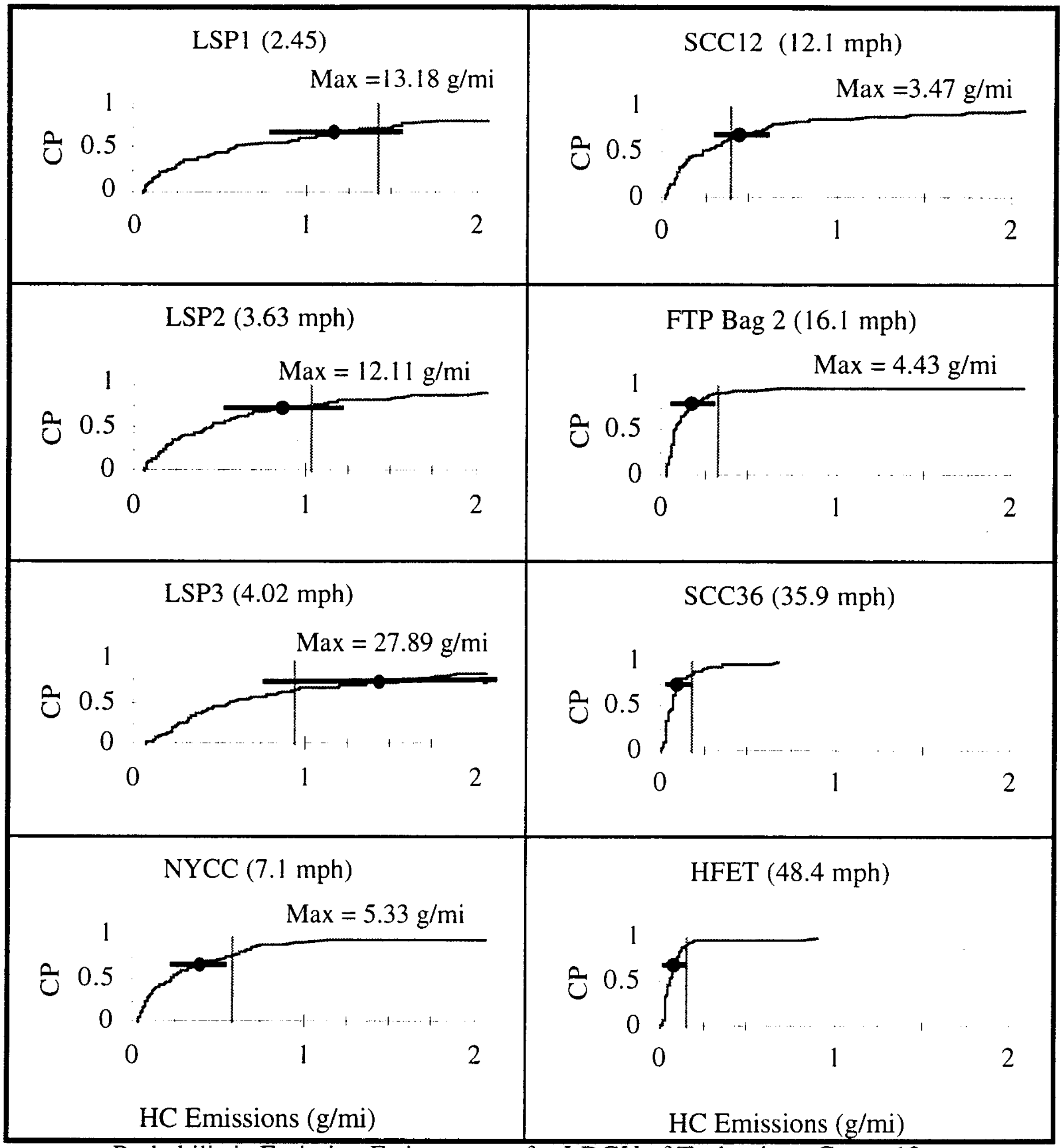


Figure 6. Comparison of Mobilizer Data Set and the Mixture Distribution for Speed Using Different Driving Cycles

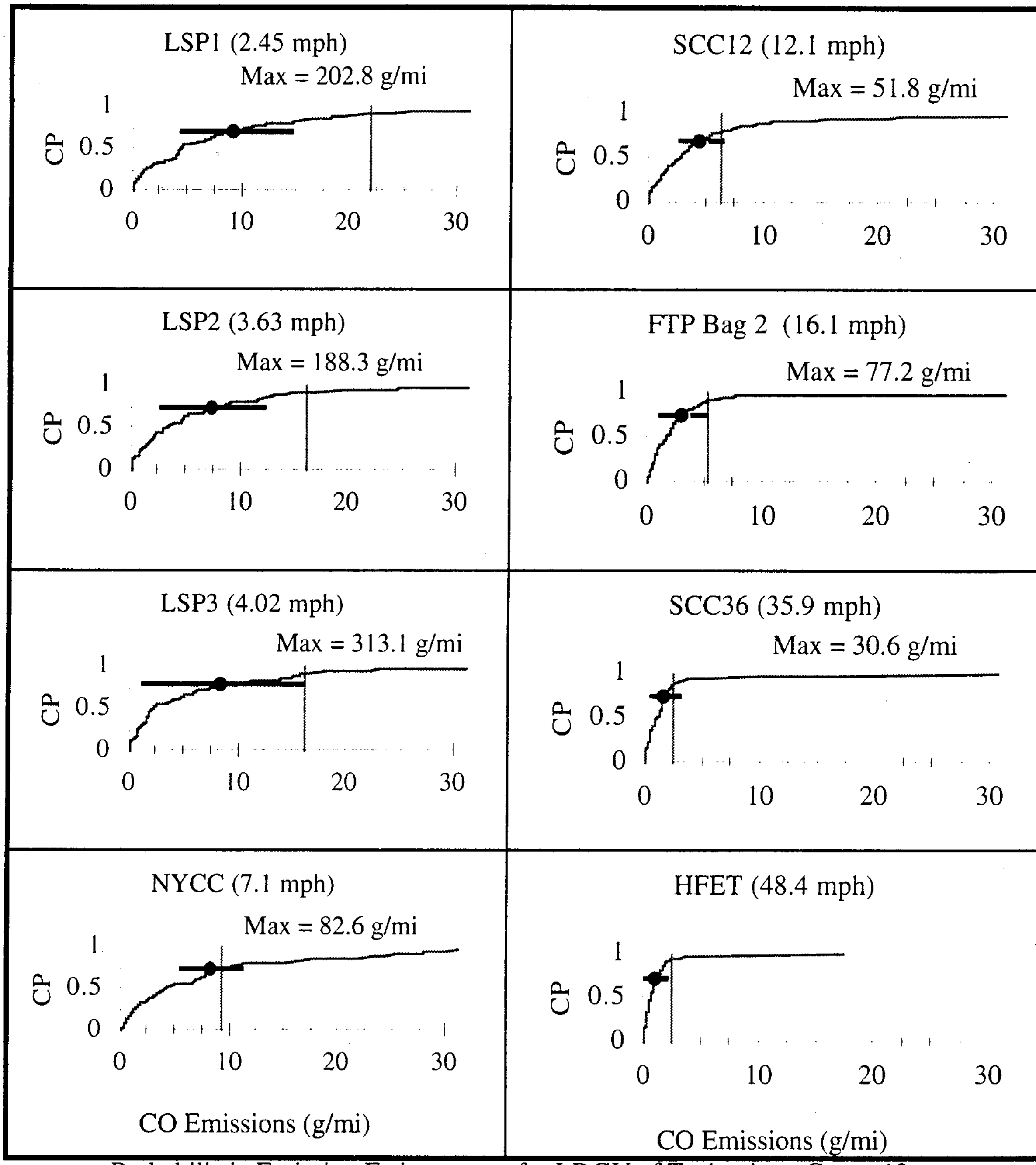


Probabilistic Emission Estimates are for LDGV of Technology Group 12.
Deterministic Emission Estimates are for LDGV of All 13 Technology Groups

Key: CP = Cumulative Probability 111 Vehicles Tested

Inter-Vehicle Variability | Mean of Emissions with 95% Confidence Interval | Mobile5a Result for Average Speed of Cycle

Figure 7. Comparison of Observed Variations in Exhaust HC Emissions for Technology Group 12 for Different Driving Cycles to Mobile5a Predicted Value for All Light Duty Gasoline Vehicles



Probabilistic Emission Estimates are for LDGV of Technology Group 12.
Deterministic Emission Estimates are for LDGV of All 13 Technology Groups

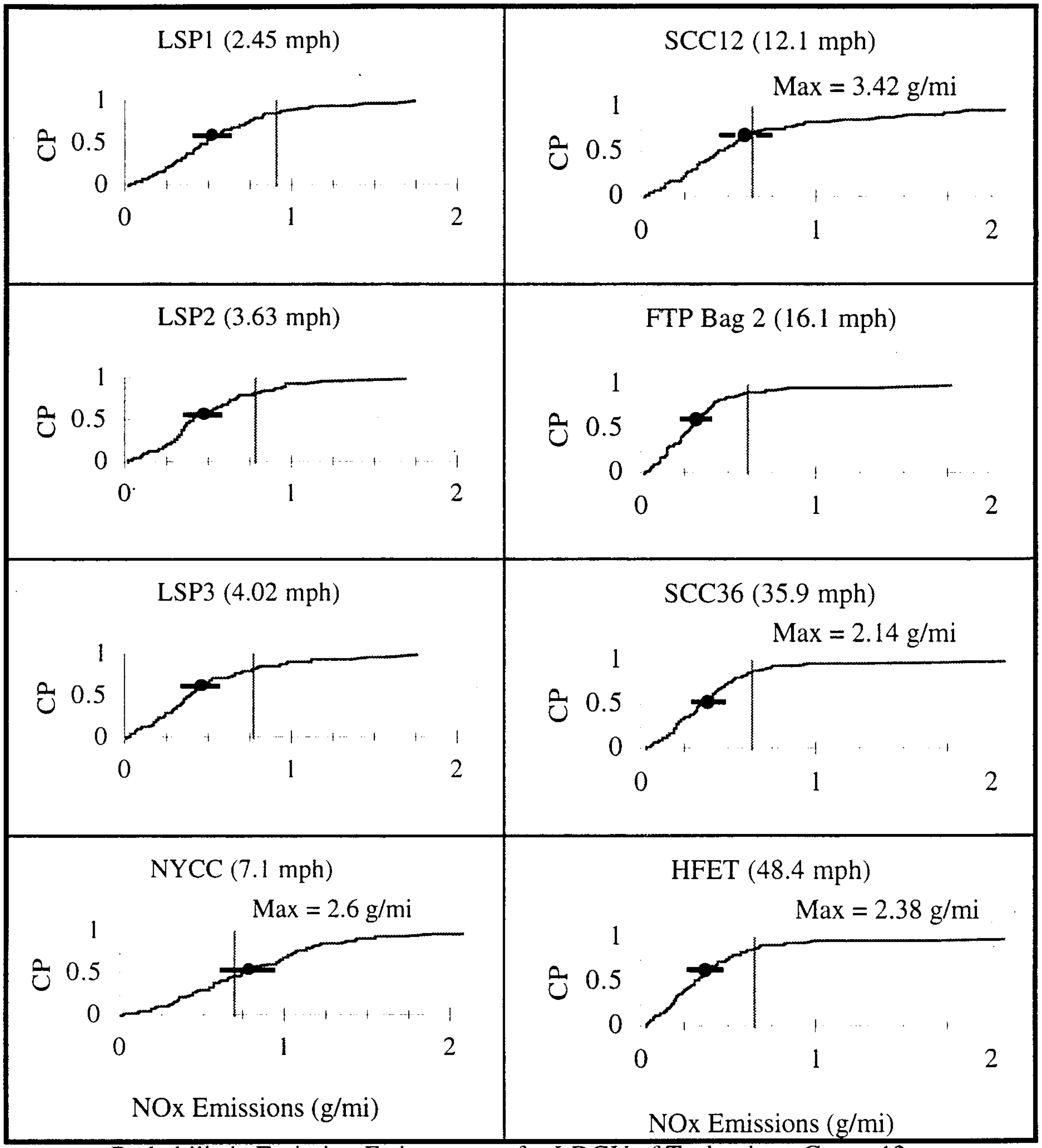
Key: CP = Cumulative Probability 111 Vehicles Tested

Inter-Vehicle Variability

Mean of Emissions with 95% Confidence Interval

Mobile5a Result for Average Speed of Cycle

Figure 8. Comparison of Observed Variations in Exhaust CO Emissions for Technology Group 12 for Different Driving Cycles to Mobile5a Predicted Value for All Light Duty Gasoline Vehicles

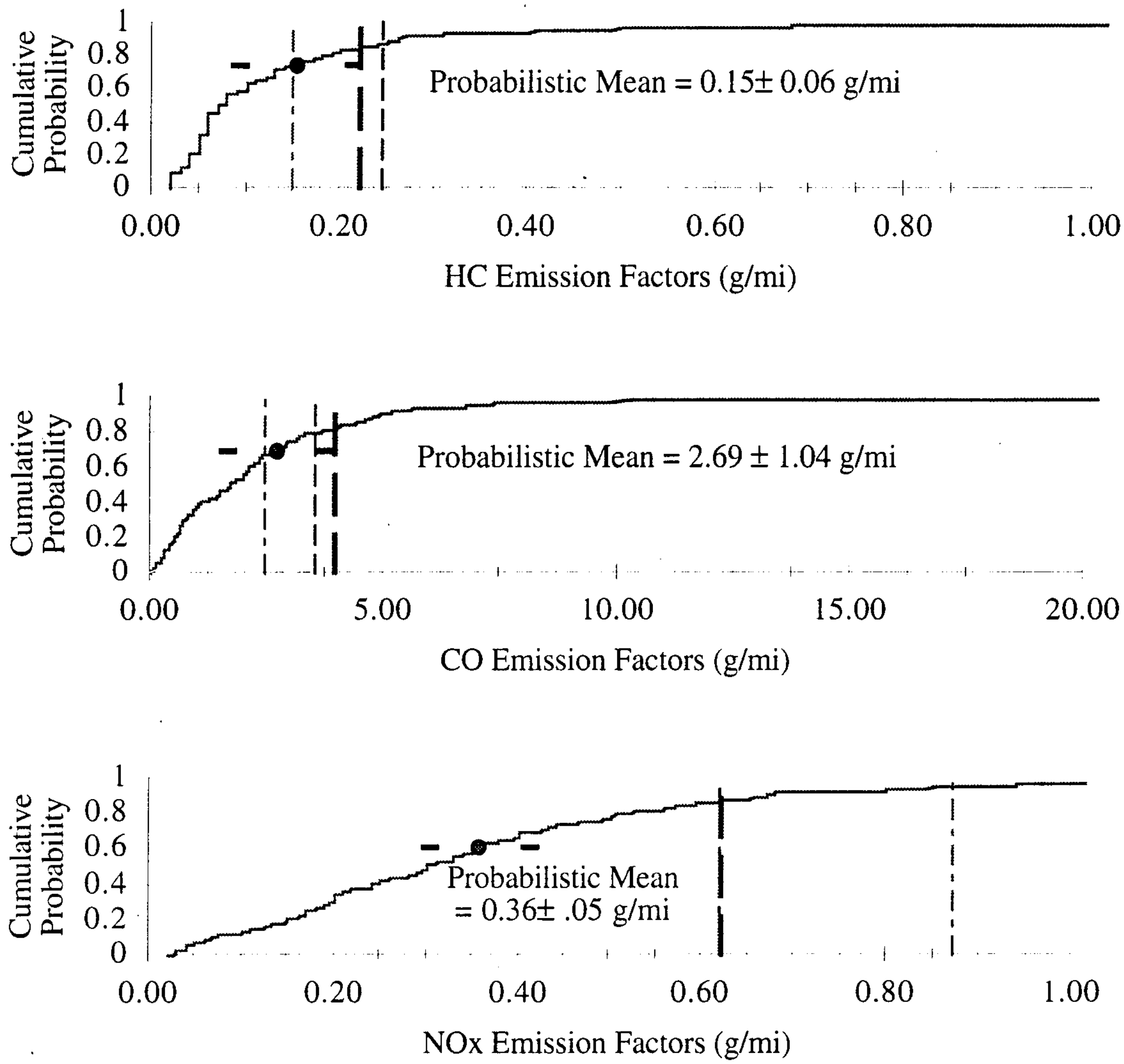


Probabilistic Emission Estimates are for LDGV of Technology Group 12.
Deterministic Emission Estimates are for LDGV of All 13 Technology Groups

Key: CP = Cumulative Probability   111 Vehicles Tested

Inter-Vehicle Variability   Mean of Emissions with 95% Confidence Interval   Mobile5a Result for Average Speed of Cycle

Figure 9 Comparison of Observed Variations in Exhaust NO_X Emissions for Technology Group 12 for Different Driving Cycles to Mobile5a Predicted Value for All Light Duty Gasoline Vehicles.

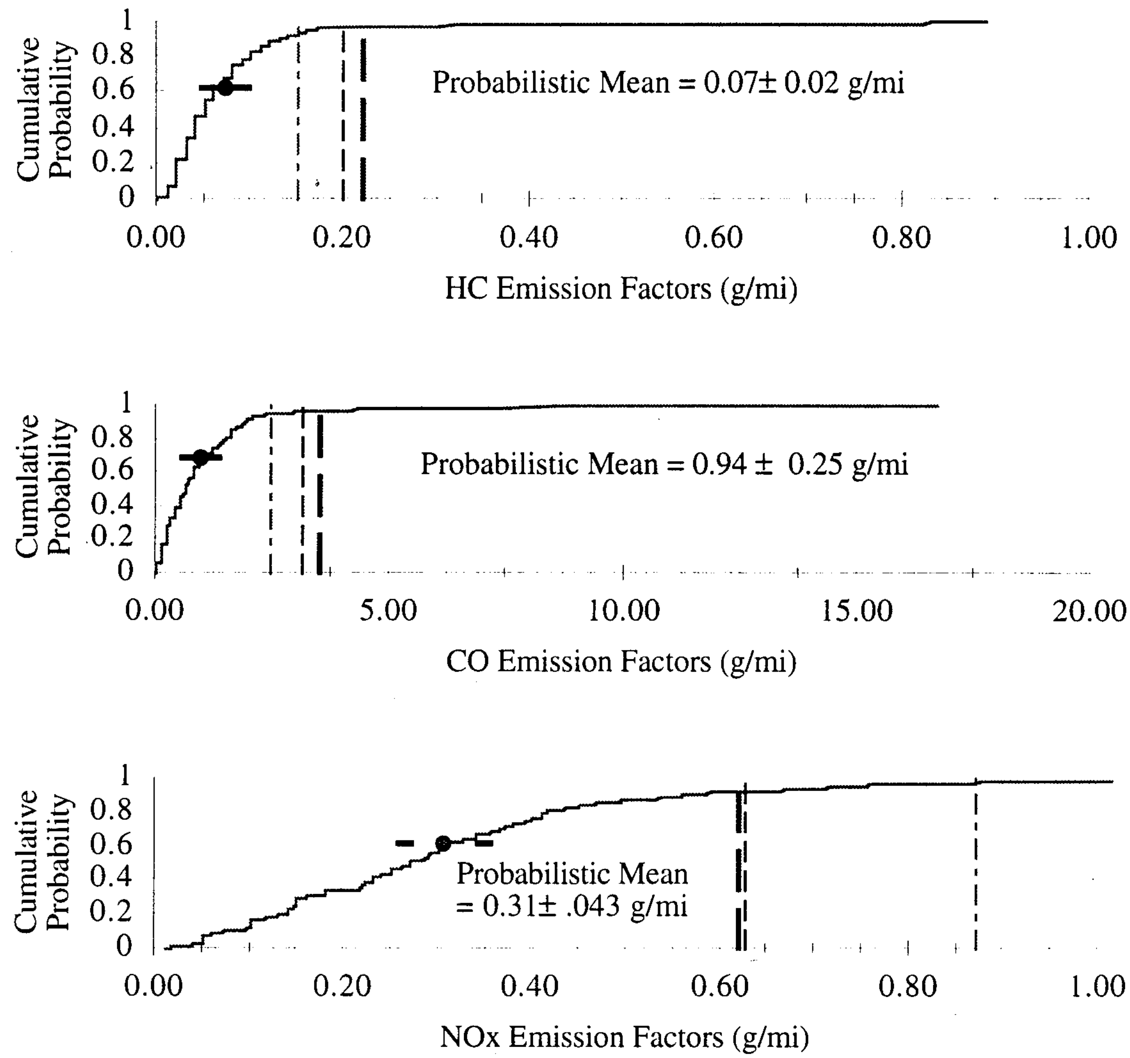


Probabilistic Emission Estimates are for LDGV of Technology Group 12.
Deterministic Emission Estimates are for LDGV of All 13 Technology Groups.
Model Results are based upon data collected for I-40 on May 31, 1995.
Average Speed of Lane2 was 26 mph
Mixture Distribution for Speed for Lane 2 of I-40:
20 % SCC12, 35 % FTP Bag 2, 35 % SCC36 and 10% HFET

Key:

———	Probabilistic Estimate for Variability in Emissions	- - - - - -	Deterministic Estimate for Average Speed
— - -	Deterministic Estimate for 58.1 mph	▬ ▬	Weighted Average of Point Estimate for Cycle Emissions

Figure 10. Estimated Variability in Exhaust Emissions Based upon a Mixture Distribution for Variation in Speed for Lane 2 of I-40



Probabilistic emission estimates are for LDGV of Technology Group 12.
Deterministic emission estimates are for LDGV of All 13 Technology Groups.
Model results are based upon data collected for I-40 on May 31, 1995.
Average speed of All Lanes was 28.8 mph
Mixture Distribution for Speed for All Lanes of I-40:
50 % FTP Bag 2; 40 % SCC36 and 10% HFET

Key:

——	Probabilistic Estimate for Variability in Emissions	------	Deterministic Estimate for Average Speed
— -	Deterministic Estimate for 58.1 mph	— —	Weighted Average of Point Estimate for Cycle Emissions

Figure 11. Estimated Variability in Exhaust Emissions Based upon a Mixture Distribution for Variation in Speed for All Lanes of I-40.

8.0 ANALYSIS OF UNCERTAINTY AND VARIABILITY IN EMISSION FACTORS

This chapter focuses more specifically on the development of probabilistic representations of emission factors for individual driving cycles than does the previous chapter. The purpose is to take a bottoms-up approach to the development of an alternative probabilistic version of Mobile5a. The method involves a detailed analysis of the data used to develop the BERs and the SCFs. This method can be extended to other components of the model. The results of the analysis provide insight regarding uncertainty and variability in predicted emission factors. Differences in the approach can have implications for the characterization of bias due to the way the data were analyzed in developing the deterministic model.

This chapter analyzes the effects of the transforming the IM240 data to FTP data on the BERs in the Mobile5a model. As a starting point for investigating the variability and uncertainty in the emission factors predicted by the Mobile5a model, two models to predict the emission factors as a function of the BERs and SCFs were developed in a probabilistic environment called Analytica. The analysis in this paper is focused on vehicles classified as TG12 and Technology Group 8 (TG8) in the Mobile5a model. These two groups were chosen for the analysis because they comprise about 95 percent of the most recent model year vehicles of the on-road fleet. The variability and uncertainty in the predicted emission factors is illustrated by analyzing the results obtained from the new probabilistic models. The probabilistic case studies and comparable point estimates were developed for each of the 11 driving cycles underlying Mobile5a at a mileage accumulation level of 50,000 miles. To begin with, alternative models for BERs of LDGV from TG12 and TG8 were developed using the transformed IM240 to FTP dataset. These BERs were then corrected for non-standard average driving cycle speeds by using a speed correction ratio (SCR). A point estimate of emissions for each driving cycle was calculated for comparison with the means of the probabilistic case study. The point estimates were calculated as a product of the BERs developed in this analysis and technology-specific SCFs. The technology specific SCFs used in the point estimate analysis were obtained by using regression coefficients developed by EPA in their analysis of the SCF data.

8.1 Similar Studies

Studies at the University of Tennessee have investigated the uncertainty in the speed correction factors in Mobile5a using the bootstrap approach (Guensler, 1993; NCHRP, 1995). A bootstrap approach is a Monte Carlo style simulation technique (Berg, 1992; Efron and Tibshirani, 1993; NCHRP, 1995) that can be employed to estimate the upper and lower bounds of an analytical confidence interval and to develop a probability distribution function for an analysis. In the study at the University of Tennessee, a basic program was written to develop 1000 resampled data sets, calculate the average emission rate and the baseline exhaust emission rate (Bag 2) results of the resampled data for each test cycle, estimate the regression intercept and slope coefficients for the regression function. The regression function used in this analysis was:

$$\mathbf{ER_s/ER_{Bag2} = B0 + B1(1/Speed) + e} \qquad (6)$$

The output predicted SCFs for average speeds in 2 mph increments. For each speed in 2 mph increments, the SCF results from the 1,000 runs are rank ordered to establish the probability distribution function, where the probability of each predicted value is established as 1/1,000. The rank order values at 2.5 percent and 97.5 percent represent the 95 percent confidence interval around the mean response for any average speed (NCHRP, 1995).

These studies had their own limitations. They assumed that the SCF model in Mobile5a was correct. That might not be the case. Also, these studies interpolated between average speeds of different driving cycles which again is not appropriate. The analysis described in this chapter does not have these limitations.

8.2 Data for BERs and SCFs in Mobile5a

The data files used to develop the BERs and SCFs in Mobile5a were obtained from the EPA's National Motor Vehicle Fuels and Emissions Laboratory, Office of Mobile Sources at Ann Arbor, Michigan.

The datafiles for the BERs contained HC, CO and NO_x emissions data from 646 vehicles tested on the IM240 and FTP driving cycles. These data were used by the EPA to develop the regression equations to transform IM240 data to corresponding FTP data. The datafiles also contained information on the predicted values and residuals obtained from the regression analysis. In addition to this, the Mobile5a BER dataset also contained emissions data and mileage information for cars tested on the IM240 cycle in the Hammond Program. These emissions data were transformed to predicted emissions data for the FTP driving cycle data. The predicted FTP values were then used to develop the ZML and deterioration rates in the Mobile5a model (SAI, 1994; Sierra, 1994). The data used for the development of the BERs are not the same as those used for the development of the SCFs. The data for the SCF have been described in Chapter 7.

8.3 Methodology

The BER equation used by Mobile5a has been described in Chapter 4. In the BER equation, EPA does not account for the error introduced by transforming the IM240 data to predicted FTP data. In addition, the EPA model does not account for the residual error that arises from the regression of the predicted FTP values versus the mileage accumulation. This later regression provide the ZML, DR1 and DR2 for the BER. The error for the IM240 to FTP regression model estimate is multiplicative in case of HC and CO, since the IM240 to FTP regressions for HC and CO were done by EPA using a log-log transformation. In case of NO_x this error is additive since no log transformations were done. For the development of the BER model, linear regressions were done as a function of mileage accumulation. Therefore, the error term in this case is additive.

To account for these sources of error and to analyze the uncertainty and variability in the emission factors, alternative probabilistic models to predict the exhaust emissions for light duty gasoline vehicles were developed and implemented in Analytica. Two alternative functional forms were considered in developing the equztions for the BER. A Linear model based on EPA's current approach was used. In addition a log-linear BER model was developed to more appropriately represent the variation in base emissions. The additional error components described above were included in both of the new models. These model consisted of a BER module which was then corrected by a SCF module to calculate the emission factors for each driving cycle.

The BER module consists of a zero mile level and a deterioration rate. These were obtained from regression analysis of the IM240-to-FTP transformed data versus the mileage accumulation. The residual errors from this mileage accumulation model and the

IM240-to-FTP transformation model used by EPA, were also included in the BER module as Error 1 and Error 2 respectively. The functional forms of the emission factor model based upon a linear BER for HC and CO is given below:

$$\mathbf{EF = [\ \{ZML + DR1 \bullet MA + Err\ 1\} \bullet Err\ 2] \bullet SCF} \qquad (7)$$

where:

EF = Emission Factor in grams/mile

ZML = Zero Mile Level (grams/mile)

DR = Deterioration Rate for mileage less than 50,000 miles

MA = Mileage Accumulation

Err1 = Additive Error term in the regression model consisting of the residuals from the mileage accumulation model

Err2 = Multiplicative Error term consisting of the ratio of predicted to residuals from the Log linear model used to transform the IM240 dataset to corresponding FTP dataset

SCF = Speed Correction Factor

For predicting NOx emission factors, the functional form of the emission factor models based upon a linear BER expression was:

$$\mathbf{EF = [\ \{ZML + DR1 \bullet MA + Err\ 1\} + Err\ 2] \bullet SCF} \qquad (8)$$

As described above, the Error 2 term in the models for NO_x emissions is additive because the transformations of the IM240-to-FTP NO_x data were done by EPA in a linear space and not in a log space.

Figure 12 and Figure 14 show that the estimated FTP emissions vary by an order-of-magnitude or more, and also that the residual error from the linear regression is not normally distributed. Thus, the basic assumption inherent in linear least squares regression is not satisfied. Therefore a second set of alternative models were developed to analyze the BERs and the emission factors in log space. The residuals for the logarithm of emissions are more nearly normally distributed; therefore, a log-linear approach is more appropriate in these cases. The following log model was assumed for the BERs:

$$\textbf{Log BERs} = (\textbf{ZML} + \textbf{DR1} \bullet \textbf{MA} + \textbf{Err1}) \qquad (9)$$

which was equivalent to

$$\textbf{BER} = \textbf{Exp}(\textbf{ZML} + \textbf{DR1} \bullet \textbf{50,000} + \textbf{Err1}) \qquad (10)$$

Using this BER model, log-linear models for calculating emission factors for different driving cycles were developed. The functional form of the log-linear BER based emission factor models is shown by:

$$\textbf{EF} = [\ \textbf{Exp}\{\textbf{ZML} + \textbf{DR1} \bullet \textbf{MA} + \textbf{Err 1}\} \bullet \textbf{Err 2}] \bullet \textbf{SCF} \qquad (11)$$

Similarly, for predicting NO_x emission factors, the functional form of the log-linear models is:

$$\textbf{EF} = [\ \textbf{Exp}\{\textbf{ZML} + \textbf{DR1} \bullet \textbf{MA} + \textbf{Err 1}\} + \textbf{Err 2}] \bullet \textbf{SCF} \qquad (12)$$

8.4 Case Study Assumptions

For the purpose of a demonstration case study, the emission factors were analyzed assuming a mileage accumulation of 50,000 miles. The data used to develop the BERs in Mobile5a were sorted to obtain vehicles with a mileage accumulation equal to or less than 50,000 miles. In EPA's analysis, the emissions data from vehicles with zero mileage were ignored (SAI, 1994). For this analysis also, the vehicles with zero mileage accumulation were deleted from the dataset.

8.5 Variability Analysis

From the datafile received from EPA, 1506 vehicles were identified as vehicles of TG12. The datafile contained 796 vehicles that were identified as vehicles of TG8. A regression analysis was carried out on the emissions data set to obtain a value for ZML and DR1 for each pollutant for this analysis. The distribution of the residuals from the regression analysis was used to develop a probabilistic representation of the ERR1 term. Figure 12- Figure 15 show the estimated and predicted HC, CO and NO_x FTP emissions for the LDGV of TG12 and TG8 for the linear and log linear models respectively. The estimated FTP emissions are the transformed IM240 data collected at Hammond while the predicted emissions were calculated using the ZMLs and DR1s shown in Table 12. The residuals were obtained as the difference between the observed and the predicted emissions. These residuals were input as a Fractile distribution in the probabilistic models. The residuals from the dataset used to obtain the IM240 to FTP transformations were used as the multiplicative ERR2 term in the analysis. Figure 16 shows the ERR2 data used in this analysis. These were also input as Fractile distribution in the probabilistic models.

The SCRs for each of the driving cycles for LDGV of TG12, for each of the three pollutants (viz., HC, CO and NOx) were calculated as ratios of the driving cycle emissions of each car tested across the driving cycles, to their own FTP Bag 2 emissions. The SCRs for each driving cycle were also input as Fractile distributions in the probabilistic models. As mentioned in Chapter 7, the use of a fractile distribution does not require making assumptions regarding selection of an arbitrary parametric probability distribution to represent the data. Figure 17 to Figure 22 show the SCFs for HC, CO and NO_x emissions for TG12 and TG8 respectively.

The point estimates for the low and mid speed cycle SCFs were developed using the model for the SCF (Equation 4) described in Chapter 4. The technology specific regression coefficients "A" and "B" were obtained from EPA. Thus, the point estimates shown in Figure 17 to Figure 22 represent technology-specific speed correction factors. The point estimates for the high speed cycles could not be developed because of lack of information on the regression equation and coefficients used by EPA in the Mobile5a model.

8.6 Uncertainty

Uncertainty in the mean emissions represents the uncertainty in the fleet average emissions. The uncertainty in the mean emissions can typically be attributed to a large inter-vehicle variability, a small sample size or both. Uncertainty analysis of the mean emissions provides insights regarding the random and systematic errors in the emission estimates.

For analyzing the uncertainty in the mean emissions, the mean SCFs for each driving cycle were assumed to be normally distributed with means and standard deviations (standard error of the means) shown in Table 12. This assumption was based on a result derived from the Central Limit Theorem. The result is that for a large sample size, the distribution of means for any distribution tends towards a normal distribution (Hahn and Shapiro, 1994). The assumption for normal distribution of the mean SCFs was further justified with bootstrap simulations on the SCF data. These simulations were done in

Analytica. Using the random Monte Carlo feature in Analytica, distributions of mean emissons for each driving cycle were generated by changing the random seed.

Figure 23-Figure 28 compare the residual distributions for the mileage accumulation term (Err1) from the linear and log linear models. In the uncertainty analysis, the mean Err1 and Err2 terms were assumed to be normally distributed. The inputs described in Table 12 were used in the linear and log-linear models described above to calculate distributions for the mean HC, CO and NO_x emissions. These distributions for the mean emissions represent the uncertainty in mean emissions. The results of the demonstrative case studies for variability and uncertainty are discussed in the next section.

8.7 Results

The probabilistic models for variability and uncertainty analysis were run using the Monte Carlo simulation feature in Analytica to obtain 1000 samples of emission factors across each driving cycle. These samples are a measure of the variability in emission factors and uncertainty in the mean emission factors, across each driving cycle in Mobile5a. To analyze the effect of the multiplicative error term (Err2) on the HC BER and CO BER, the linear and Log linear models were run with and without the Err2 term.

The results from the uncertainty analysis were used to provide insights regarding the systematic and random error inherent in the point estimates predicted by Mobile5a when compared to probabilistic results. The random errors can be calculated based on a 90 percent confidence interval for the mean. The following equation can be used to calculate the 90 percent confidence interval for the mean

$$CI_{90} = \pm \frac{1.645 \bullet S}{n^{0.5}} \qquad (13)$$

where:

CI_{90}	= Confidence Interval on the Mean on a 90 percent probability range
S	= Standard Deviation of dataset under consideration
n	= number of samples in the dataset under consideration

The random errors can be quantified on a relative basis as the fractional difference between the mean and the 5th percentile value of the mean obtained from the probabilistic analysis divided by the mean value. For example, the value of the 5th percentile of the distribution of mean HC emission factors for LDGV of TG12 for the LSP1 cycle is 7.4 g/mi while the value of the mean is 9.5 g/mi. Therefore the random error would be calculated as (9.5-7.4)/9.5 = 0.23. The distribution for the mean emission factors is symmetric and, therefore, random error can also be calculated by using the 95th percentile value instead of the 5th percentile value. Also, using the 95th percentile value and the mean of the normal distribution, other parameters such as the standard deviation and coefficient of variation for the normal distribution can be obtained using standard tables for areas under a normal curve. For example, at the 95th percentile, a standard normal distribution [N(0,1)] has a value of 1.645. Therefore, the standard deviation can be calculated as:

$$S = \frac{f_{0.95} - \overline{X}}{1.645} \tag{14}$$

The coefficient of variation can be calculated as the standard deviation divided by the mean value and is given as:

$$h = \frac{S}{\overline{X}} \tag{15}$$

The systematic error can be calculated as the difference between the mean of the probabilistic distribution for the mean emissions and the point estimate for the HC, CO and NO_x emissions for each driving cycle. The point estimates for the emission factors were obtained by multiplying the BERs with point estimates of technology specific speed correction factors. The BERs used for the deterministic point estimate were calculated using the ZML and DR1 obtained from regression analysis of the BER data. As explained above, in this analysis, the point estimates for SCFs for the high speed cycles were not calculated. Therefore, in this study, no point estimate for the emissions factors for the high speed cycles could be calculated.

To analyze the effect of accounting for the IM240-to-FTP residual error on the HC, CO and NO_x BER, the linear and log-linear models were run with and without the Err2 term. Figure 29-Figure 32 show the results of this analysis. For both TG12 and TG8 vehicles, the BER for all three pollutants predicted by the linear and log-linear models with the IM240 to FTP residual error show greater variability as compared to the cases without the IM240 to FTP residual error. The mean CO and HC BERs increase by about 25 percent as a result of accounting for the multiplicative IM240 to FTP residual error term (Err2) in the log-linear BER model. This is because the distribution for the residuals is lognormal with a median of one. The mean is larger than the median because the residuals are positively skewed. This implies that failure to include this source of error leads to underprediction of the BERs. In case of NO_x, the additive Err2 term does not affect the mean BER significantly because magnitude of the residual error term is very small.

8.7.1 Variability Analysis Results

The results of the variability analyses are shown in Figure 33-Figure 44. For vehicles of both TG12 and TG8, the HC, CO and NO_x emissions across the low speed cycles (LSP1 to NYCC) show greater variation as compared to those across the medium

(SCC12 to HFET) and high speed cycles (HSP1 to HSP3). The HC and CO emissions vary by about two to three orders-of-magnitude while the NO_x emissions vary by about one to two orders-of-magnitude.

The variability in HC, CO and NO_x emissions predicted by the linear model are not significantly different from those predicted by the log-linear model. The magnitude of variability in the BERs based on a 95 percent probability range, predicted by both the linear and log-linear models is similar. Also, other components of the linear and log linear models such as the Err2 term and the SCF used in the emission factor variability analysis are identical. Therefore using either models does not significantly affect the range of variability in emissions. Therefore it appears that for purpose of analyzing variability in emission factors the use of a log-linear model would not provide any significant advantage over a linear model. However, an analyst would typically be more interested in the uncertainty on the fleet average emission factors. The next section describes the results of the uncertainty analysis on the mean emission factors and the appropriateness of a log-linear model for emission factors as opposed to the currently employed linear model.

8.7.2 Uncertainty Analysis Results

The results of the uncertainty analyses are shown in Figure 45-Figure 50. Table 13-Table 24 show the systematic and random error in the mean HC, CO and NO_x emissions, for LDGV of TG12 and TG8 obtained using linear and log-linear models.

Figure 45 and Figure 46 show that for the low speed cycles, the random error in the mean HC emission factor predicted by the linear and log-linear models for both TG12 and TG8 is plus or minus 20 to 30 percent on a 90 percent probability range. In comparison to the mean, the point estimate underestimates emissions by a factor of 1.5 to 3 across the low speed cycles. Across the mid speed cycles, the uncertainty in the mean HC emissions is plus or minus 15 to 30 percent on a 90 percent probability range. The point estimates across these cycles underestimate emissions in comparison to the mean by a factor of up to 3. The uncertainty in the mean HC emission factors across the high speed cycles is plus or minus 25 to 55 percent. As mentioned earlier, no point estimate was calculated for the high speed cycles.

Figure 47 and Figure 48 show that for the low speed cycles, the random error in the mean CO emission factor predicted by the linear and log-linear models for both TG12 and TG8 is plus or minus 20 to 55 percent. The random error for the three lowest speed cycles appears to be on the higher side and ranges from 35 to 55 percent. The mean CO emission factor for the NYCC cycle exhibits a random error of about 20 percent. For the two lowest speed cycles, the point estimate for CO emissions is overestimated by a factor of 1.2 to 2 in comparison to the mean. But for the other two low speed cycles (viz., LSP3 and NYCC) the point estimate underestimates emissions by a factor of 1.5 to 2. Across the mid speed cycles, the uncertainty in the mean CO emissions is plus or minus 10 to 30 percent. The systematic error across these cycles is approximately a factor of 1.2 to 2.5 on the lower side. The uncertainty in the mean CO emission factors across the high speed cycles is plus or minus 10 to 50 percent.

Figure 49 and Figure 50 show that for the low speed cycles, the random error in the mean NO_x emission factor predicted by the linear and log-linear models for both TG12 and TG8 is plus or minus 20 to 35 percent for a 90 percent probability range. The systematic error across the low speed cycles is approximately a factor of 2 to 10 on the lower side. Across the mid speed cycles, the uncertainty in the mean NO_x emissions is plus or minus 20 to 40 percent on a 90 percent probability range. The point estimate across these cycles underestimates emissions by a factor of about 2. The uncertainty in the mean NO_x emission factors across the high speed cycles is plus or minus 25 to 80 percent.

From the uncertainty analysis results, it can be seen that the uncertainty in the mean emissions is higher for the high speed cycles in comparison to the low speed and mid speed cycles. For the high speed cycles, the uncertainty in the mean is attributed to a very small sample size. The uncertainty in the mean for the low speed cycles is mostly due to large inter-vehicle variability as shown by Figure 33 to Figure 44. A part of the uncertainty for the low speed cycles can also attributed to the small sample size from which the SCFs were developed.

The magnitude of random error on the mean emissions obtained by using both the linear as well as the log-linear models is similar. However, the mean HC, CO and NO_x emission factors predicted by the log-linear models are less than the mean emission factors predicted by the linear models by approximately ten percent. From Figure 23 to Figure 28, it can be concluded that the residual errors for the mileage accumulation term in the BERs is more normal for the log-linear models than for the linear case. This conclusion is based upon the Shapiro-Wilk test for normality. Thus, the assumption of the mileage accumulation residuals error term (Err1) being normally distributed is more valid for the log-linear models than for the linear case. Therefore, the log-linear models for the mean emissions would provide more accurate results than the corresponding linear models.

The Tables 13 - 24 can be used by to estimate the probabilistic mean fleet emissions. To obtain the average fleet emissions, the systematic error term is subtracted from the point estimate. The random error on the mean gives a 90 percent confidence interval range for the mean. Thus, using Table 14 the probabilistic mean CO fleet emissions for LDGV of TG12 for the FTP Bag 2 driving cycle can be calculated as 10.01

g/mi - (-1.10 g/mi) = 11.11 g/mi. Using the random error term in Table 14, it can be said with 90 percent confidence that the mean CO fleet emissions for LDGV of TG12 for the FTP Bag 2 driving cycle could vary by around 9 percent of the probabilistic mean.

To determine which components of the uncertainty model contribute the most to uncertainty in the final emission estimates, rank correlations for different parameters of the uncertainty models were deterimned. Table 25 shows the rank correlations for the different parameters of the uncertainty models for TG12. It can be seen that in most cases, the SCF parameter contributes the most to uncertainty in the final emission estimates. This indicates that the SCF module in the emission factor model needs to be re-analyzed.

8.8 Discussion

Linear and log-linear models were used in this analyses to investigate uncertainty and variability in the emission factors. This analyses employed fractile distributions for analyzing the variability and normal distributions for analyzing the uncertainty in the mean emission factors. Previous studies on uncertainty in mean emissions have employed bootstrap approaches where no parametric distributions were assumed to represent the input data. However, the previous analyses on uncertainty in speed correction factors have interpolated between driving cycles using an assumed speed correction equation. Interpolation between driving cycles is actually a form of extrapolation. Therefore, the results obtained in this analysis are more robust in comparison to the previous studies because the variability and uncertainty analyses carried out in this study does not interpolate between driving cycles.

Chapter 9 describes the conclusions to the probabilistic analysis and provides recommendations for future analysis.

Table 12. Input Assumptions for Uncertainty Analysis

Inputs		Technology Group 12		Technology Group 8	
		Model 1 (Linear Model)	Model 2 (Log-linear Model)	Model 1 (Linear Model)	Model 2 (Log-linear Model)
HC BER (g/mi)	ZML	0.2946	-1.231	0.3257	-1.332
	DR1	0.0000077	0.0000095	0.0000037	0.0000094
	Error 1	N(0, 0.024)	N(0,0.014)	N(0, 0.0191)	N(0, 0.185)
	Error 2	N(1.33, 0.064)	N(1.33, 0.064)	N(1.33, 0.064)	N(1.33, 0.064)
HC SCF	LSP1	N(10.56, 1.308)	N(10.56, 1.308)	N(9.87, 1.54)	N(9.87, 1.54)
	LSP2	N(7.56, 1.01)	N(7.56, 1.01)	N(10.46, 1.38)	N(10.46, 1.38)
	LSP3	N(12.67, 2.06)	N(12.67, 2.06)	N(17.74, 2.56)	N(17.74, 2.56)
	NYCC	N(3.42, 0.408)	N(3.42, 0.408)	N(3.03, 0.60)	N(3.03, 0.60)
	SCC12	N(3.92, 0.50)	N(3.92, 0.50)	N(2.92, 0.526)	N(2.92, 0.526)
	FTP Bag2	N(1, 0)	N(1, 0)	N(1, 0)	N(1, 0)
	SCC36	N(0.8, 0.097)	N(0.8, 0.097)	N(0.569, 0.059)	N(0.569, 0.059)
	HFET	N(0.72, 0.06)	N(0.72, 0.06)	N(0.463, 0.049)	N(0.463, 0.049)
	HSP1	N(0.7, 0.147)	N(0.7, 0.147)	N(1.21, 0.199)	N(1.21, 0.199)
	HSP2	N(1.1, 0.192)	N(1.1, 0.192)	N(1.155, 0.218)	N(1.155, 0.218)
	HSP3	N(2.6,0.84)	N(2.6,0.84)	N(1.16, 0.294)	N(1.16, 0.294)
CO BER (g/mi)	ZML	4.355	1.071	4.195	1.0372
	DR1	0.000072	0.0000119	0.0000576	0.0000146
	Error 1	N(0, 0.317)	N(0,0.019)	N(0, 0.23)	N(0, 0.026)
	Error 2	N(1.39, 0.056)	N(1.39, 0.056)	N(1.39, 0.056)	N(1.39, 0.056)
CO SCF	LSP1	N(5.5, 1.14)	N(5.5, 1.14)	N(4.14, 1.23)	N(4.14, 1.23)
	LSP2	N(4.42,1.056)	N(4.42,1.056)	N(4.60, 1.49)	N(4.60, 1.49)
	LSP3	N(5.89, 1.81)	N(5.89, 1.81)	N(6.17, 1.92)	N(6.17, 1.92)
	NYCC	N(4.401, 0.5)	N(4.401, 0.5)	N(3.75, 0.43)	N(3.75, 0.43)
	SCC12	N(2.37, 0.322)	N(2.37, 0.322)	N(1.62, 0.22)	N(1.62, 0.22)
	FTP Bag2	N(1,0)	N(1,0)	N(1,0)	N(1,0)
	SCC36	N(0.95, 0.143)	N(0.95, 0.143)	N(0.76, 0.073)	N(0.76, 0.073)
	HFET	N(0.714, 0.098)	N(0.714, 0.098)	N(0.473, 0.046)	N(0.473, 0.046)
	HSP1	N(0.7, 0.0334)	N(0.7, 0.0334)	N(0.513, 0.106)	N(0.513, 0.106)
	HSP2	N(0.102, 0.0251)	N(0.102, 0.0251)	N(0.029, 0.006)	N(0.029, 0.006)
	HSP3	N(0.149, 0.0359)	N(0.149, 0.0359)	N(0.031, 0.009)	N(0.031, 0.009)
NOx BER (g/mi)	ZML	0.4858	-0.86196	0.531	-0.7009
	DR1	0.0000057	0.0000103	0.0000076	0.0000101
	Error 1	N(0, 0.008)	N(0,0.014)	N(0, 0.015)	N(0, 0.016)
	Error 2	N(0.0021, 0.109)	N(0.0021, 0.109)	N(0.0021, 0.109)	N(0.0021, 0.109)
NOx SCF	LSP1	N(2.54, 0.336)	N(2.54, 0.336)	N(3.22, 0.39)	N(3.22, 0.39)
	LSP2	N(2.44, 0.33)	N(2.44, 0.33)	N(3.11, 0.32)	N(3.11, 0.32)
	LSP3	N(2.74, 0.45)	N(2.74, 0.45)	N(3.67, 0.504)	N(3.67, 0.504)
	NYCC	N(3.07, 0.18)	N(3.07, 0.18)	N(2.29, 0.163)	N(2.29, 0.163)
	SCC12	N(1, 0)	N(1, 0)	N(2.55, 0.55)	N(2.55, 0.55)
	FTP Bag2	N(1, 0)	N(1, 0)	N(1, 0)	N(1, 0)
	SCC36	N(1.5, 0.104)	N(1.5, 0.104)	N(1.09, 0.062)	N(1.09, 0.062)
	HFET	N(1.44, 0.1)	N(1.44, 0.1)	N(0.888, 0.05)	N(0.888, 0.05)
	HSP1	N(0.8, 0.079)	N(0.8, 0.079)	N(1.77, 0.476)	N(1.77, 0.476)
	HSP2	N(0.5, 0.15)	N(0.5, 0.15)	N(0.25, 0.095)	N(0.25, 0.095)
	HSP3	N(1.3, 0.44)	N(1.3, 0.44)	N(0.289, 0.14)	N(0.289, 0.14)

Table 13. Uncertainty in Predicted Mean HC Emission Factors for LDGV of Technology Group 12 Using a Linear Model

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	5.586	7.39	9.556	11.931	-3.97	0.23
LSP2	3.64	3.763	5.179	6.794	8.46	-3.031	0.24
LSP3	4.02	3.396	8.298	11.385	14.731	-7.989	0.27
NYCC	7.1	1.914	2.417	3.08	3.769	-1.166	0.22
SCC12	12.1	1.115	2.739	3.547	4.372	-2.432	0.23
FTP BAG 2	16.1	0.833	0.813	0.904	0.997	-0.071	0.10
SCC36	35.9	0.362	0.568	0.721	0.887	-0.359	0.21
HFET	48.4	0.263	0.545	0.649	0.759	-0.386	0.16
HSP1	50.9		0.407	0.629	0.863		0.35
HSP2	57.6		0.694	0.992	1.302		0.30
HSP3	64.3		1.084	2.337	3.668		0.54

Table 14. Uncertainty in Predicted Mean CO Emission Factors for LDGV of Technology Group 12 Using a Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	74.61	40.19	61.03	83.73	13.59	0.34
LSP2	3.64	49.84	28.92	48.78	69.21	1.06	0.41
LSP3	4.02	44.85	30.33	65.87	98.54	-21.02	0.54
NYCC	7.10	24.71	39.26	48.63	58.68	-23.92	0.19
SCC12	12.10	13.84	19.67	26.33	32.90	-12.49	0.25
FTP BAG 2	16.10	10.01	10.06	11.11	12.15	-1.10	0.09
SCC36	35.90	7.93	7.78	10.53	13.26	-2.60	0.26
HFET	48.40	5.59	5.93	7.88	9.88	-2.29	0.25
HSP1	50.90		6.88	7.77	8.70		0.11
HSP2	57.60		0.65	1.12	1.61		0.42
HSP3	64.30		0.95	1.67	2.33		0.43

a: = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error = $\frac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 15. Uncertainty in Predicted Mean NO_x Emission Factors for LDGV of Technology Group 12 Using a Linear Model

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	0.38	1.42	1.95	2.61	-1.56	0.27
LSP2	3.64	0.05	1.32	1.87	2.58	-1.83	0.30
LSP3	4.02	0.13	1.45	2.17	3.01	-2.03	0.33
NYCC	7.10	0.48	1.80	2.39	3.00	-1.91	0.25
SCC12	12.10	0.67	1.14	1.52	1.93	-0.85	0.25
FTP BAG 2	16.10	0.74	0.60	0.78	0.96	-0.04	0.23
SCC36	35.90	0.77	0.87	1.16	1.46	-0.39	0.25
HFET	48.40	0.82	0.83	1.11	1.42	-0.30	0.25
HSP1	50.90		0.46	0.62	0.81		0.25
HSP2	57.60		0.20	0.38	0.61		0.48
HSP3	64.30		0.41	1.00	1.63		0.59

Table 16. Uncertainty in Predicted Mean HC Emission Factors for LDGV of Technology Group 12 Using a Log-Linear Model

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	3.86	5.20	6.61	8.06	-2.75	0.21
LSP2	3.64	2.60	3.64	4.69	5.80	-2.09	0.22
LSP3	4.02	2.35	5.64	7.87	10.13	-5.52	0.28
NYCC	7.10	1.32	1.67	2.13	2.60	-0.81	0.22
SCC12	12.10	0.77	1.93	2.44	3.02	-1.67	0.21
FTP BAG 2	16.10	0.58	0.58	0.62	0.68	-0.05	0.08
SCC36	35.90	0.47	0.39	0.50	0.61	-0.03	0.21
HFET	48.40	0.35	0.38	0.45	0.52	-0.10	0.15
HSP1	50.90		0.28	0.43	0.59		0.35
HSP2	57.60		0.48	0.68	0.90		0.30
HSP3	64.30		0.77	1.61	2.52		0.52

a: = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error $= \dfrac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 17. Uncertainty in Predicted Mean CO Emission Factors for LDGV of Technology Group 12 Using a Log Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	49.63	26.79	40.34	55.19	9.29	0.34
LSP2	3.64	33.15	19.29	32.60	45.83	0.55	0.41
LSP3	4.02	29.83	19.91	43.73	65.74	-13.89	0.54
NYCC	7.10	16.43	26.14	32.29	38.72	-15.86	0.19
SCC12	12.10	9.20	13.21	17.47	21.87	-8.27	0.24
FTP BAG 2	16.10	6.66	6.83	7.38	7.92	-0.73	0.08
SCC36	35.90	5.28	5.15	7.01	8.74	-1.73	0.27
HFET	48.40	3.72	4.00	5.25	6.52	-1.53	0.24
HSP1	50.90		4.63	5.17	5.71		0.10
HSP2	57.60		0.44	0.75	1.07		0.42
HSP3	64.30		0.64	1.10	1.54		0.42

Table 18. Uncertainty in Predicted Mean NO_x Emission Factors for LDGV of Technology Group 12 Using a Log-Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	0.35	1.28	1.79	2.43	-1.43	0.28
LSP2	3.64	0.04	1.18	1.72	2.39	-1.68	0.31
LSP3	4.02	0.12	1.31	1.98	2.79	-1.86	0.34
NYCC	7.10	0.44	1.61	2.20	2.79	-1.75	0.27
SCC12	12.10	0.62	1.03	1.40	1.80	-0.78	0.26
FTP BAG 2	16.10	0.68	0.54	0.71	0.90	-0.04	0.25
SCC36	35.90	0.71	0.78	1.07	1.36	-0.36	0.27
HFET	48.40	0.75	0.75	1.02	1.32	-0.27	0.27
HSP1	50.90		0.41	0.56	0.75		0.27
HSP2	57.60		0.18	0.35	0.56		0.48
HSP3	64.30		0.37	0.92	1.52		0.60

a = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error $= \dfrac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 19. Uncertainty in Predicted Mean HC Emission Factors for LDGV of Technology Group 8 Using a Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	2.91	4.91	6.71	8.57	-3.80	0.27
LSP2	3.64	2.02	5.41	7.06	8.86	-5.04	0.23
LSP3	4.02	1.84	9.00	12.02	15.18	-10.18	0.25
NYCC	7.10	1.11	1.36	2.05	2.77	-0.94	0.34
SCC12	12.10	0.72	1.41	1.98	2.63	-1.26	0.29
FTP BAG 2	16.10	0.59	0.61	0.68	0.75	-0.09	0.10
SCC36	35.90	0.51	0.31	0.39	0.47	0.12	0.19
HFET	48.40	0.43	0.26	0.31	0.38	0.11	0.19
HSP1	50.90		0.58	0.81	1.05		0.28
HSP2	57.60		0.52	0.78	1.05		0.33
HSP3	64.30		0.46	0.78	1.12		0.42

Table 20. Uncertainty in Predicted Mean CO Emission Factors for LDGV of Technology Group 8 Using a Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	69.13	20.96	40.62	61.66	28.51	0.48
LSP2	3.64	46.08	20.39	45.06	70.07	1.03	0.55
LSP3	4.02	41.44	27.67	61.29	92.32	-19.85	0.55
NYCC	7.10	22.69	29.83	36.93	44.48	-14.23	0.19
SCC12	12.10	12.59	12.12	16.06	19.99	-3.47	0.25
FTP BAG 2	16.10	9.02	9.04	9.87	10.73	-0.85	0.08
SCC36	35.90	7.09	6.18	7.50	8.82	-0.41	0.18
HFET	48.40	4.91	3.82	4.66	5.52	0.25	0.18
HSP1	50.90		3.27	5.06	6.91		0.35
HSP2	57.60		0.19	0.29	0.40		0.32
HSP3	64.30		0.15	0.30	0.45		0.50

a: = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error $= \frac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 21. Uncertainty in Predicted Mean NO_x Emission Factors for LDGV of Technology Group 8 Using a Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	1.78	2.21	2.92	3.78	-1.14	0.24
LSP2	3.64	1.46	2.14	2.83	3.66	-1.38	0.25
LSP3	4.02	1.39	2.40	3.36	4.45	-1.97	0.28
NYCC	7.10	1.13	1.65	2.11	2.62	-0.98	0.22
SCC12	12.10	0.99	1.41	2.33	3.43	-1.35	0.40
FTP BAG 2	16.10	0.94	0.74	0.92	1.10	0.02	0.20
SCC36	35.90	0.91	0.79	1.00	1.21	-0.09	0.21
HFET	48.40	0.88	0.64	0.81	1.00	0.07	0.21
HSP1	50.90		0.86	1.60	2.45		0.46
HSP2	57.60		0.09	0.23	0.38		0.60
HSP3	64.30		0.05	0.26	0.48		0.83

Table 22. Uncertainty in Predicted Mean HC Emission Factors for LDGV of Technology Group 8 Using a Log-Linear Model

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	2.40	4.08	5.55	7.06	-3.14	0.26
LSP2	3.64	1.67	4.56	5.87	7.25	-4.20	0.22
LSP3	4.02	1.52	7.42	9.91	12.52	-8.39	0.25
NYCC	7.10	0.92	1.13	1.70	2.28	-0.78	0.33
SCC12	12.10	0.60	1.16	1.64	2.16	-1.04	0.29
FTP BAG 2	16.10	0.48	0.52	0.56	0.61	-0.08	0.08
SCC36	35.90	0.42	0.26	0.32	0.38	0.10	0.18
HFET	48.40	0.35	0.21	0.26	0.31	0.09	0.18
HSP1	50.90		0.49	0.67	0.87		0.27
HSP2	57.60		0.44	0.64	0.86		0.32
HSP3	64.30		0.39	0.65	0.93		0.40

a: = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error = $\frac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 23. Uncertainty in Predicted Mean CO Emission Factors for LDGV of Technology Group 8 Using a Log Linear Model.

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	57.20	17.51	33.58	51.02	23.63	0.48
LSP2	3.64	38.13	16.83	37.22	57.95	0.92	0.55
LSP3	4.02	34.29	22.78	50.69	76.36	-16.40	0.55
NYCC	7.10	18.78	24.71	30.54	36.71	-11.76	0.19
SCC12	12.10	10.41	10.05	13.30	16.53	-2.89	0.24
FTP BAG 2	16.10	7.46	7.51	8.17	8.83	-0.71	0.08
SCC36	35.90	5.87	5.13	6.20	7.29	-0.33	0.17
HFET	48.40	4.06	3.17	3.86	4.56	0.21	0.18
HSP1	50.90		2.71	4.18	5.69		0.35
HSP2	57.60		0.16	0.24	0.33		0.32
HSP3	64.30		0.12	0.25	0.37		0.50

Table 24. Uncertainty in Predicted Mean NO_x Emission Factors for LDGV of Technology Group 8 Using a Log-Linear Model

Driving Cycle	Speed (mph)	Point Estimate	5th Percentile[a]	Mean[a]	95 th Percentile[a]	Systematic Error[b]	Random Error[c]
LSP1	2.45	1.61	1.95	2.64	3.46	-1.03	0.26
LSP2	3.64	1.32	1.89	2.56	3.35	-1.24	0.26
LSP3	4.02	1.26	2.14	3.03	4.08	-1.77	0.29
NYCC	7.10	1.02	1.46	1.91	2.39	-0.89	0.24
SCC12	12.10	0.89	1.26	2.10	3.12	-1.21	0.40
FTP BAG 2	16.10	0.84	0.65	0.83	1.01	0.01	0.22
SCC36	35.90	0.82	0.69	0.90	1.11	-0.08	0.23
HFET	48.40	0.79	0.57	0.73	0.91	0.06	0.23
HSP1	50.90		0.78	1.44	2.24		0.46
HSP2	57.60		0.08	0.20	0.35		0.59
HSP3	64.30		0.04	0.24	0.44		0.83

a: = Probabilistic Results

b: Systematic Error = Point Estimate - Mean

c: Random Error $= \dfrac{\text{Mean - 5th Percentile}}{\text{Mean}}$

Table 25. Rank Correlation Coefficients for Uncertainty Model Components

Pollutant	Driving Cycle	Model			
		Base Emission Rate	Error1	Error2	SCF Uncertainty
HC	LSP1	0.43	0.22	0.35	0.90
	LSP2	0.39	0.24	0.29	0.91
	LSP3	0.36	0.18	0.29	0.94
	NYCC	0.45	0.24	0.37	0.89
	SCC12	0.40	0.21	0.33	0.91
	FTP Bag 2	1.00	0.55	0.79	0.00
	SCC 36	0.43	0.25	0.33	0.89
	HFET	0.58	0.34	0.45	0.81
	HSP1	0.26	0.10	0.24	0.96
	HSP2	0.30	0.19	0.23	0.94
	HSP3	0.14	0.10	0.11	0.98
CO	LSP1	0.22	0.21	0.10	0.96
	LSP2	0.23	0.16	0.18	0.97
	LSP3	0.17	0.11	0.13	0.98
	NYCC	0.43	0.28	0.32	0.87
	SCC12	0.39	0.26	0.29	0.91
	FTP Bag 2	1.00	0.69	0.71	0.00
	SCC 36	0.35	0.30	0.20	0.92
	HFET	0.40	0.29	0.27	0.92
	HSP1	0.74	0.53	0.50	0.62
	HSP2	0.20	0.17	0.11	0.97
	HSP3	0.21	0.15	0.17	0.97
NOx	LSP1	0.66	0.10	0.66	0.64
	LSP2	0.70	0.08	0.70	0.69
	LSP3	0.62	0.06	0.62	0.75
	NYCC	0.92	0.09	0.91	0.35
	SCC12	0.91	0.09	0.91	0.39
	FTP Bag 2	1.00	0.11	1.00	0.00
	SCC 36	0.88	0.13	0.88	0.38
	HFET	0.87	0.12	0.87	0.47
	HSP1	0.78	0.09	0.77	0.54
	HSP2	0.37	0.05	0.36	0.89
	HSP3	0.37	0.03	0.37	0.91

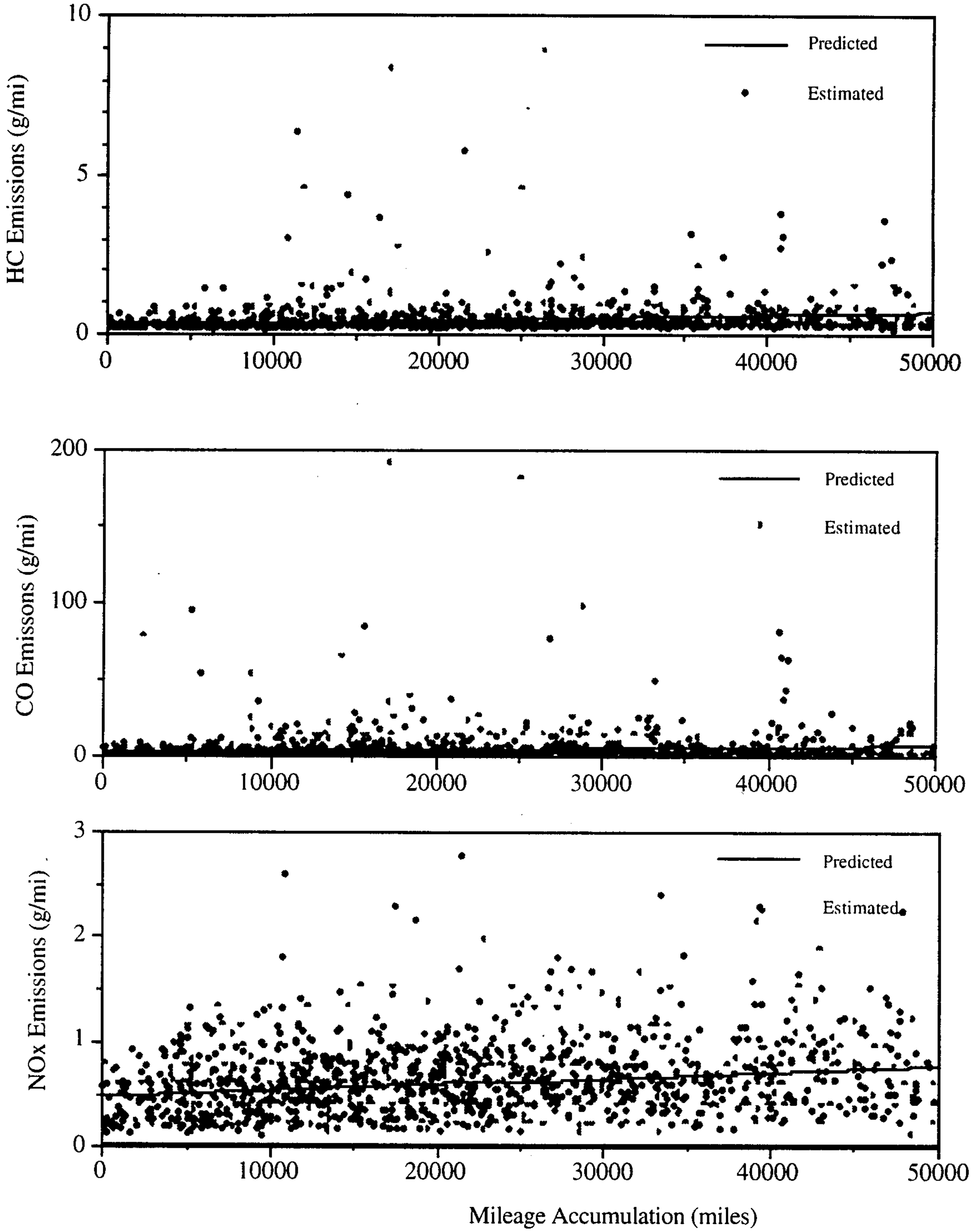


Figure 12. Comparison of estimated FTP emissions of HC, CO and NO_x emissions with predictions of a Linear Base Emission Rate model for LDGV of Technology Group 12.

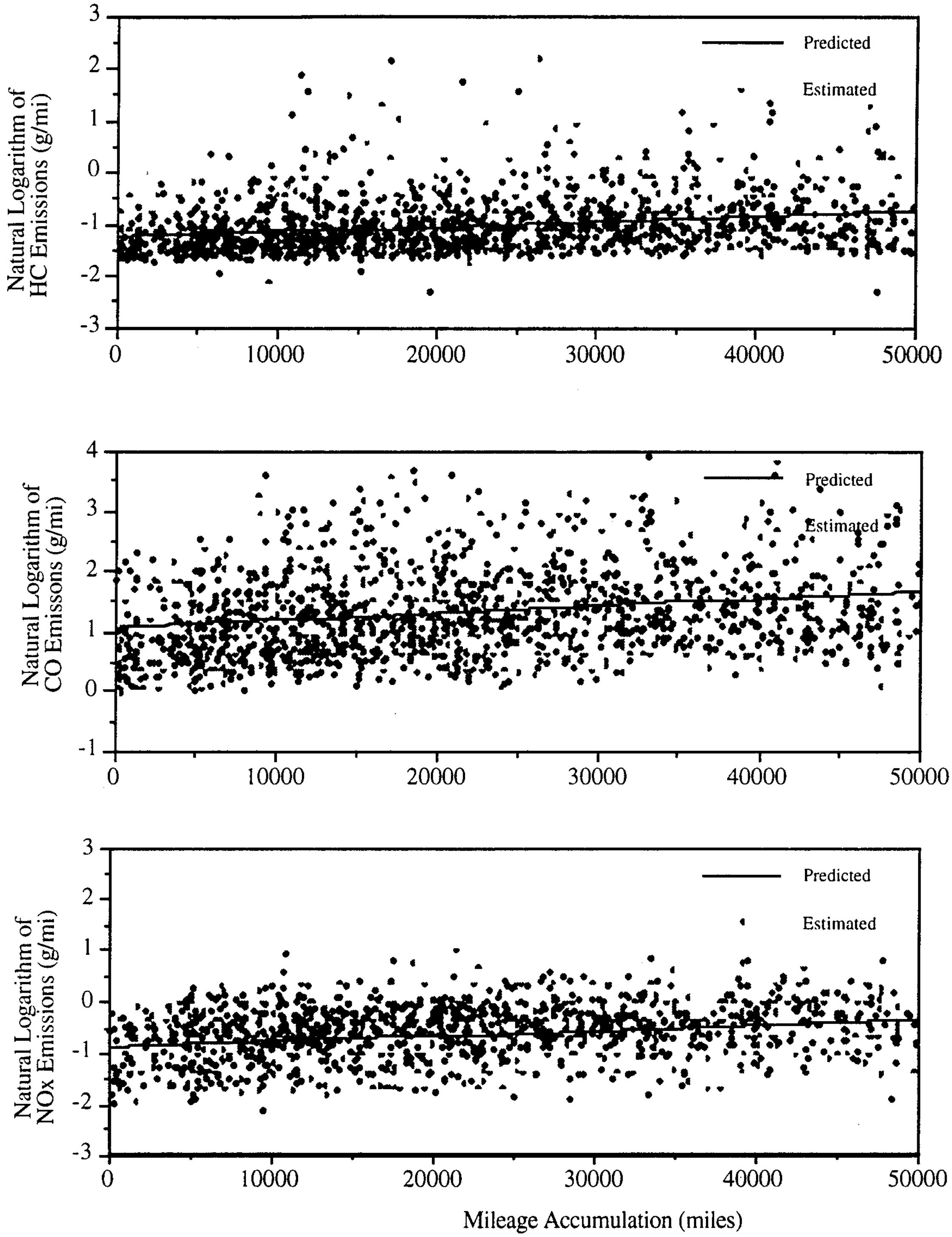


Figure 13. Comparison of estimated FTP emissions of HC, CO and NO_x emissions with predictions of a Log-Linear Base Emission Rate model for LDGV of Technology Group 12.

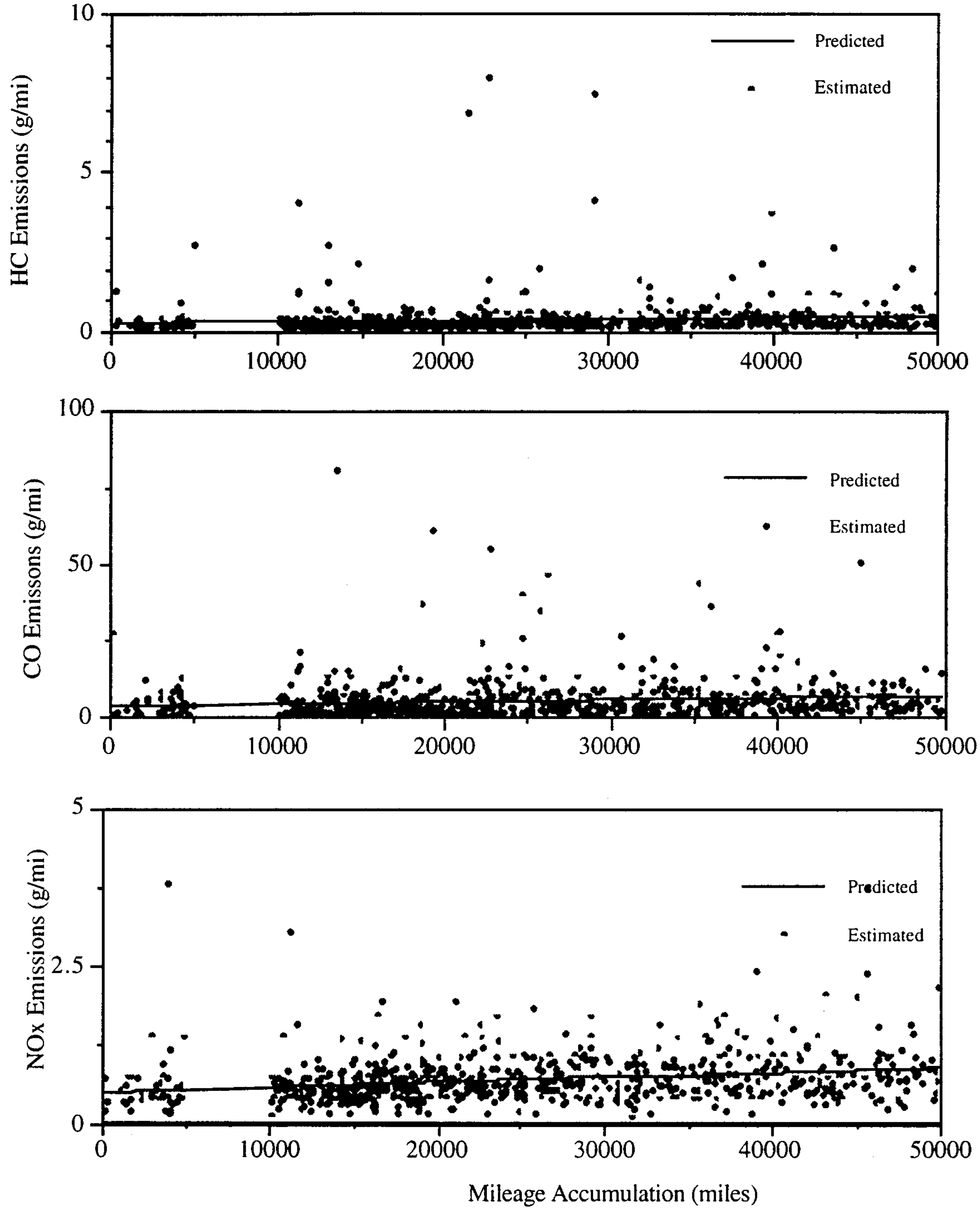


Figure 14. Comparison of estimated FTP emissions of HC, CO and NO_x emissions with predictions of a Linear Base Emission Rate model for LDGV of Technology Group 8.

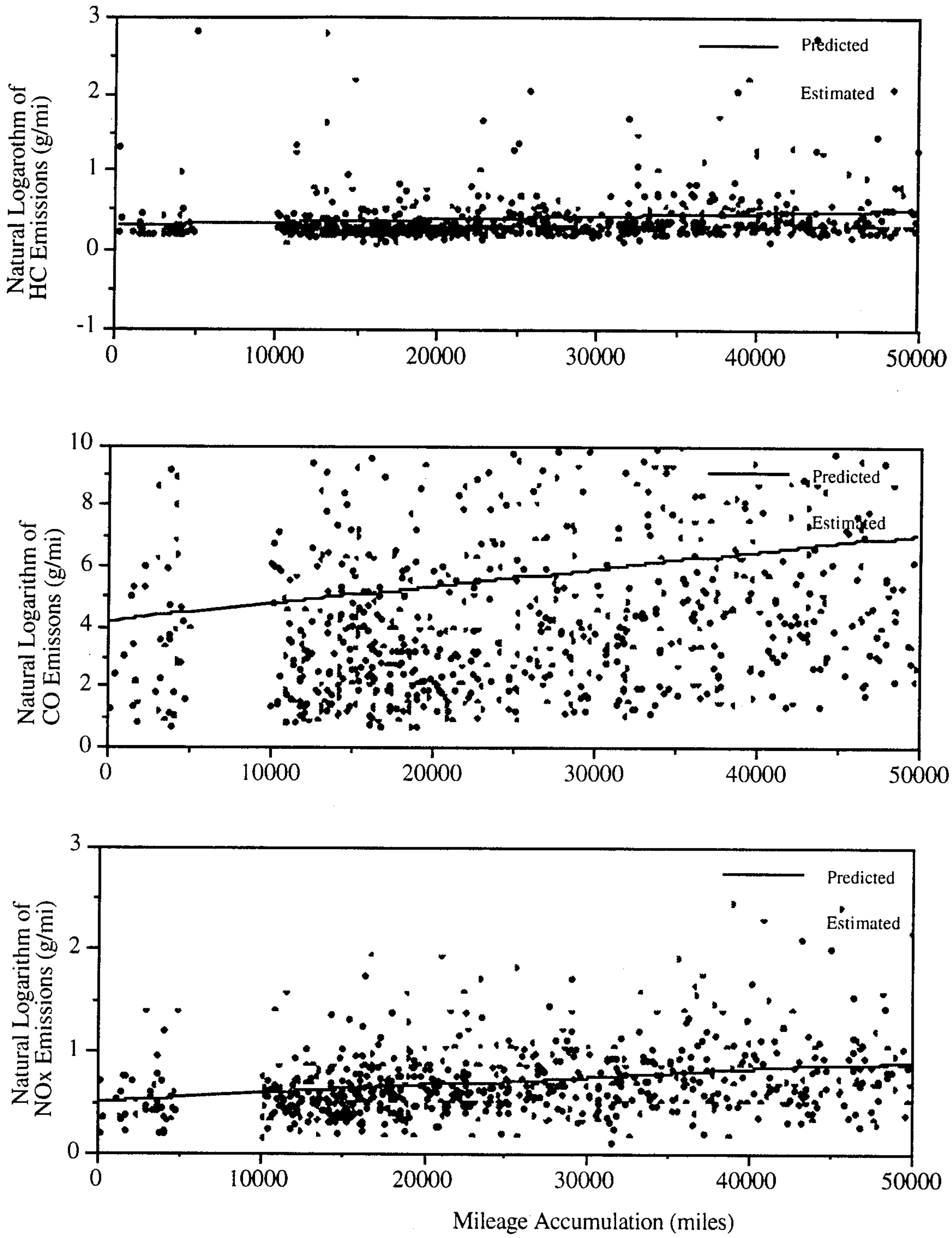


Figure 15. Comparison of estimated FTP emissions of HC, CO and NO_x emissions with predictions of a Log-Linear Base Emission Rate model for LDGV of Technology Group 8.

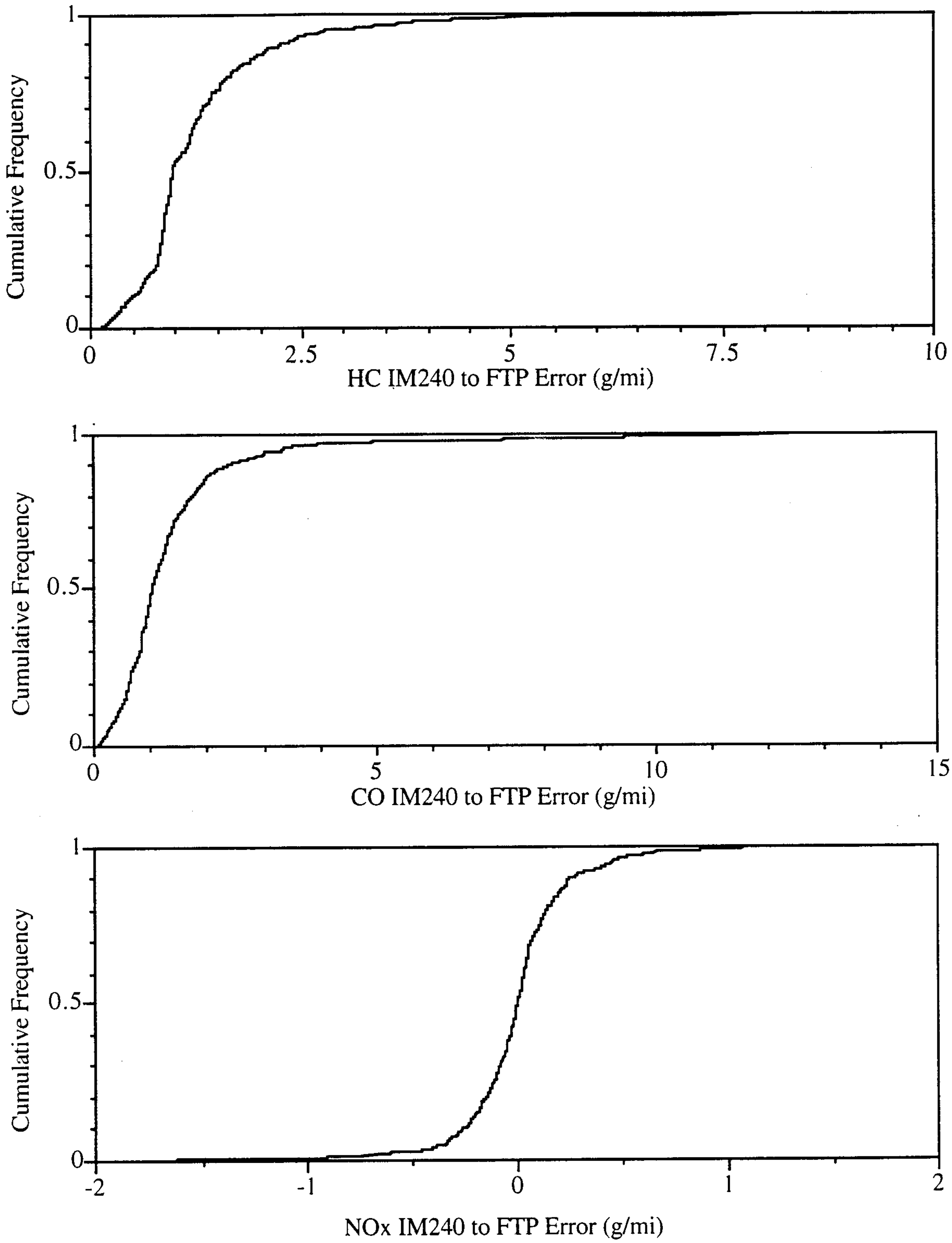
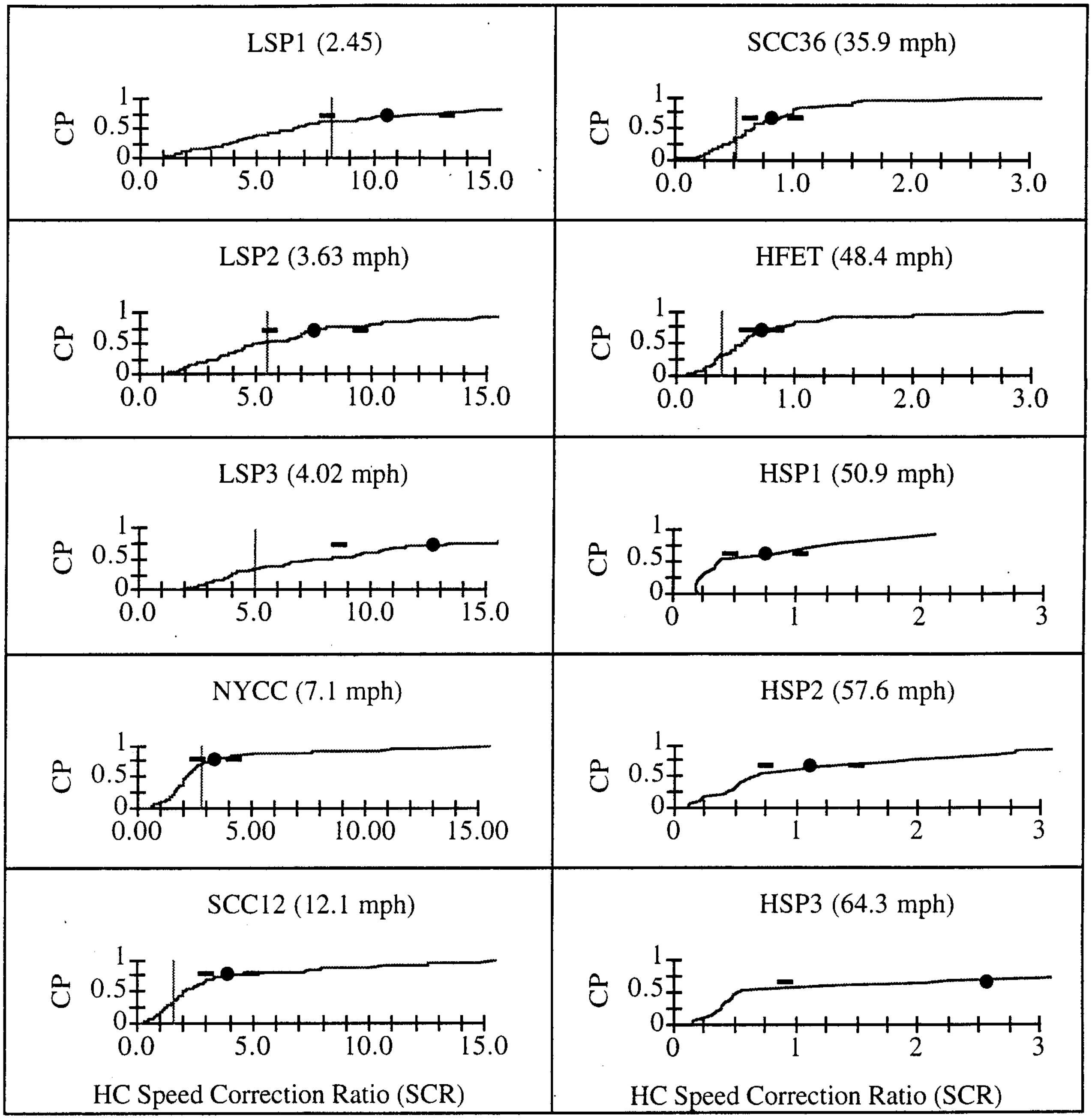


Figure 16. Residual Error from the IM240 to FTP transformation model



Key: CP = Cumulative Probability

Inter-vehicle Variability — Mean of Emissions with 95% Confidence | Mobile5a result for Average Speed of Cycle

Figure 17. Variation in the HC Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 12

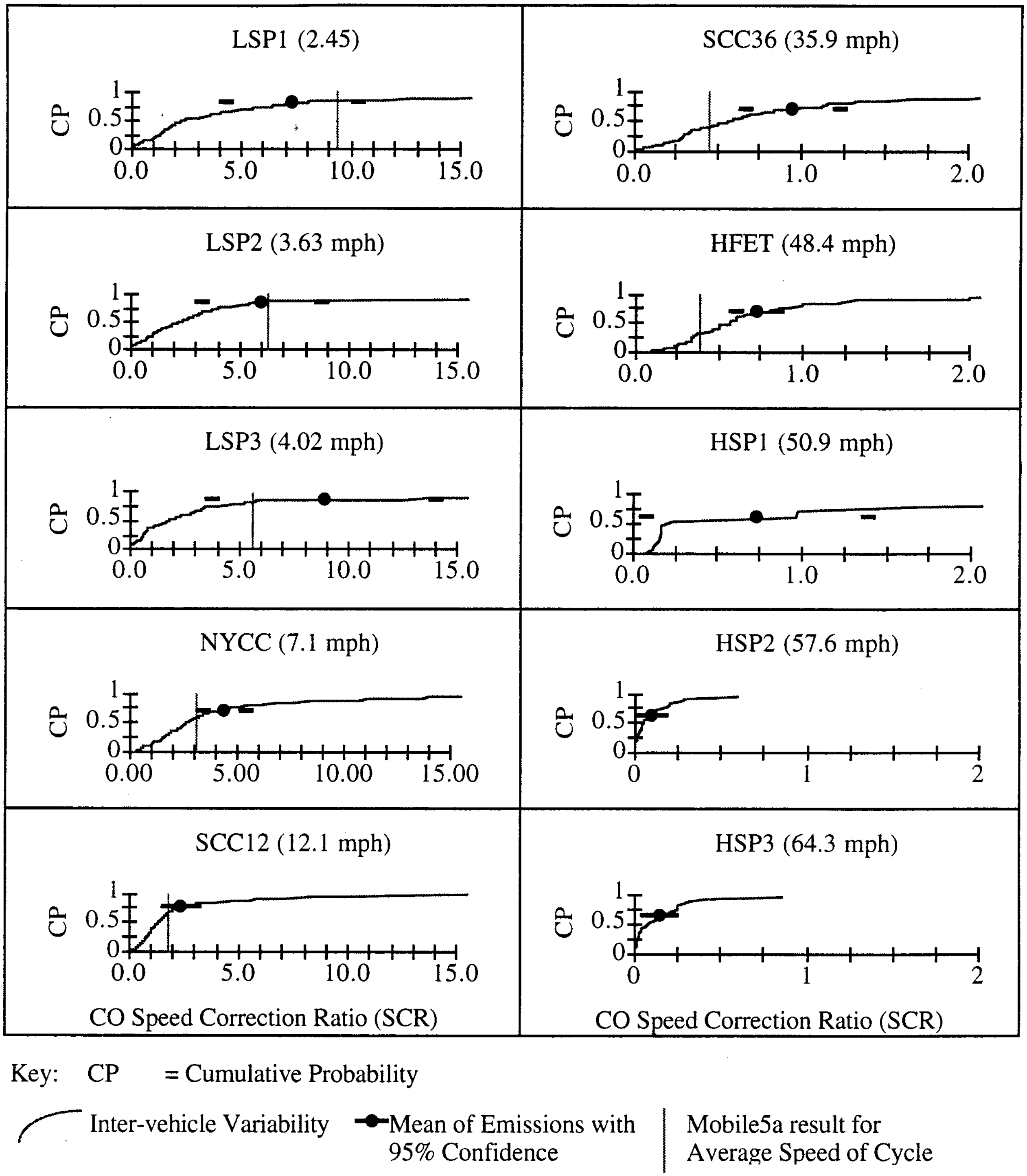


Figure 18. Variation in the CO Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 12

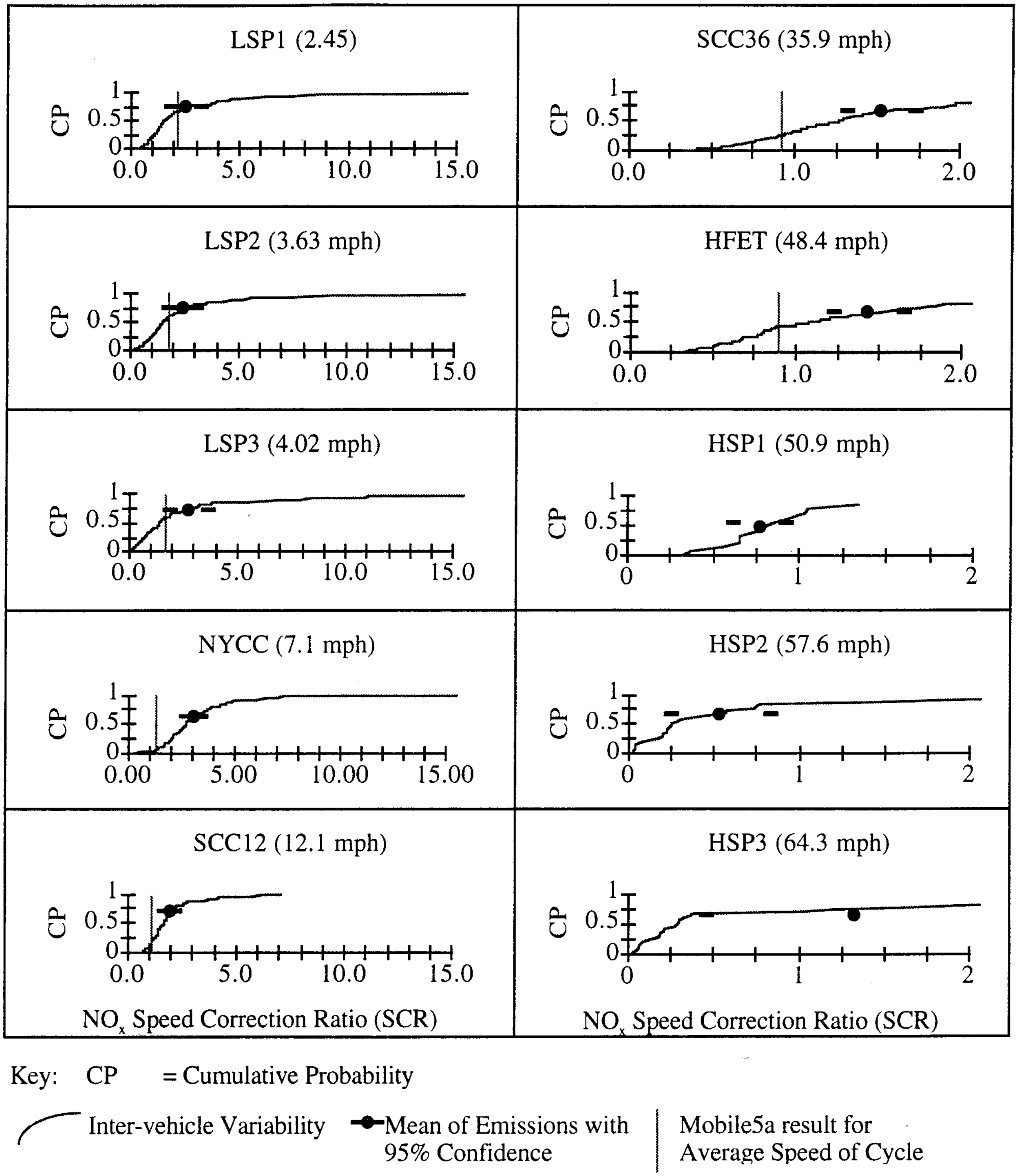
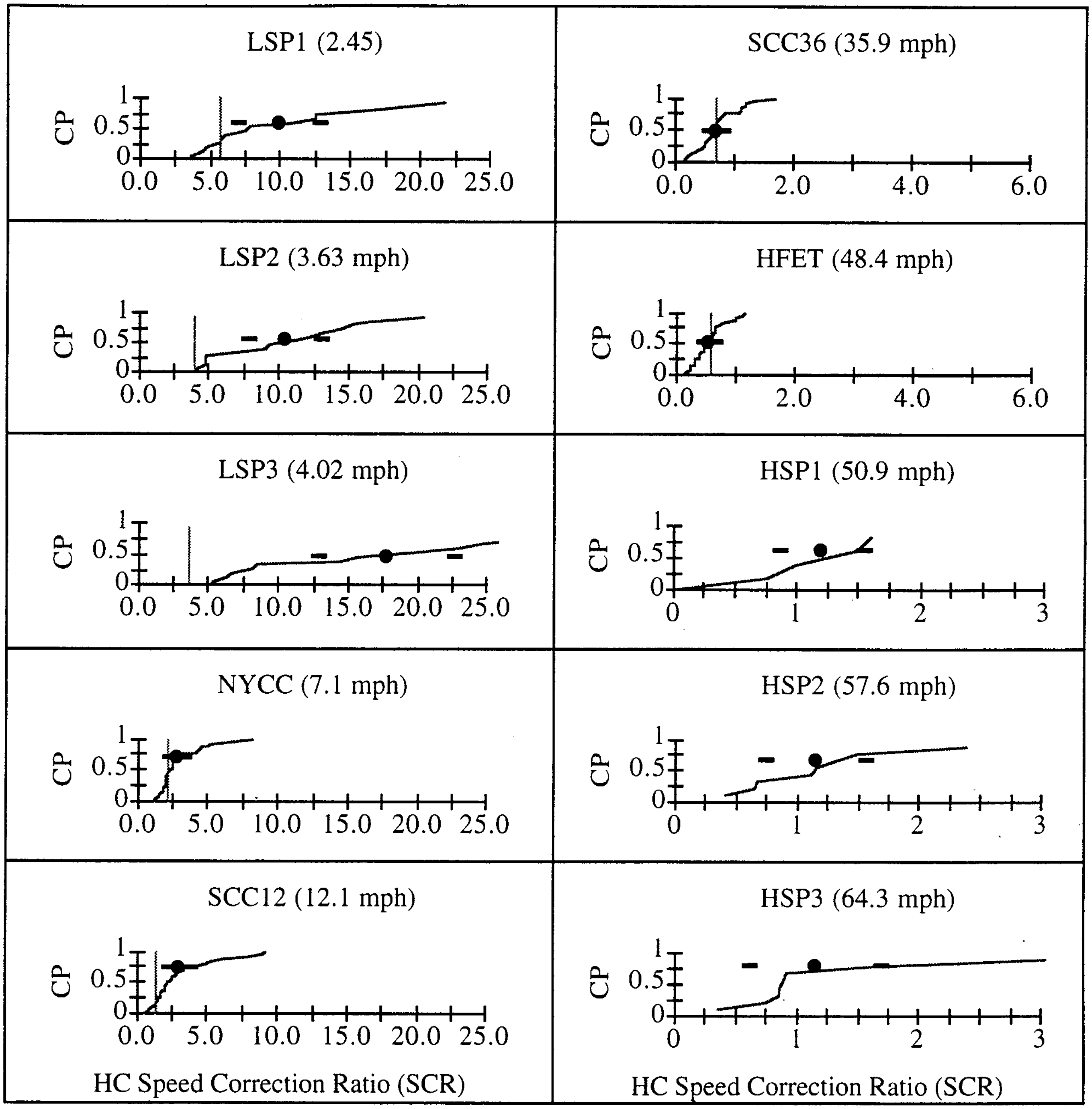


Figure 19. Variation in the NO_x Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 12.



Key: CP = Cumulative Probability

Inter-vehicle Variability — Mean of Emissions with 95% Confidence | Mobile5a result for Average Speed of Cycle

Figure 20. Variation in the HC Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 8

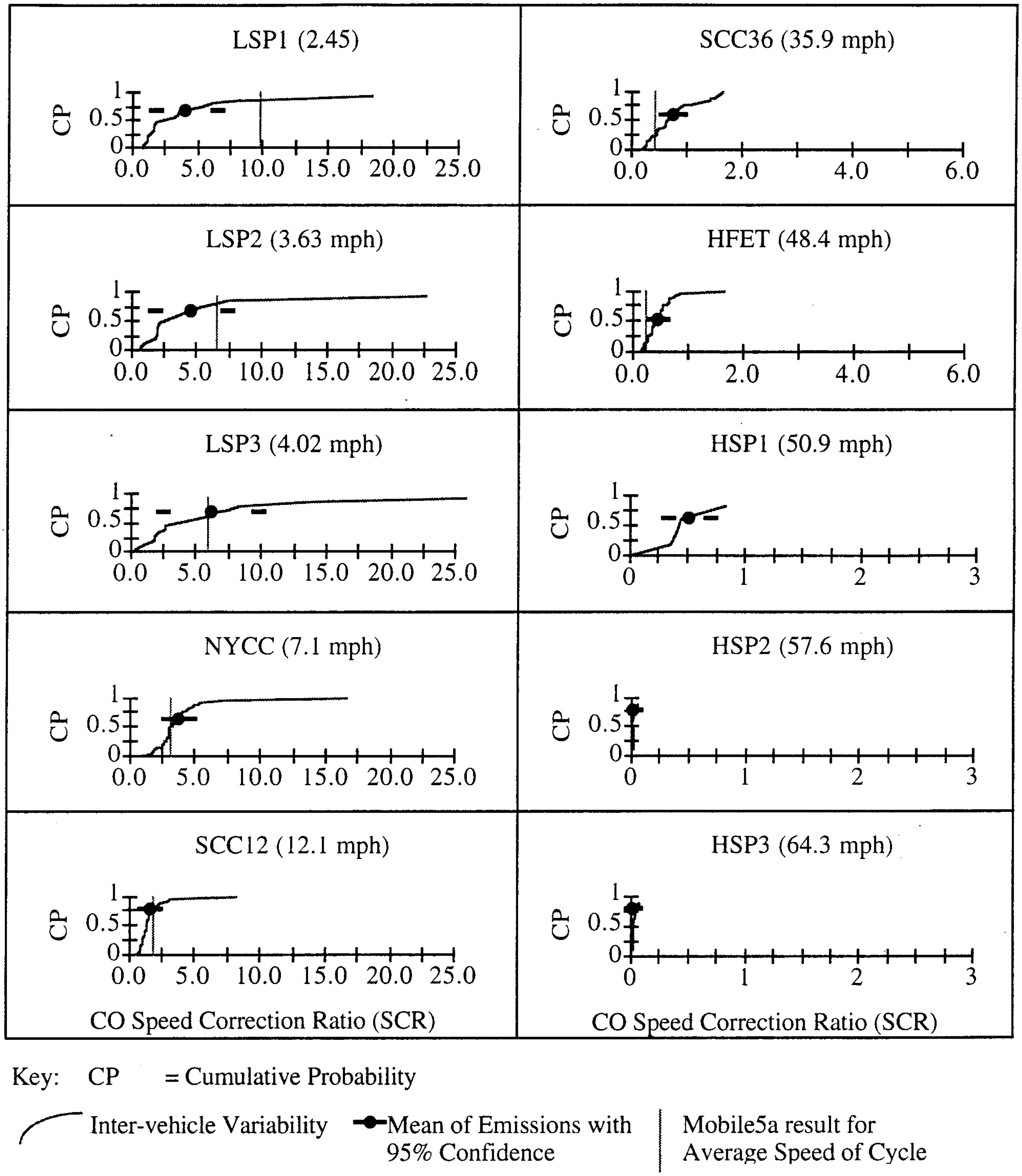


Figure 21. Variation in the CO Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 8

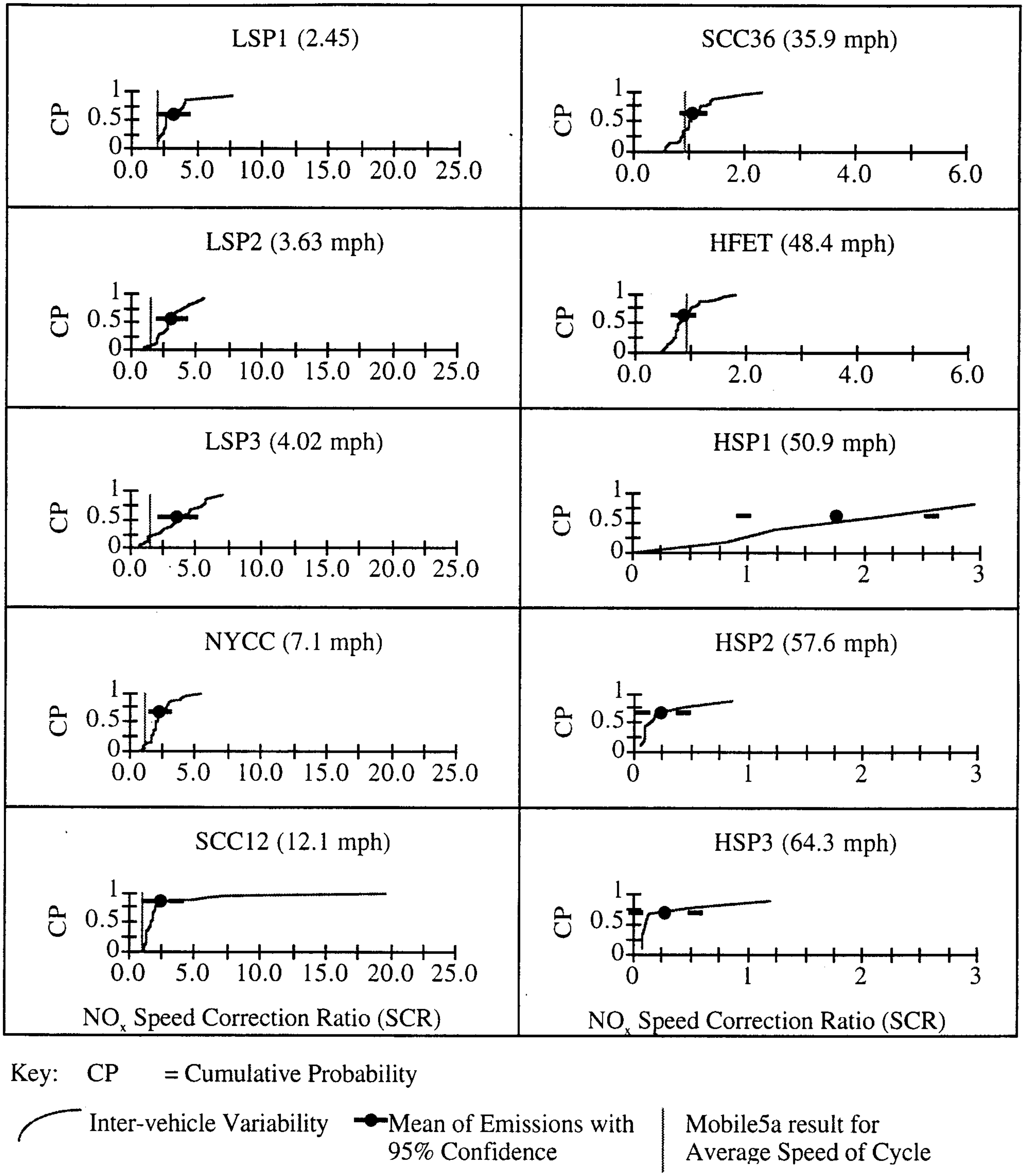
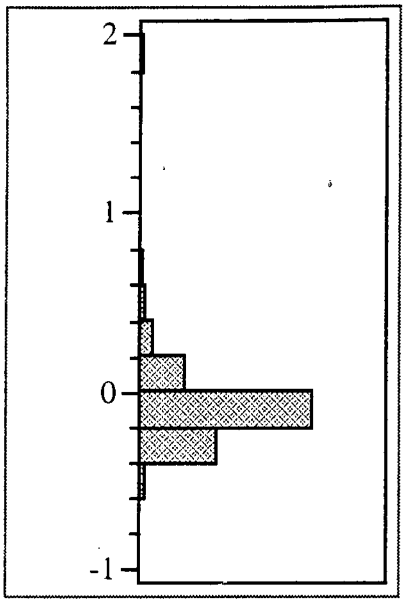


Figure 22. Variation in the NO$_x$ Speed Correction Factors for Different Driving Cycles for LDGV of Technology Group 8.

Residuals HCFTP



Quantiles

maximum	100.0%	29.836
	99.5%	4.109
	97.5%	0.937
	90.0%	0.224
quartile	75.0%	-0.009
median	50.0%	-0.110
quartile	25.0%	-0.200
	10.0%	-0.279
	2.5%	-0.378
	0.5%	-0.445
minimum	0.0%	-0.559

Moments

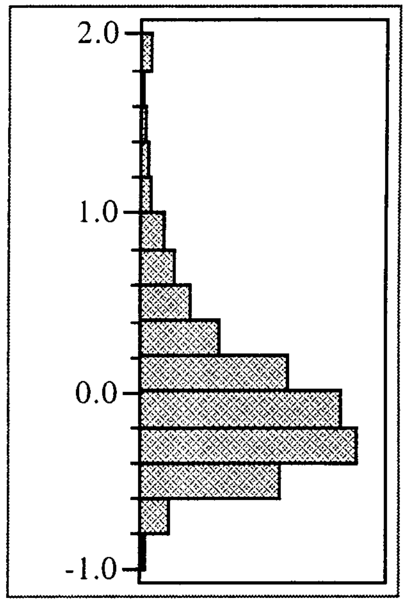
Mean	0.000
Std Dev	0.935
Std Err Mean	0.024
upper 95% Mean	0.047
lower 95% Mean	-0.047
N	1506.000
Sum Wgts	1506.000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.225160	0.0000

Residuals Ln HCFTP



Quantiles

maximum	100.0%	4.1887
	99.5%	2.5593
	97.5%	1.3439
	90.0%	0.6440
quartile	75.0%	0.1778
median	50.0%	-0.1095
quartile	25.0%	-0.3321
	10.0%	-0.4863
	2.5%	-0.6348
	0.5%	-0.8892
minimum	0.0%	-1.5259

Moments

Mean	-0.000
Std Dev	0.525
Std Err Mean	0.014
upper 95% Mean	0.027
lower 95% Mean	-0.027
N	1506.000
Sum Wgts	1506.000

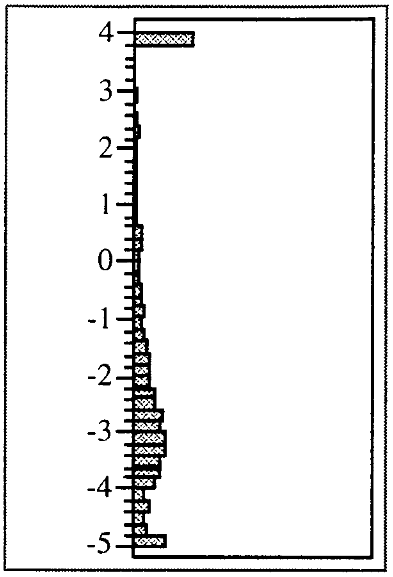
Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.860851	0.0000

Figure 23. Comparison of the Residual HC Emissions from the Linear and Log-linear Mileage Accumulation Models for LDGV of Technology Group 12.

Residuals COFTP



Quantiles

maximum	100.0%	238.38
	99.5%	77.28
	97.5%	18.12
	90.0%	3.89
quartile	75.0%	-0.38
median	50.0%	-2.50
quartile	25.0%	-3.48
	10.0%	-4.38
	2.5%	-5.35
	0.5%	-5.97
minimum	0.0%	-6.65

Moments

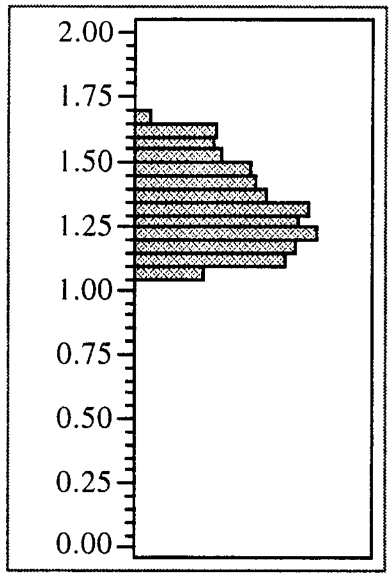
Mean	-0.000
Std Dev	12.306
Std Err Mean	0.317
upper 95% Mean	0.622
lower 95% Mean	-0.622
N	1506.000
Sum Wgts	1506.000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.313649	0.0000

Predicted Ln COFTP



Quantiles

maximum	100.0%	1.6661
	99.5%	1.6563
	97.5%	1.6375
	90.0%	1.5621
quartile	75.0%	1.4481
median	50.0%	1.3143
quartile	25.0%	1.2004
	10.0%	1.1310
	2.5%	1.0849
	0.5%	1.0739
minimum	0.0%	1.0718

Moments

Mean	1.329
Std Dev	0.158
Std Err Mean	0.004
upper 95% Mean	1.337
lower 95% Mean	1.321
N	1506.000
Sum Wgts	1506.000

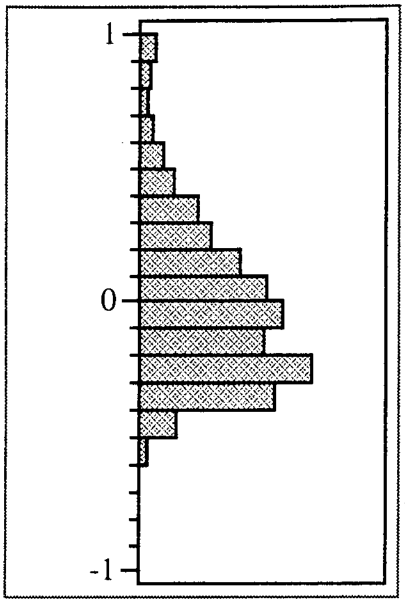
Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.940327	0.0000

Figure 24. Comparison of the Residual CO Emissions from the Linear and Log-linear Mileage Accumulation Models for LDGV of Technology Group 12

Residuals NOxFTP



Quantiles

maximum	100.0%	2.1619
	99.5%	1.4709
	97.5%	0.8053
	90.0%	0.4149
quartile	75.0%	0.1612
median	50.0%	-0.0527
quartile	25.0%	-0.2437
	10.0%	-0.3385
	2.5%	-0.4348
	0.5%	-0.5127
minimum	0.0%	-0.6119

Moments

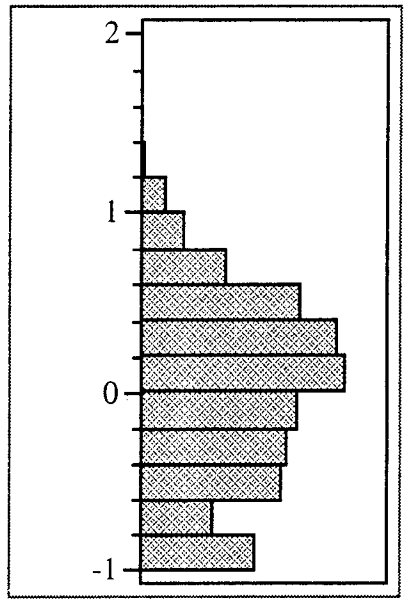
Mean	0.000
Std Dev	0.329
Std Err Mean	0.008
upper 95% Mean	0.017
lower 95% Mean	-0.017
N	1506.000
Sum Wgts	1506.000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.903584	0.0000

Residuals Ln NOxFTP



Quantiles

maximum	100.0%	1.7075
	99.5%	1.2952
	97.5%	0.9712
	90.0%	0.6399
quartile	75.0%	0.3771
median	50.0%	0.0435
quartile	25.0%	-0.3897
	10.0%	-0.7590
	2.5%	-1.0105
	0.5%	-1.2077
minimum	0.0%	-1.5330

Moments

Mean	0.000
Std Dev	0.528
Std Err Mean	0.014
upper 95% Mean	0.027
lower 95% Mean	-0.027
N	1506.000
Sum Wgts	1506.000

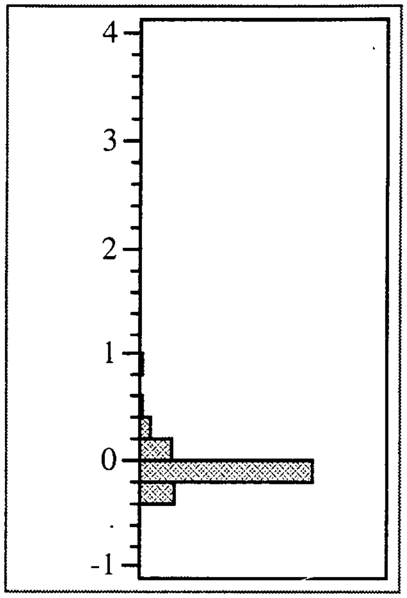
Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.979670	0.0000

Figure 25. Comparison of the Residual NO_x Emissions from the Linear and Log-linear Mileage Accumulation Models for LDGV of Technology Group 12.

Residuals HCFTP



Quantiles

maximum	100.0%	7.5469
	99.5%	3.7966
	97.5%	0.9836
	90.0%	0.1804
quartile	75.0%	-0.0200
median	50.0%	-0.1136
quartile	25.0%	-0.1692
	10.0%	-0.2145
	2.5%	-0.2698
	0.5%	-0.3122
minimum	0.0%	-0.3458

Moments

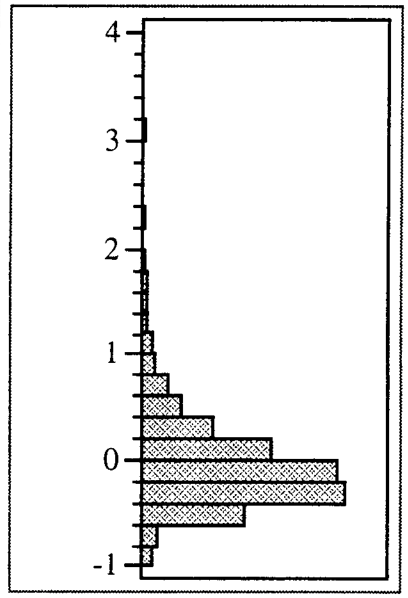
Mean	-0.0000
Std Dev	0.5646
Std Err Mean	0.0200
upper 95% Mean	0.0393
lower 95% Mean	-0.0393
N	796.0000
Sum Wgts	796.0000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.338437	0.0000

Residuals Ln HCFTP



Quantiles

maximum	100.0%	3.1927
	99.5%	2.6464
	97.5%	1.4478
	90.0%	0.5700
quartile	75.0%	0.1704
median	50.0%	-0.0998
quartile	25.0%	-0.3074
	10.0%	-0.4605
	2.5%	-0.6978
	0.5%	-1.0332
minimum	0.0%	-1.4790

Moments

Mean	0.0000
Std Dev	0.5212
Std Err Mean	0.0185
upper 95% Mean	0.0363
lower 95% Mean	-0.0363
N	796.0000
Sum Wgts	796.0000

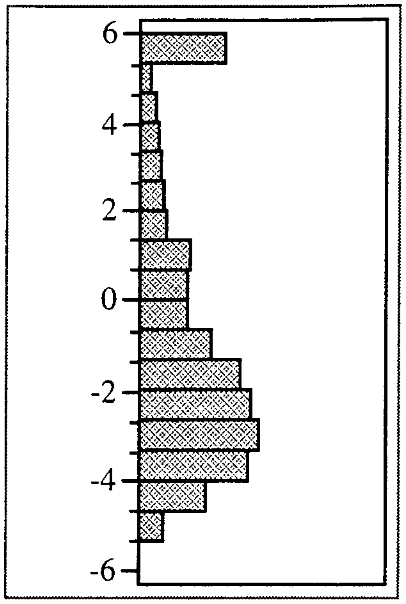
Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.843458	0.0000

Figure 26. Comparison of the Residual HC Emissions from the Linear and Log-linear Mileage Accumulation Models for LDGV of Technology Group 8.

Residuals COFTP



Quantiles

maximum	100.0%	75.916
	99.5%	44.143
	97.5%	13.095
	90.0%	4.716
quartile	75.0%	1.069
median	50.0%	-1.660
quartile	25.0%	-3.114
	10.0%	-3.976
	2.5%	-4.682
	0.5%	-5.117
minimum	0.0%	-5.383

Moments

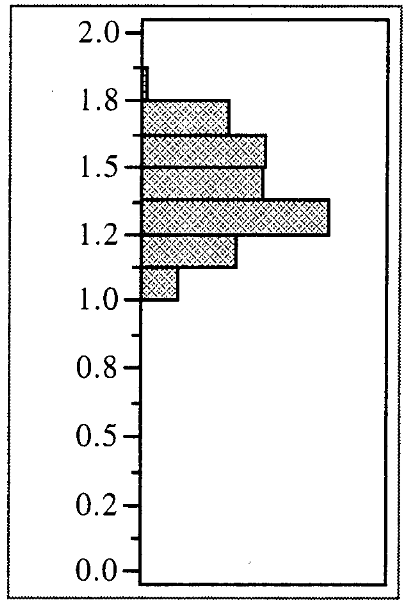
Mean	0.0000
Std Dev	6.4459
Std Err Mean	0.2285
upper 95% Mean	0.4485
lower 95% Mean	-0.4485
N	796.0000
Sum Wgts	796.0000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.566402	0.0000

Predicted Ln COFTP



Quantiles

maximum	100.0%	1.7639
	99.5%	1.7601
	97.5%	1.7336
	90.0%	1.6621
quartile	75.0%	1.5511
median	50.0%	1.3859
quartile	25.0%	1.2687
	10.0%	1.2046
	2.5%	1.0842
	0.5%	1.0528
minimum	0.0%	1.0402

Moments

Mean	1.4071
Std Dev	0.1765
Std Err Mean	0.0063
upper 95% Mean	1.4193
lower 95% Mean	1.3948
N	796.0000
Sum Wgts	796.0000

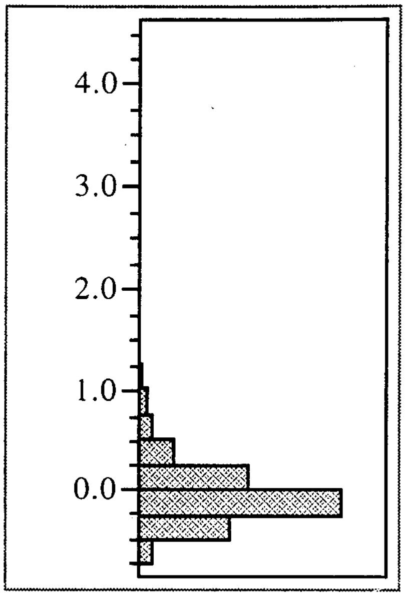
Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.949992	0.0000

Figure 27. Comparison of the Residual CO Emissions from the Linear and Log-Linear Mileage Accumulation Models for LDGV of Technology Group 8.

Residuals NOxFTP



Quantiles

maximum	100.0%	4.4958
	99.5%	2.8581
	97.5%	0.9620
	90.0%	0.3550
quartile	75.0%	0.1233
median	50.0%	-0.0773
quartile	25.0%	-0.2258
	10.0%	-0.3452
	2.5%	-0.5067
	0.5%	-0.6297
minimum	0.0%	-0.6482

Moments

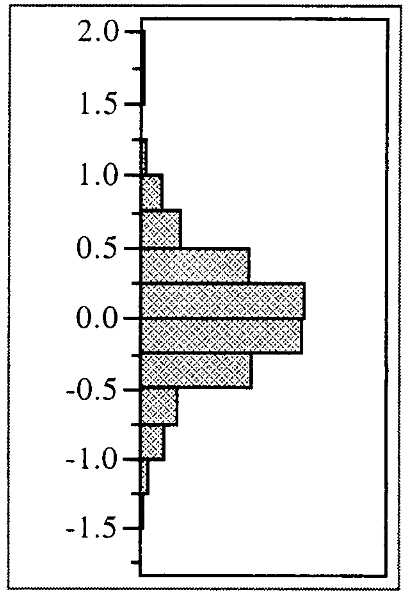
Mean	0.0000
Std Dev	0.4419
Std Err Mean	0.0157
upper 95% Mean	0.0307
lower 95% Mean	-0.0307
N	796.0000
Sum Wgts	796.0000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.690984	0.0000

Residuals Ln NOxFTP



Quantiles

maximum	100.0%	1.9977
	99.5%	1.7082
	97.5%	0.9709
	90.0%	0.5152
quartile	75.0%	0.2692
median	50.0%	0.0012
quartile	25.0%	-0.2736
	10.0%	-0.5157
	2.5%	-0.8936
	0.5%	-1.3146
minimum	0.0%	-1.7047

Moments

Mean	0.0000
Std Dev	0.4570
Std Err Mean	0.0162
upper 95% Mean	0.0318
lower 95% Mean	-0.0318
N	796.0000
Sum Wgts	796.0000

Test for Normality

Shapiro-Wilk W Test

W	Prob<W
0.973780	0.0000

Figure 28. Comparison of the Residual NO_x Emissions from the Linear and Log-Linear Mileage Accumulation Models for LDGV of Technology Group 8.

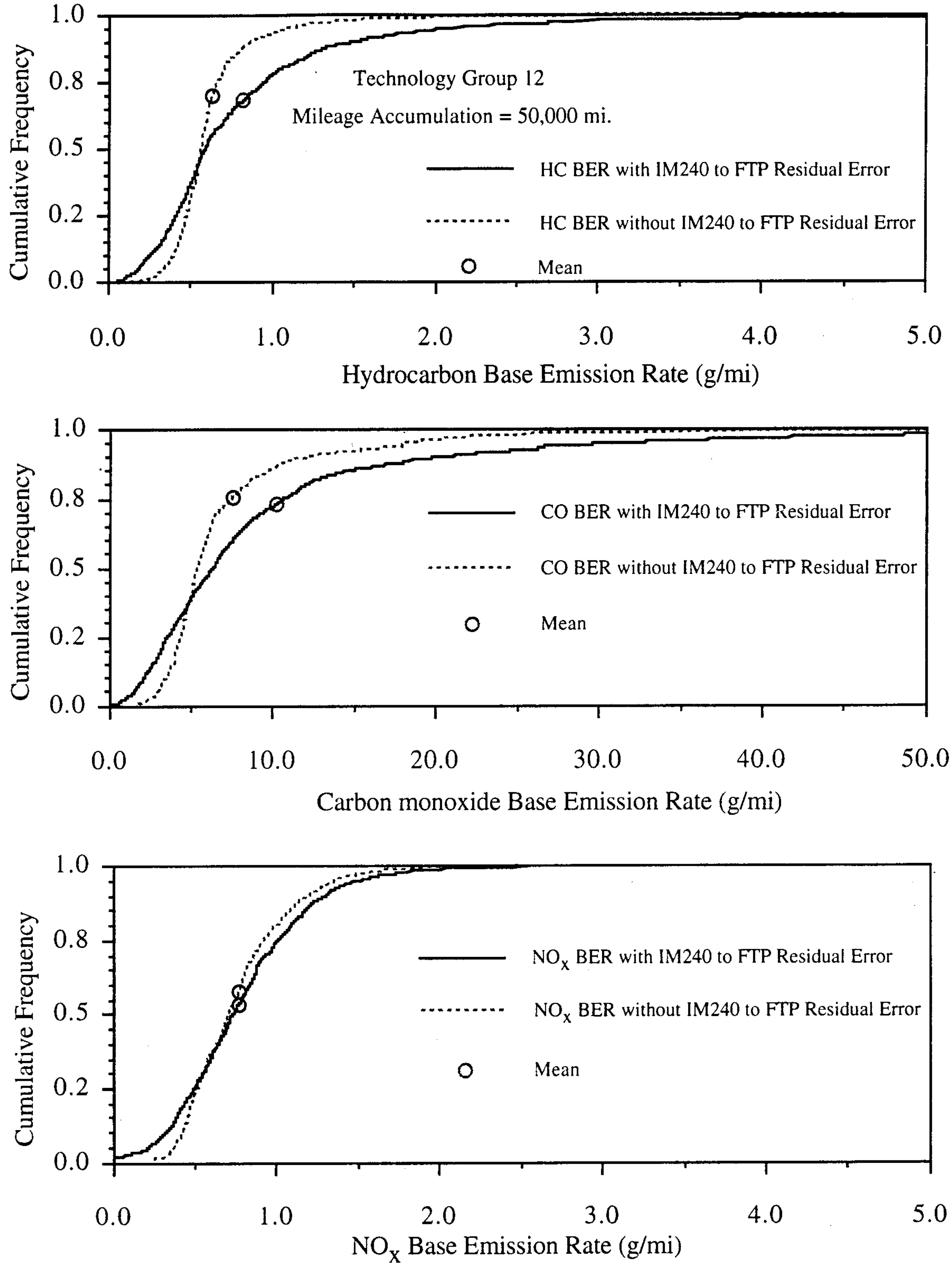


Figure 29. Comparison of Base Emission Rates with and without IM240 to FTP Residual Error using a Linear Model for LDGV of Technology Group 12.

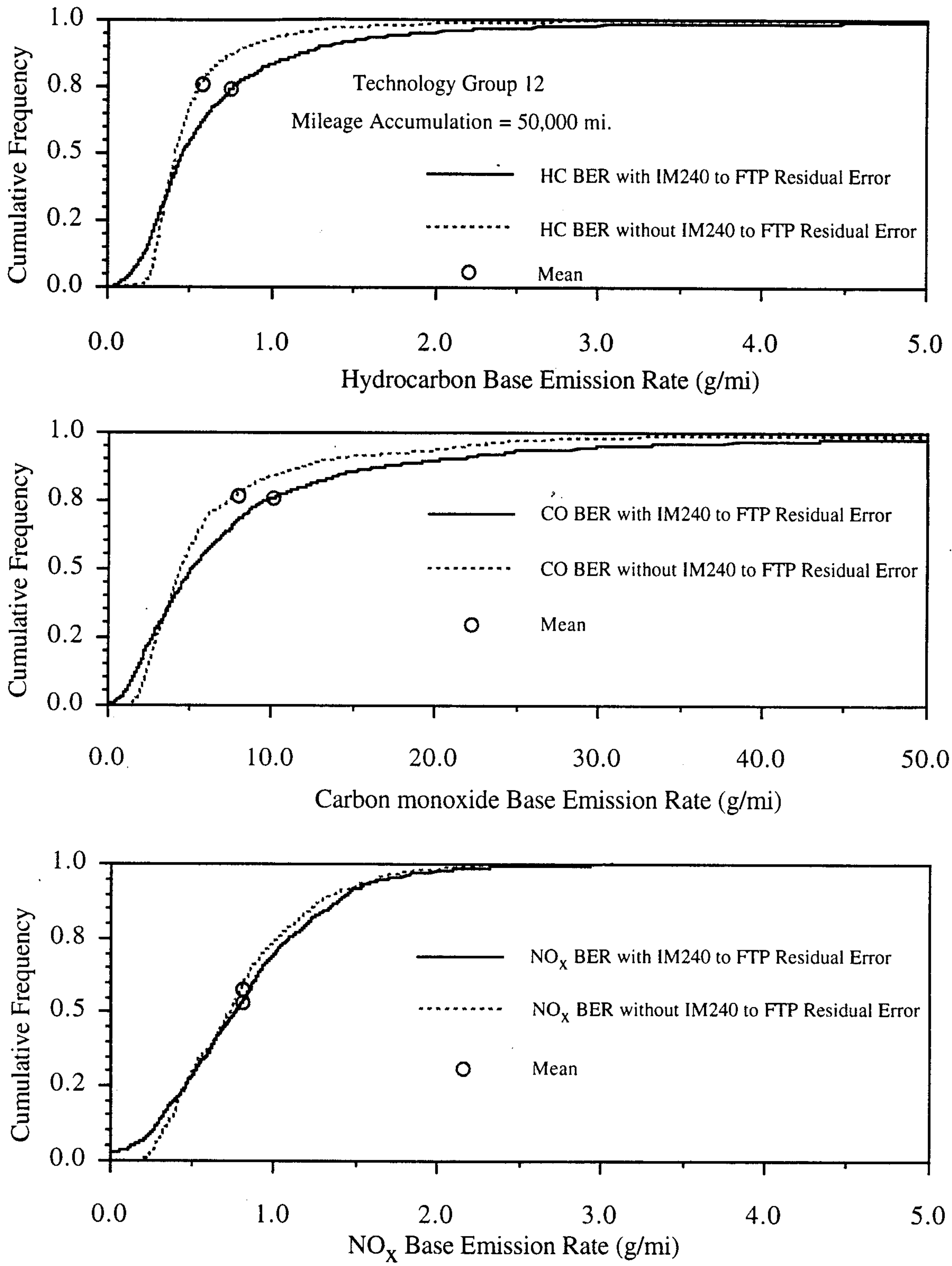


Figure 30. Comparison of Base Emission Rates with and without IM240 to FTP Residual Error using a Log-Linear Model for LDGV of Technology Group 12.

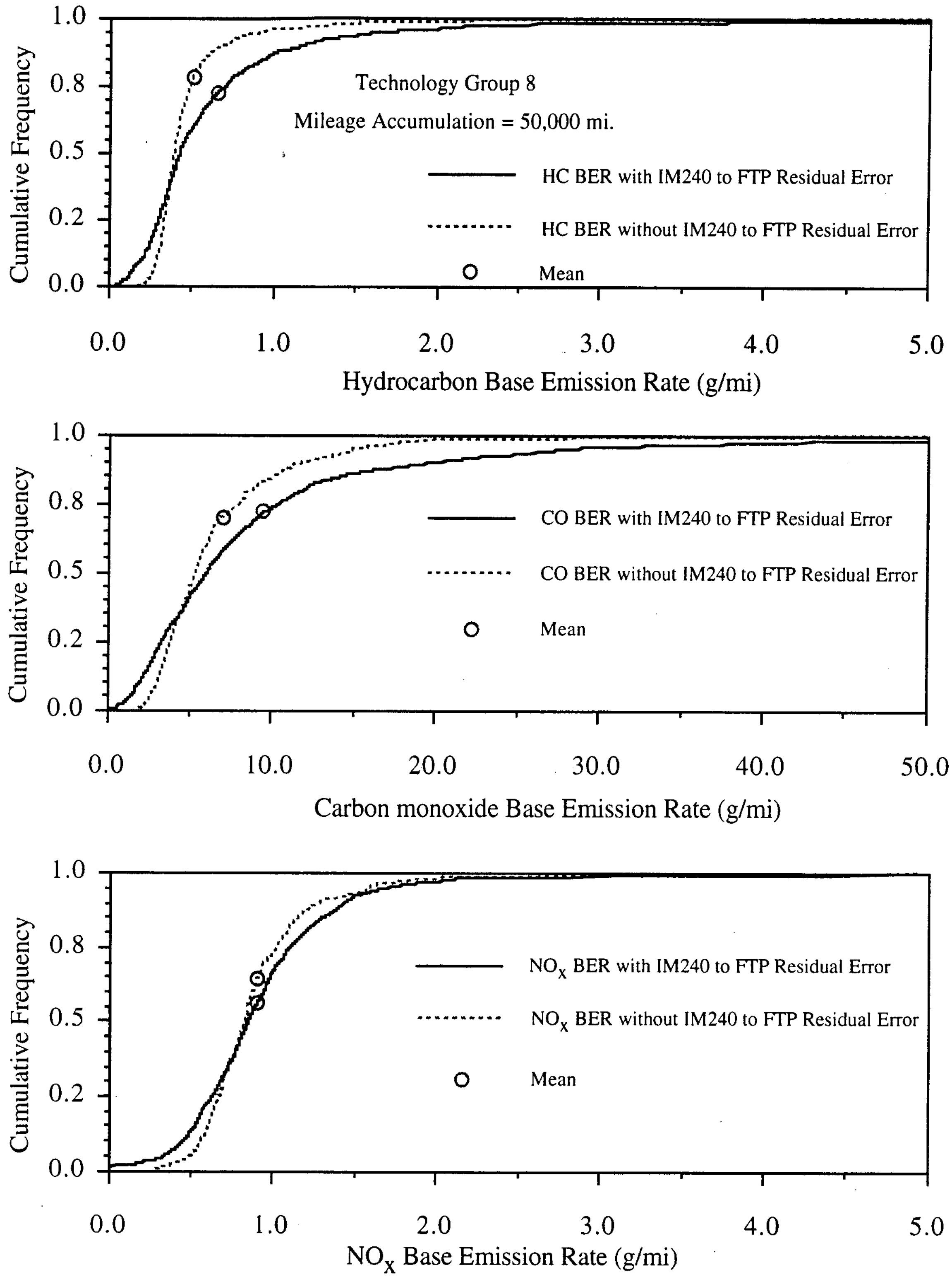


Figure 31. Comparison of Base Emission Rates with and without IM240 to FTP Residual Error using a Linear Model for LDGV of Technology Group 8.

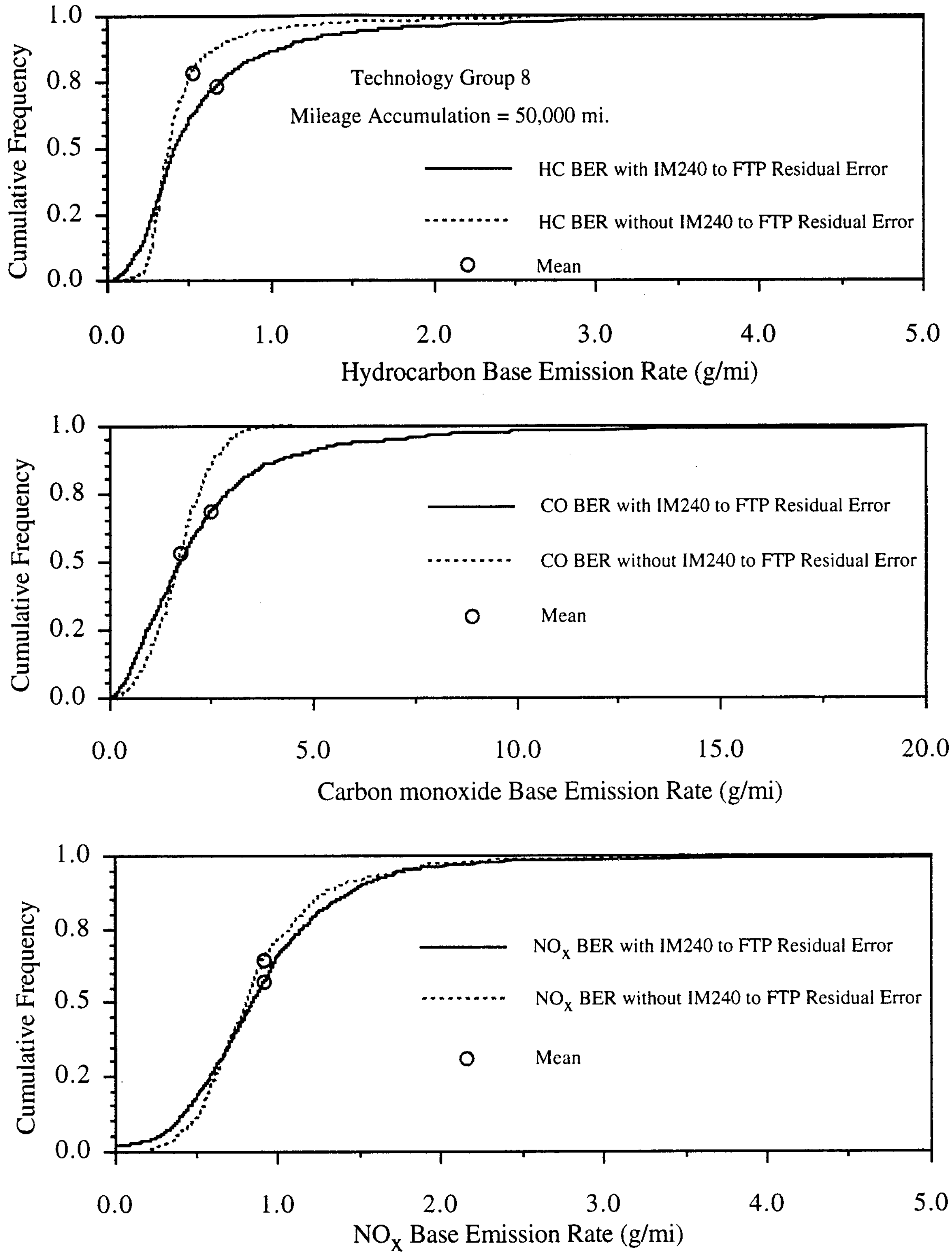


Figure 32. Comparison of Base Emission Rates with and without IM240 to FTP Residual Error using a Log-Linear Model for LDGV of Technology Group 8.

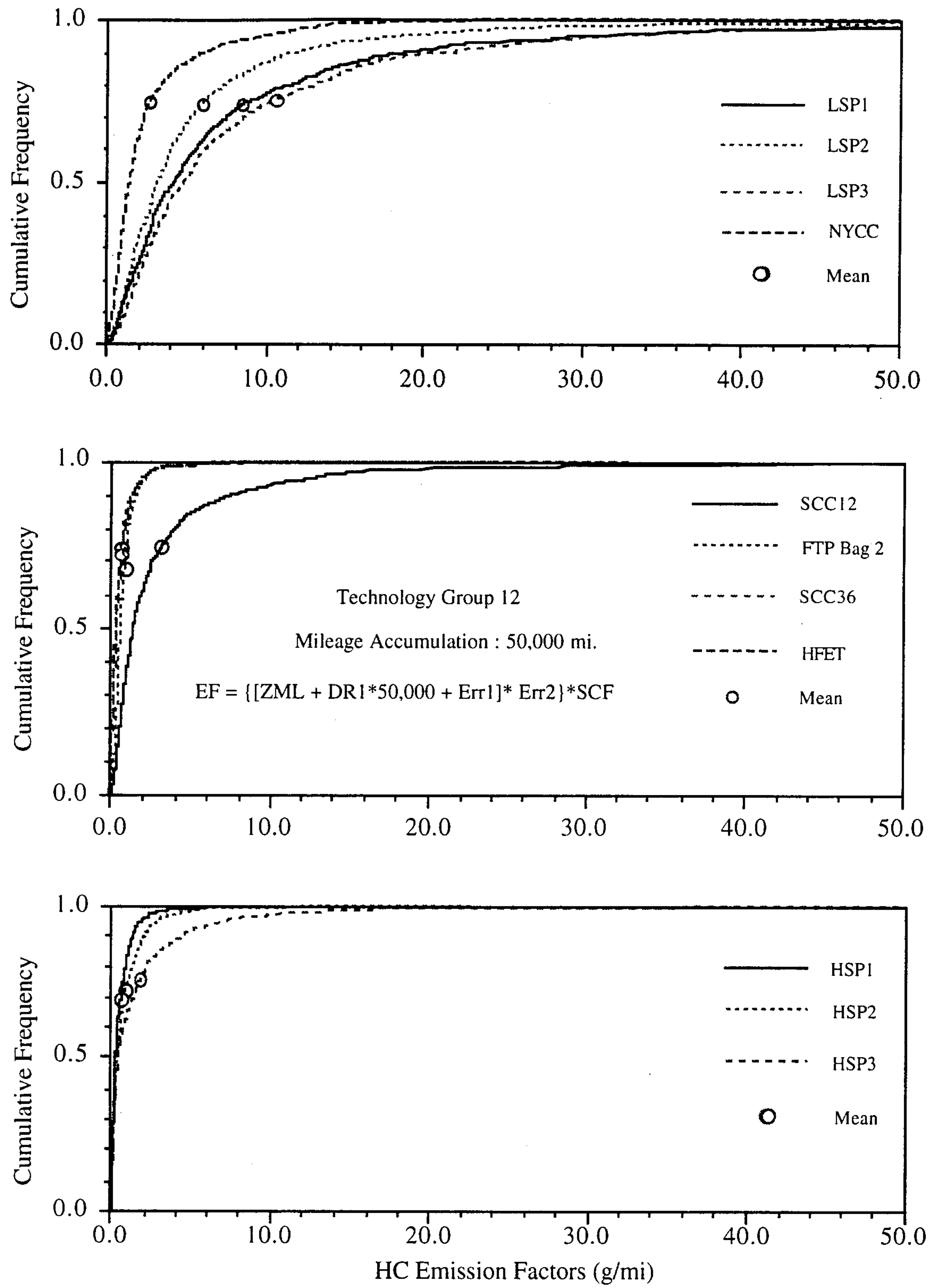


Figure 33. Predicted Variability in the HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear Model.

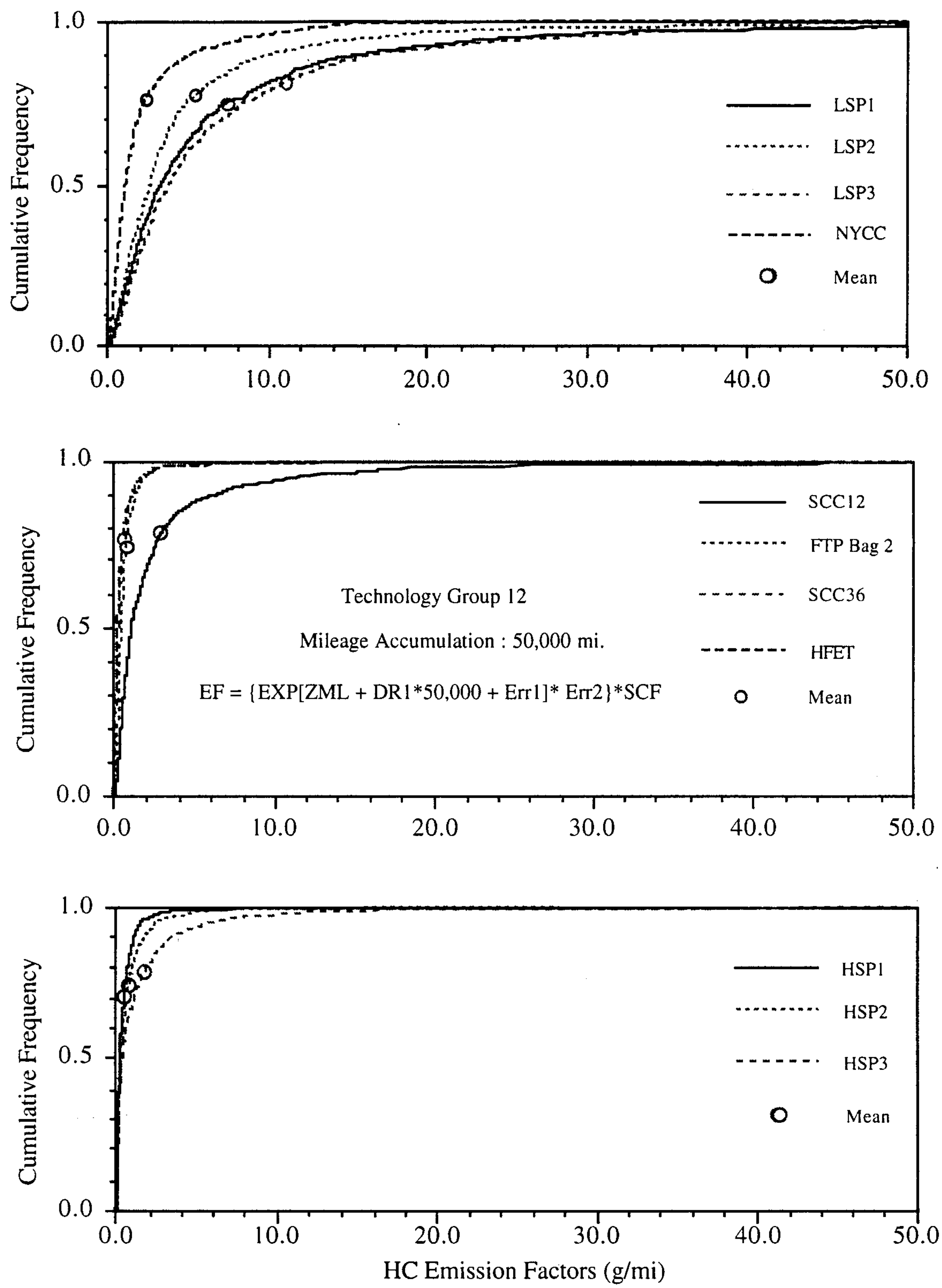


Figure 34. Predicted Variability in the HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Log-Linear Model.

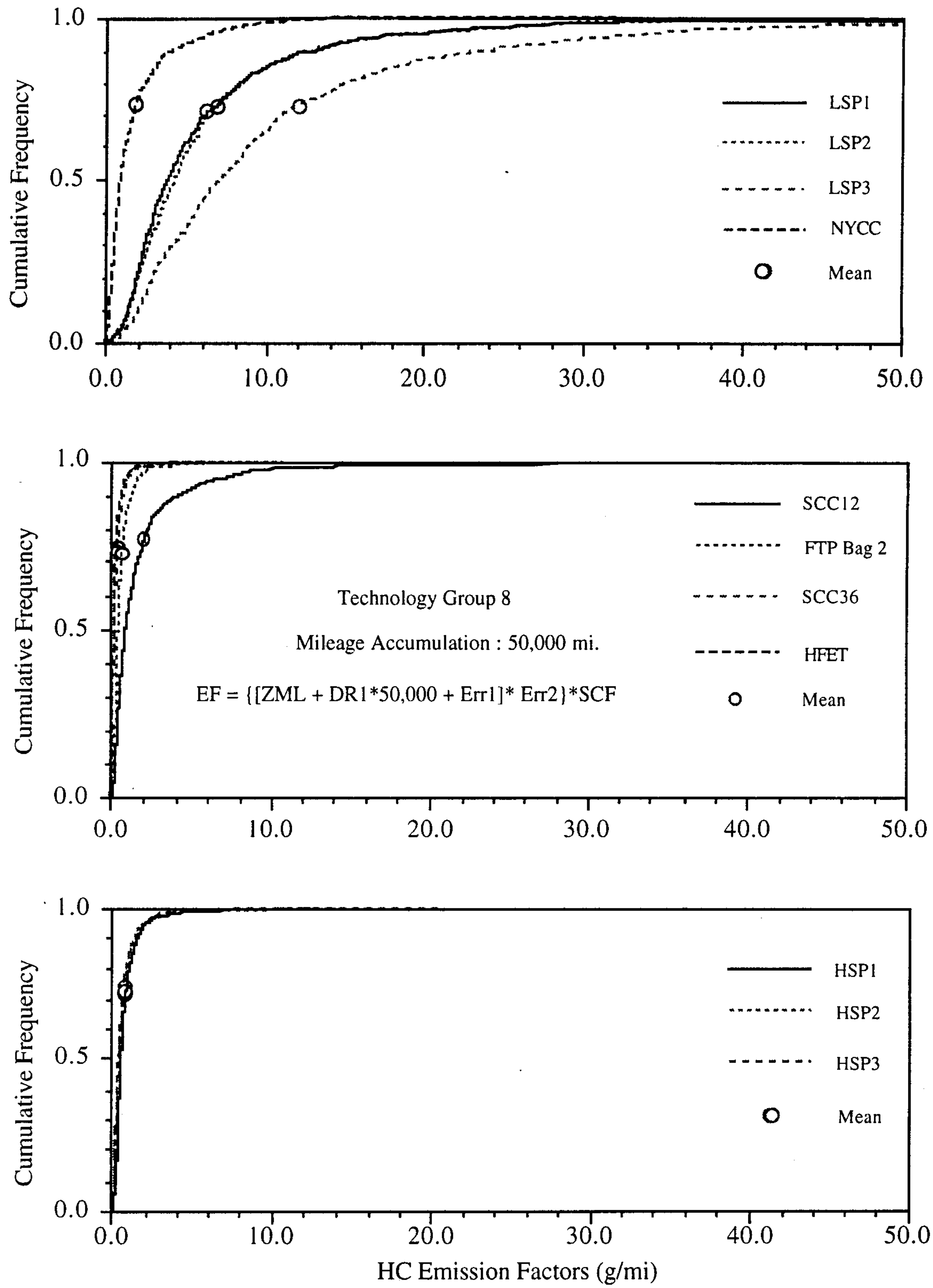


Figure 35. Predicted Variability in the HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear Model.

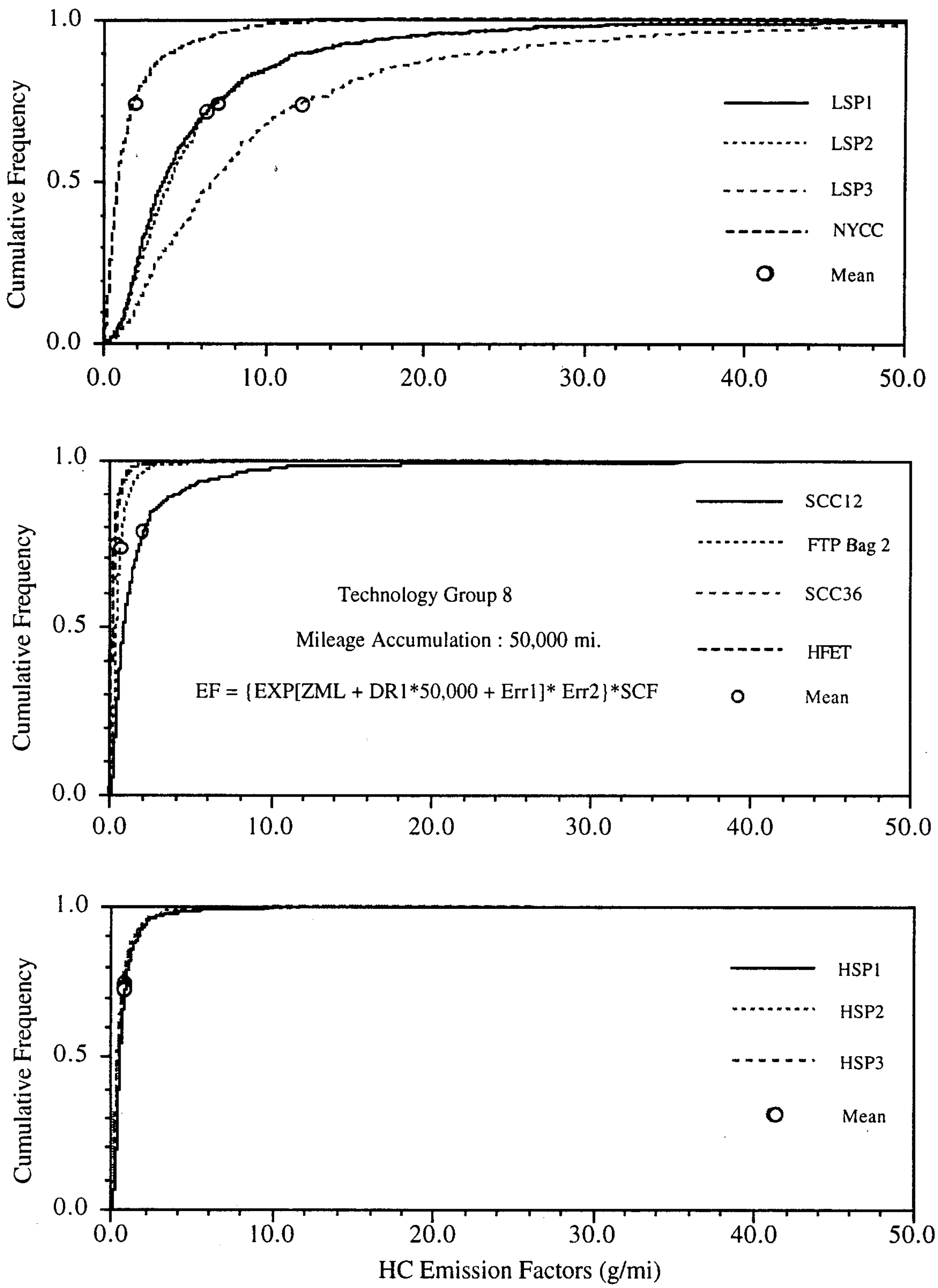


Figure 36. Predicted Variability in the HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Log-Linear Model.

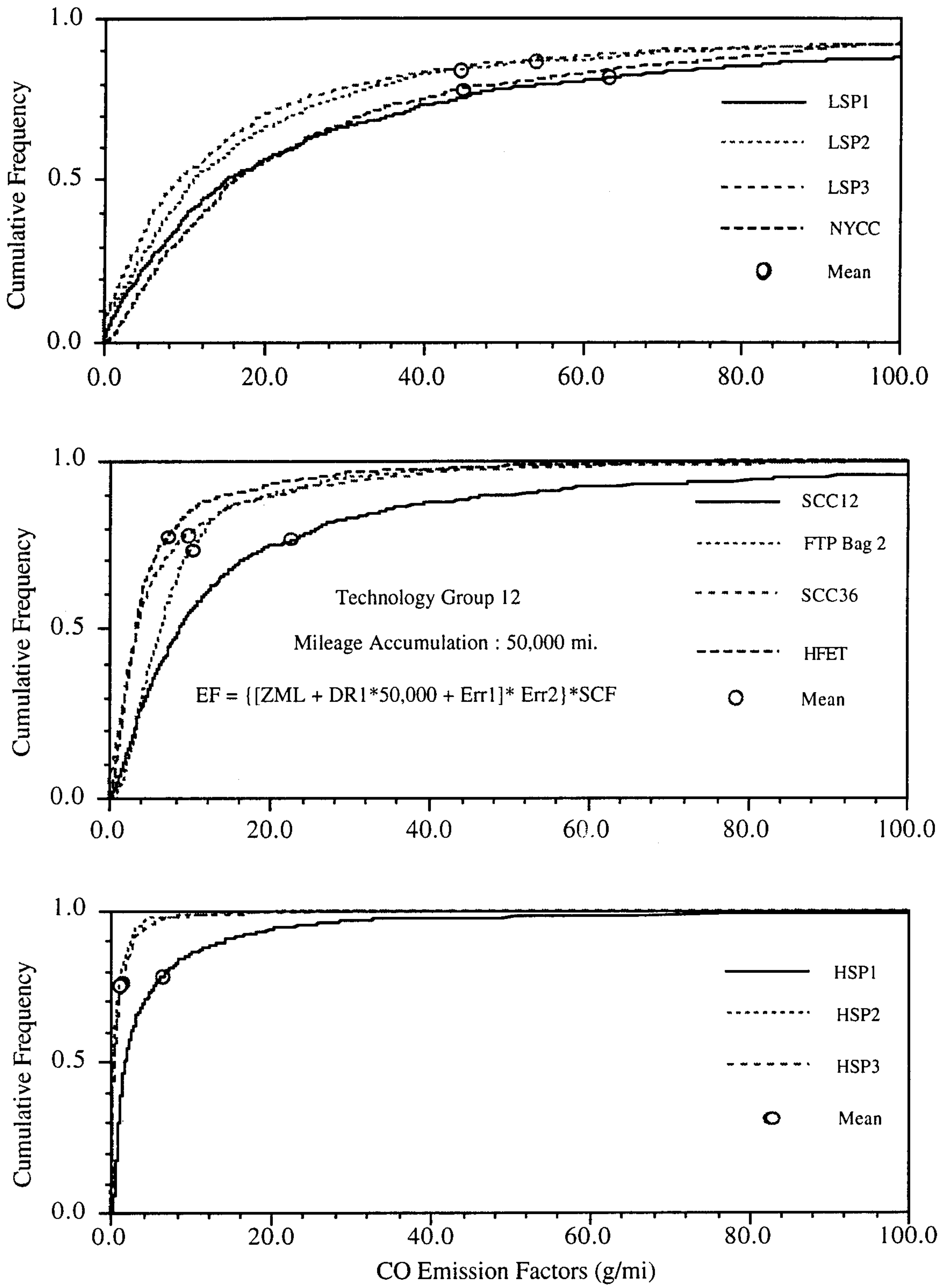


Figure 37. Predicted Variability in the CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear Model.

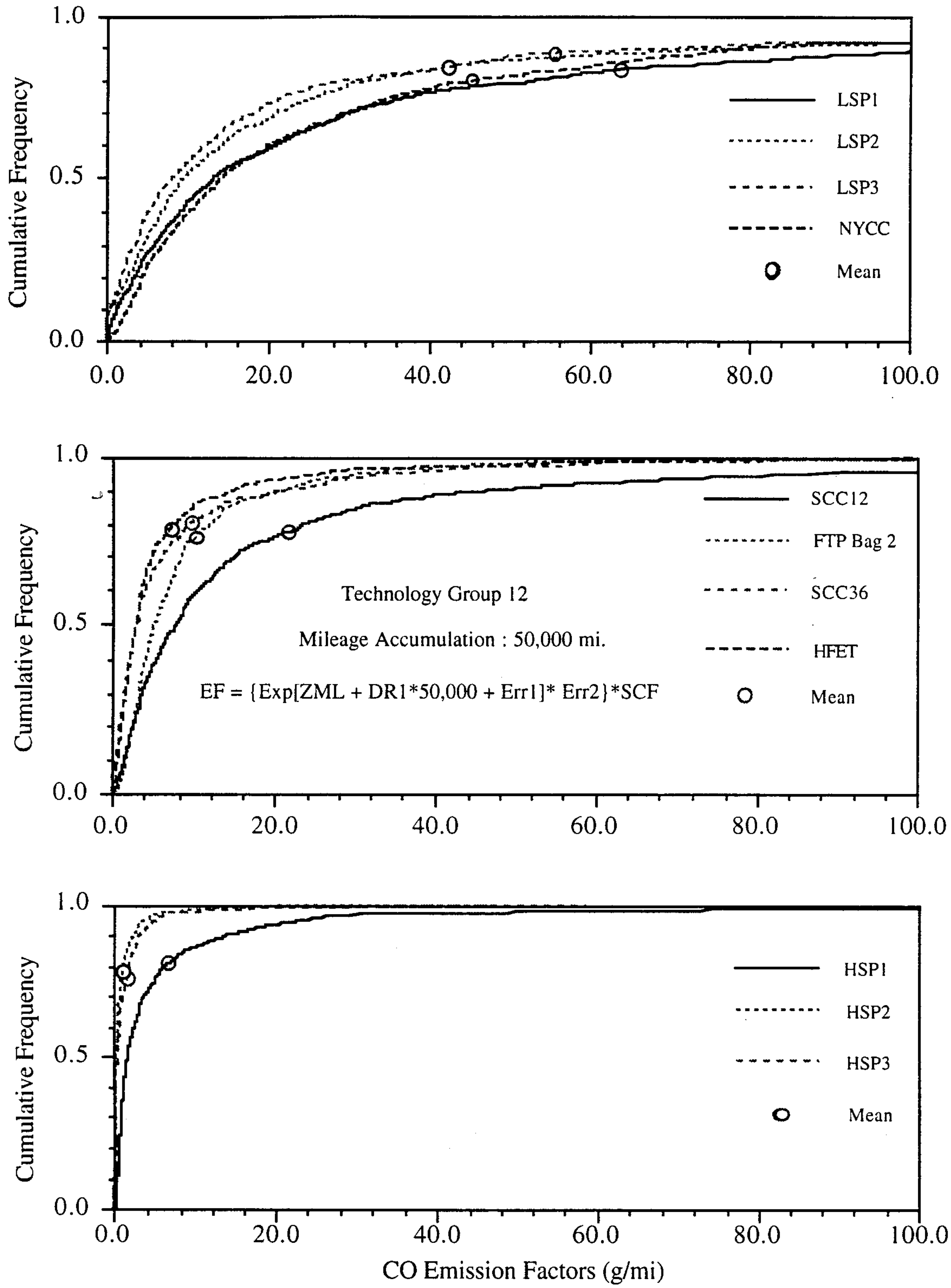


Figure 38. Predicted Variability in the CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Log-Linear Model.

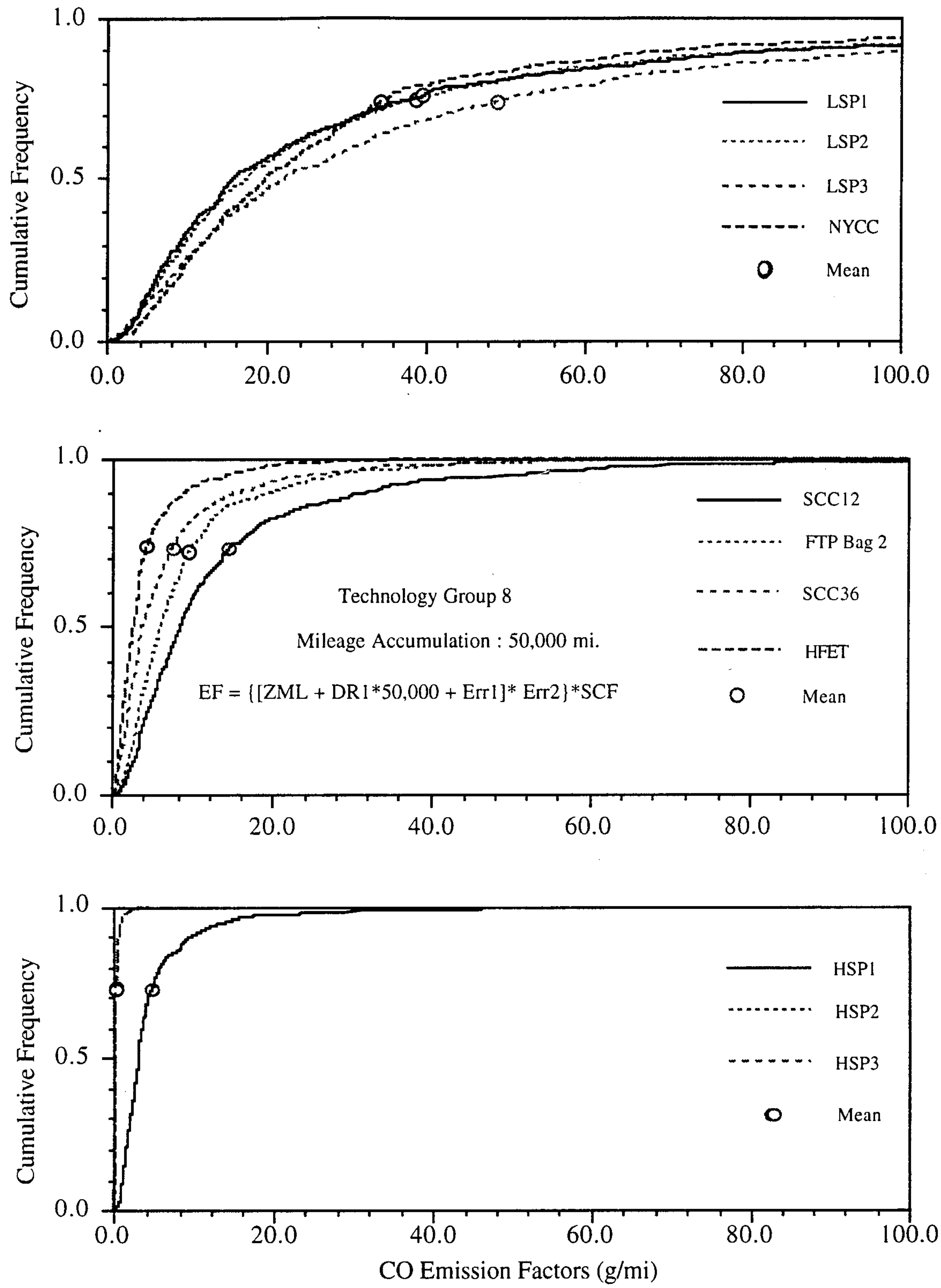


Figure 39. Predicted Variability in the CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear Model.

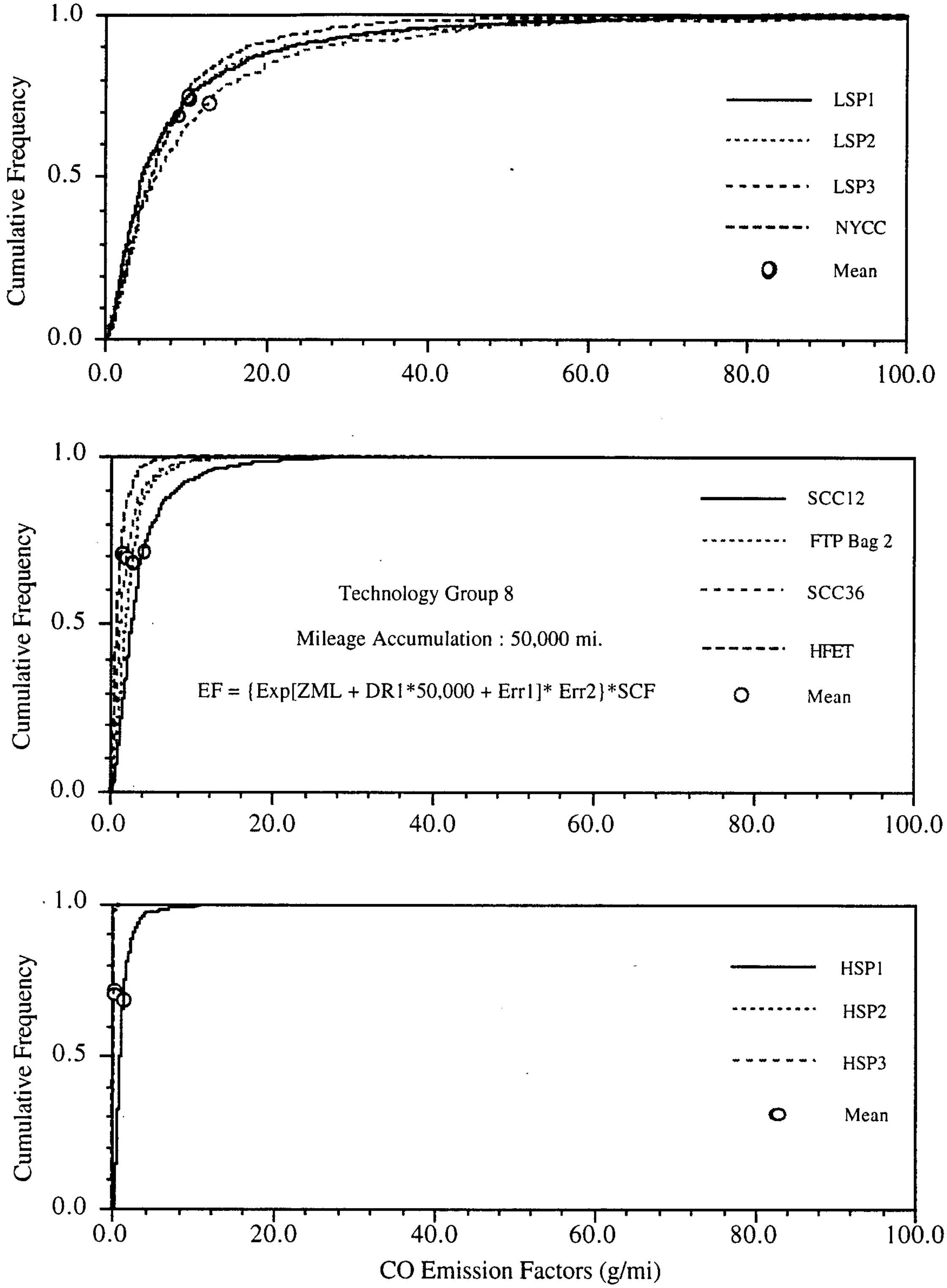


Figure 40. Predicted Variability in the CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Log-Linear Model

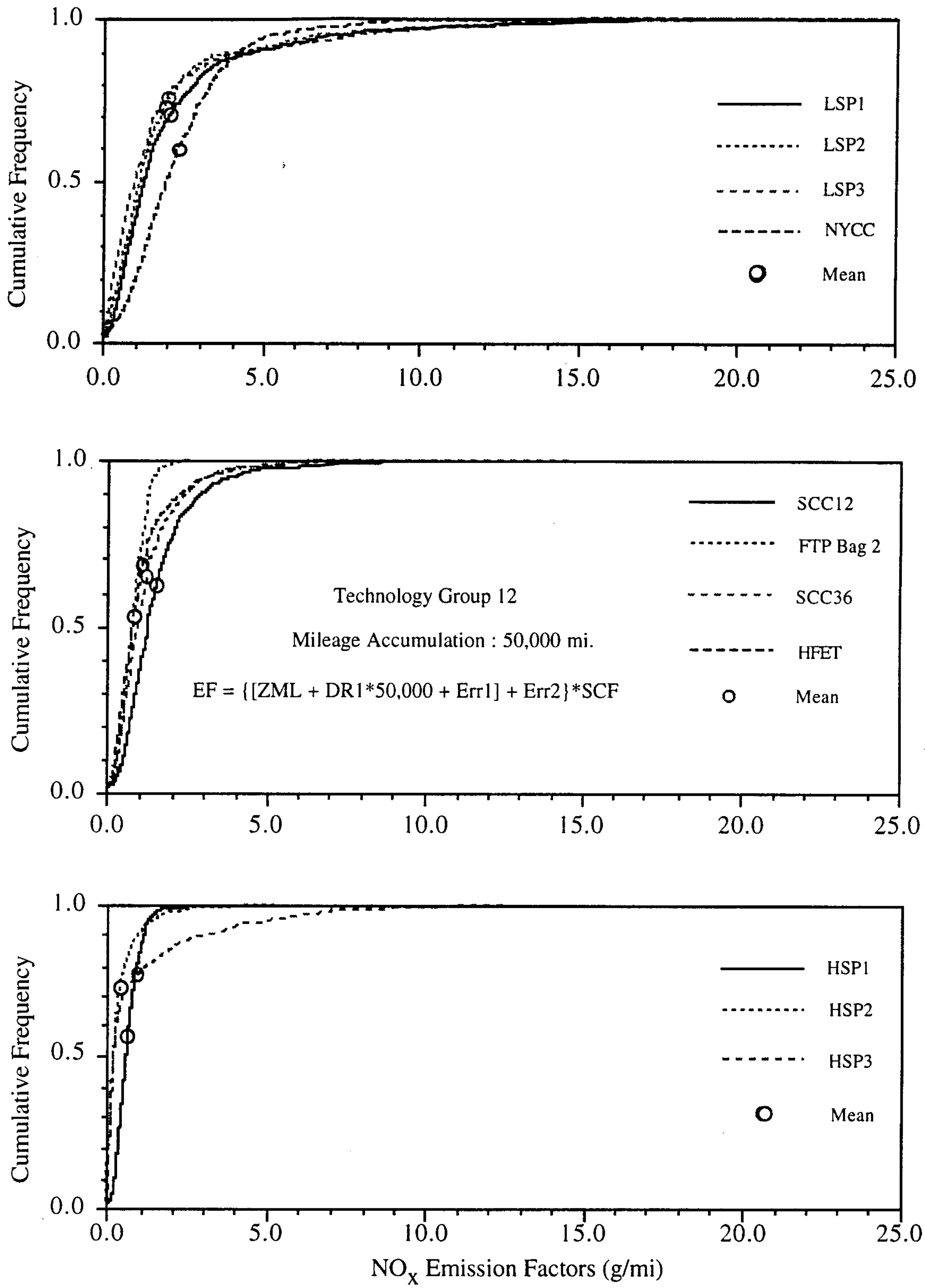


Figure 41. Predicted Variability in the NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear Model.

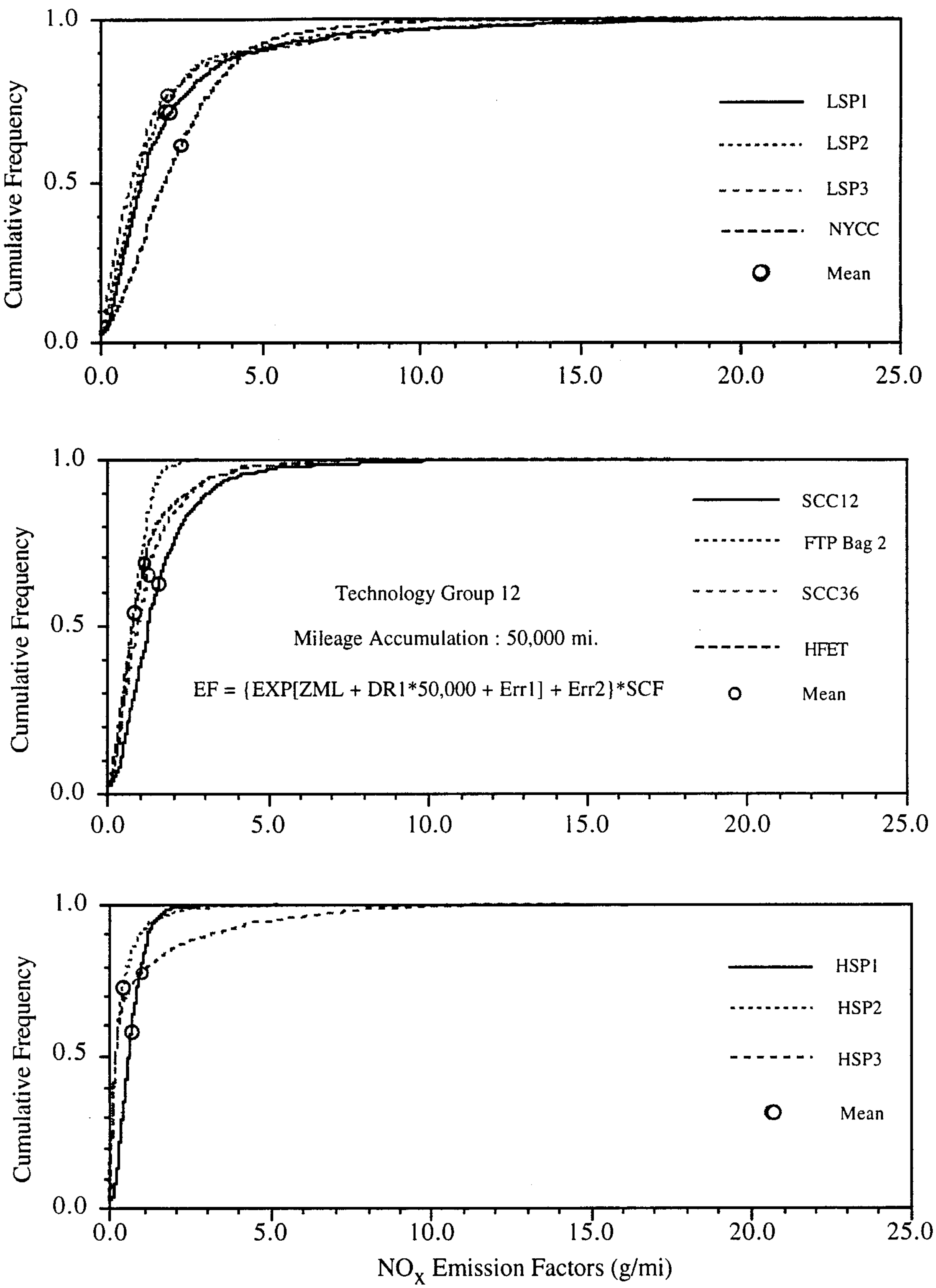


Figure 42. Predicted Variability in the NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Log-Linear Model

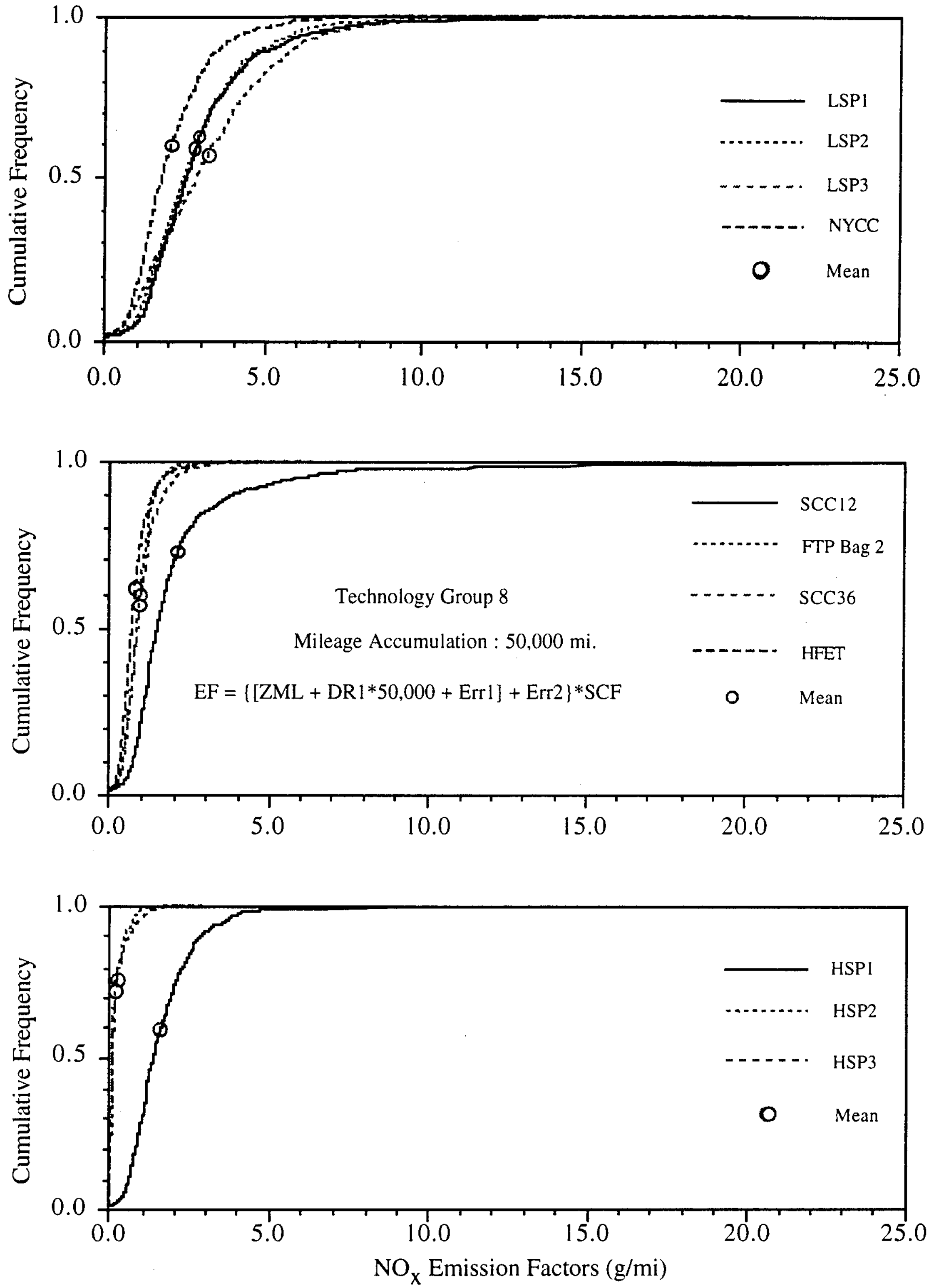


Figure 43. Predicted Variability in the NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear Model.

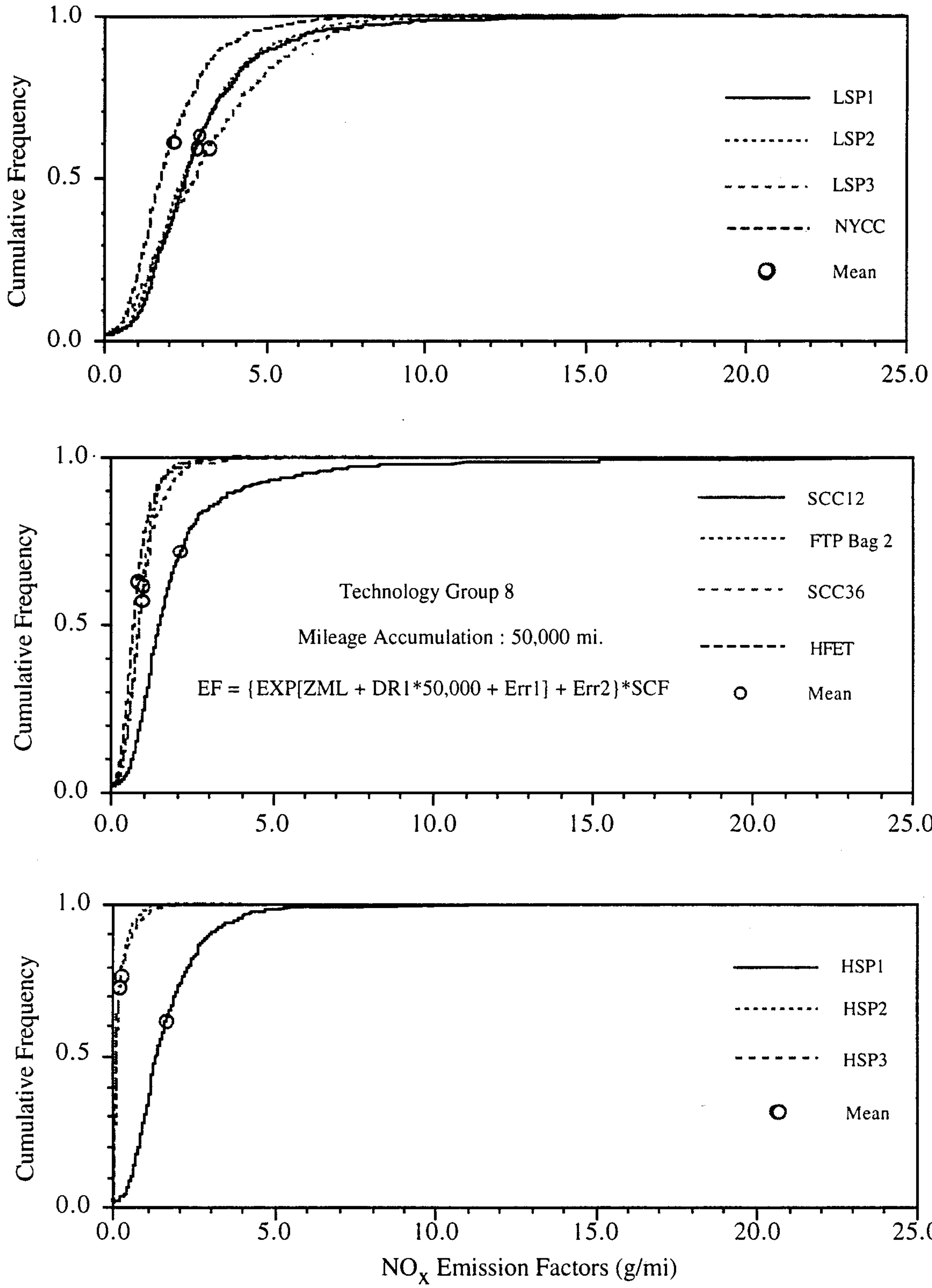
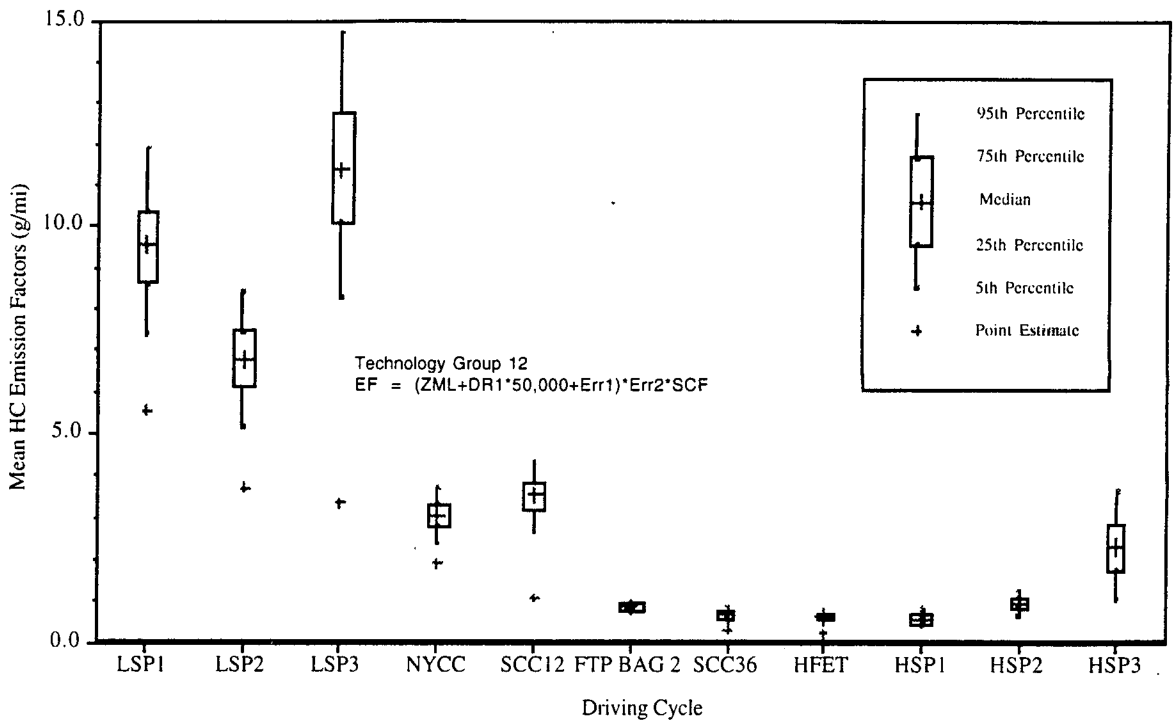


Figure 44. Predicted Variability in the NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Log-Linear Model.



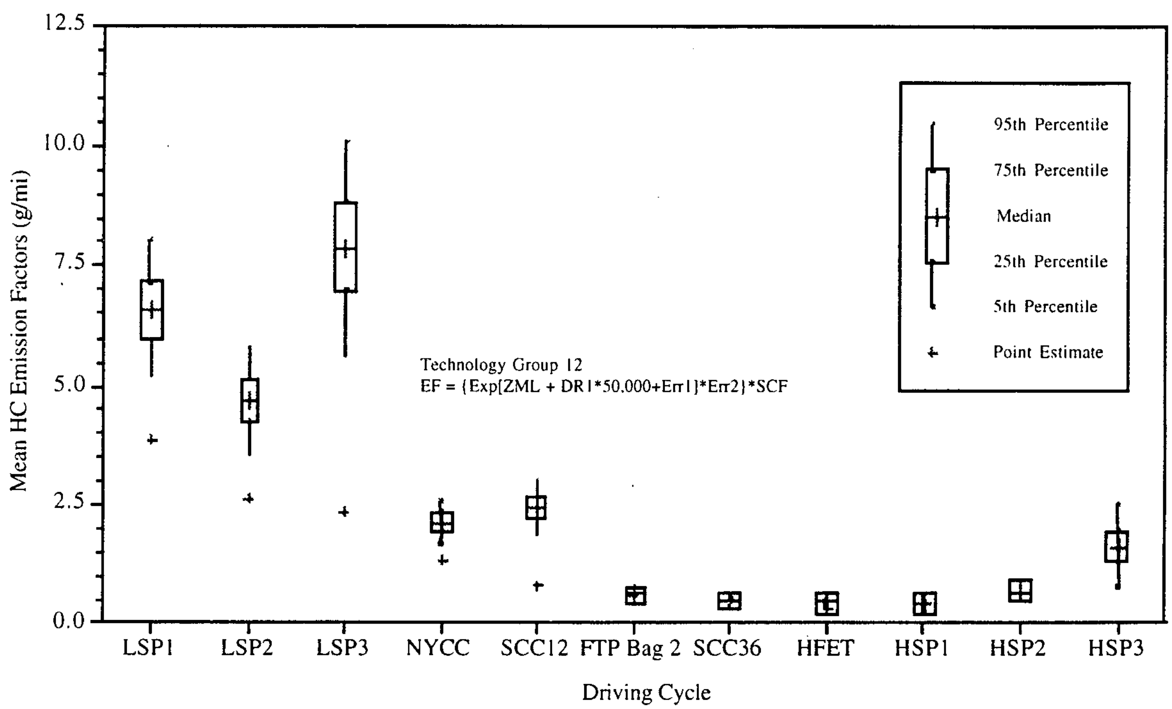
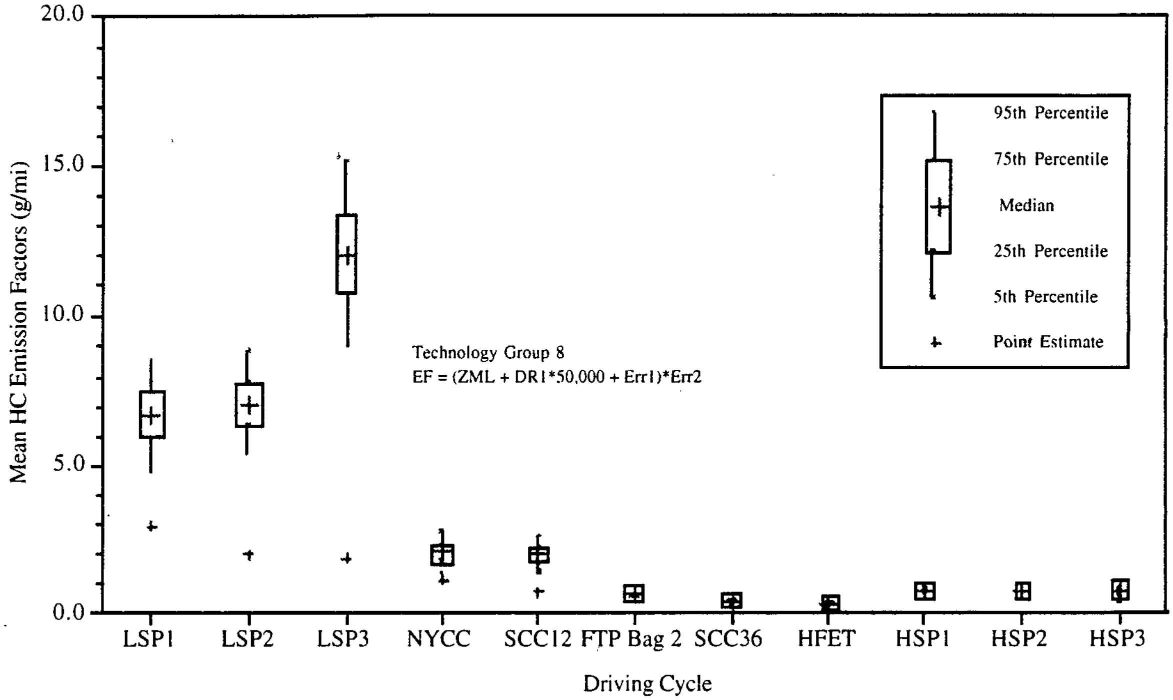


Figure 45. Predicted Uncertainty in the Mean HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear and a Log-Linear Model.



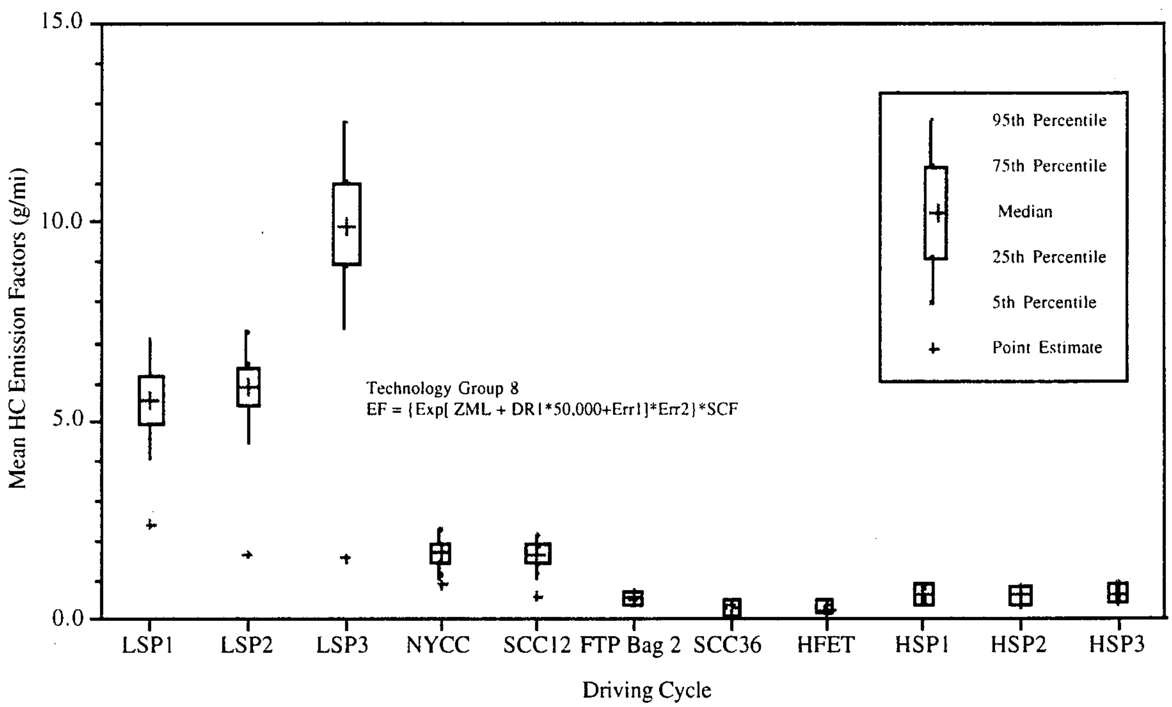
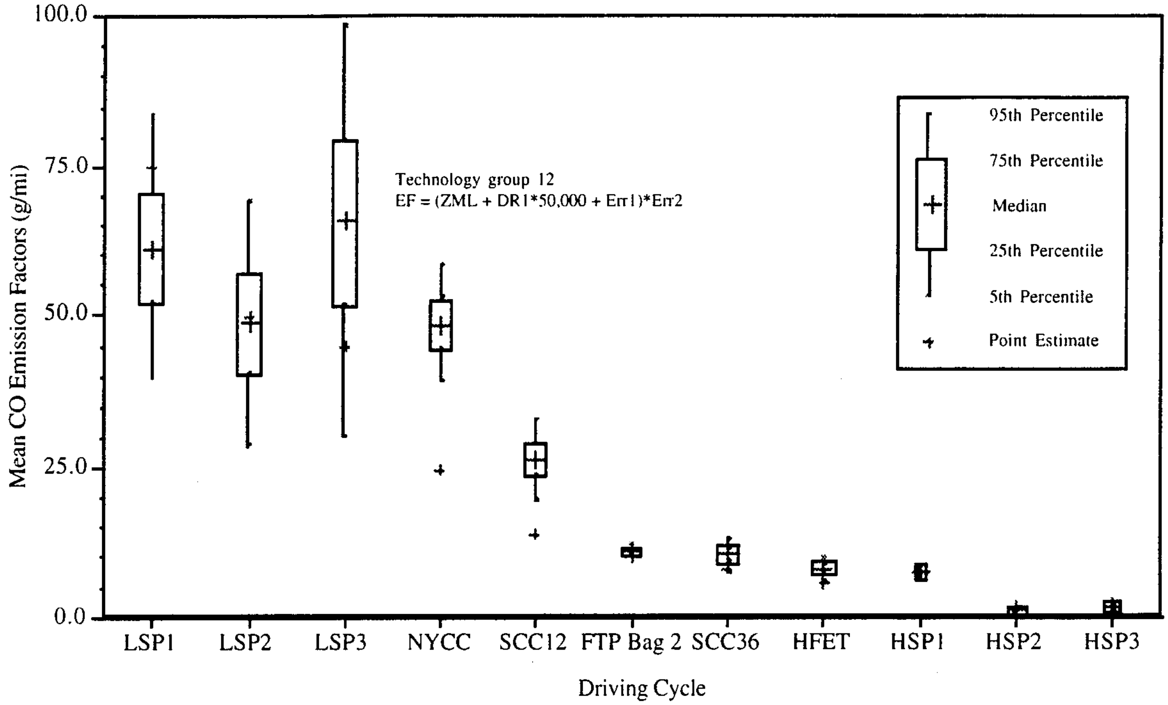


Figure 46. Predicted Uncertainty in the Mean HC Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear and a Log-Linear Model.



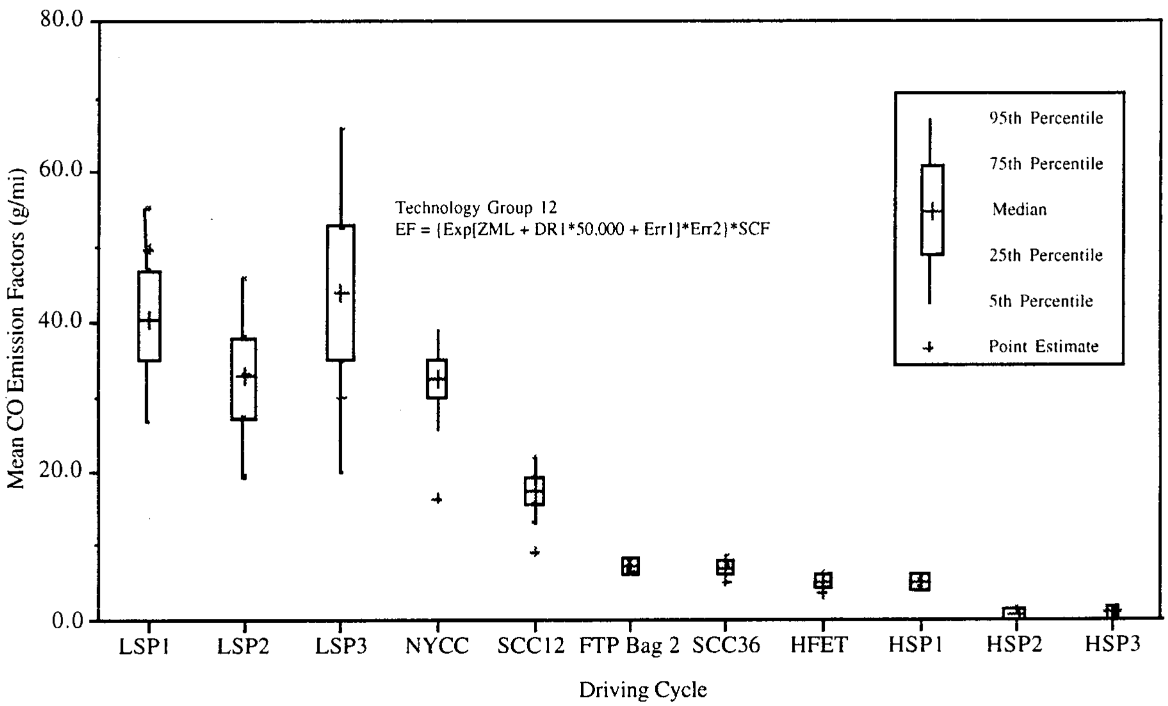
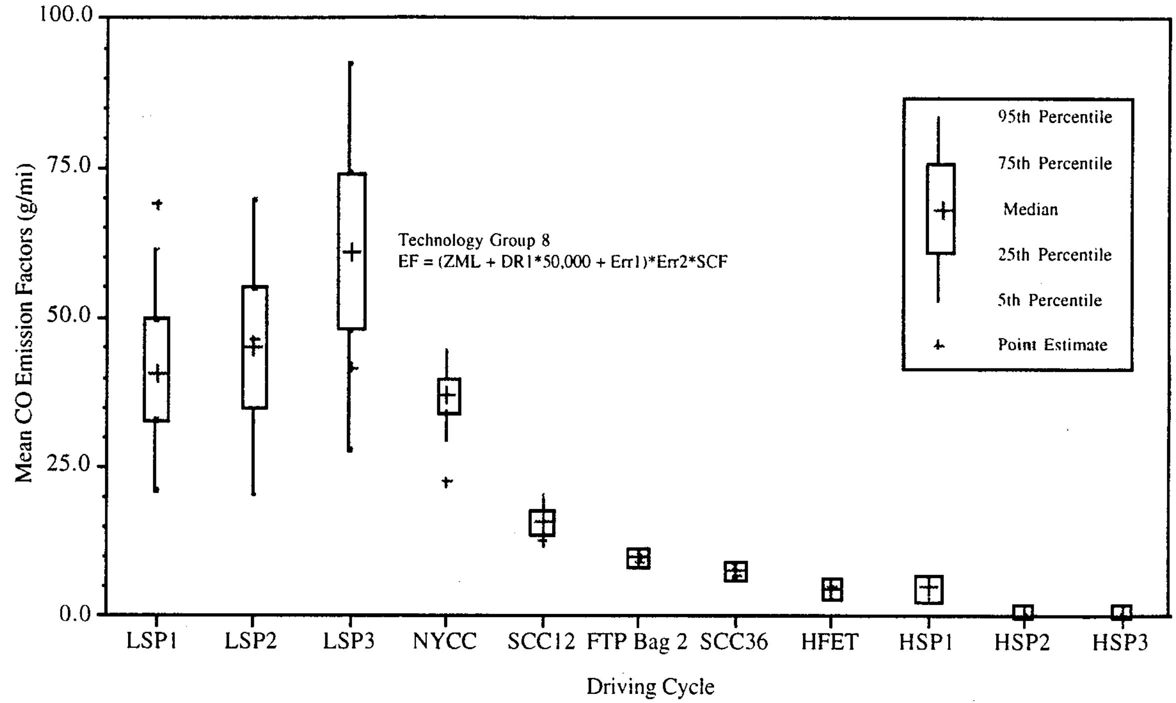


Figure 47. Predicted Uncertainty in the Mean CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear and a Log-Linear Model.



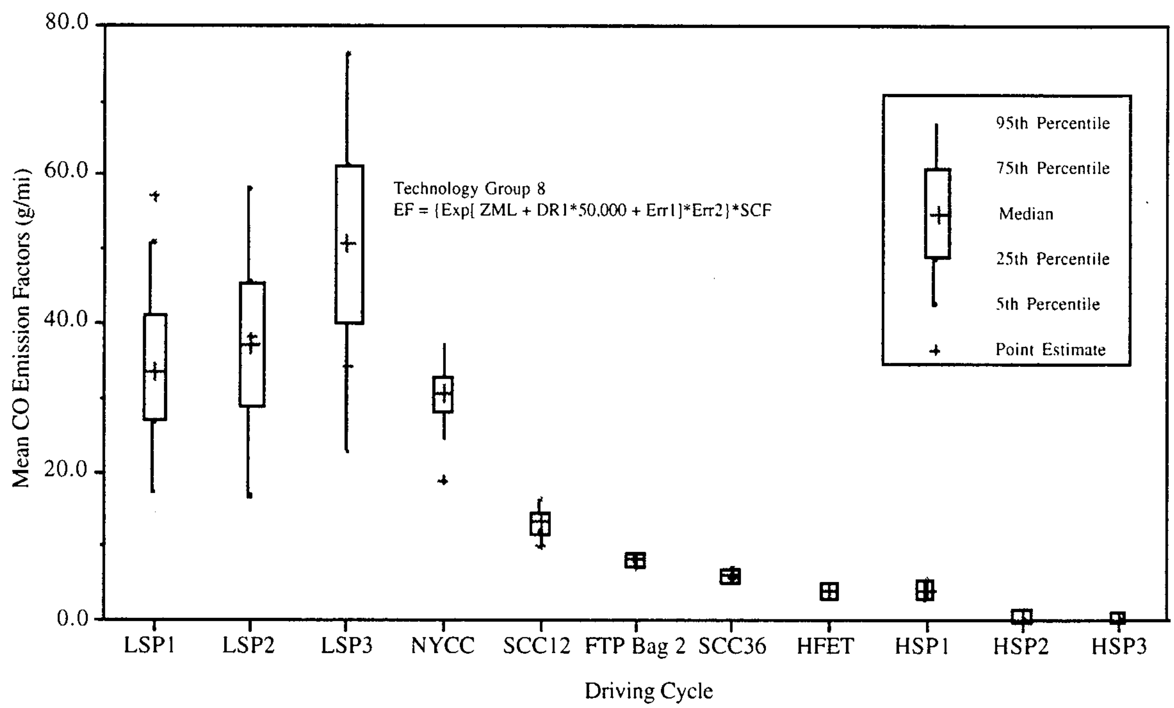


Figure 48. Predicted Uncertainty in the Mean CO Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear and a Log-Linear Model.

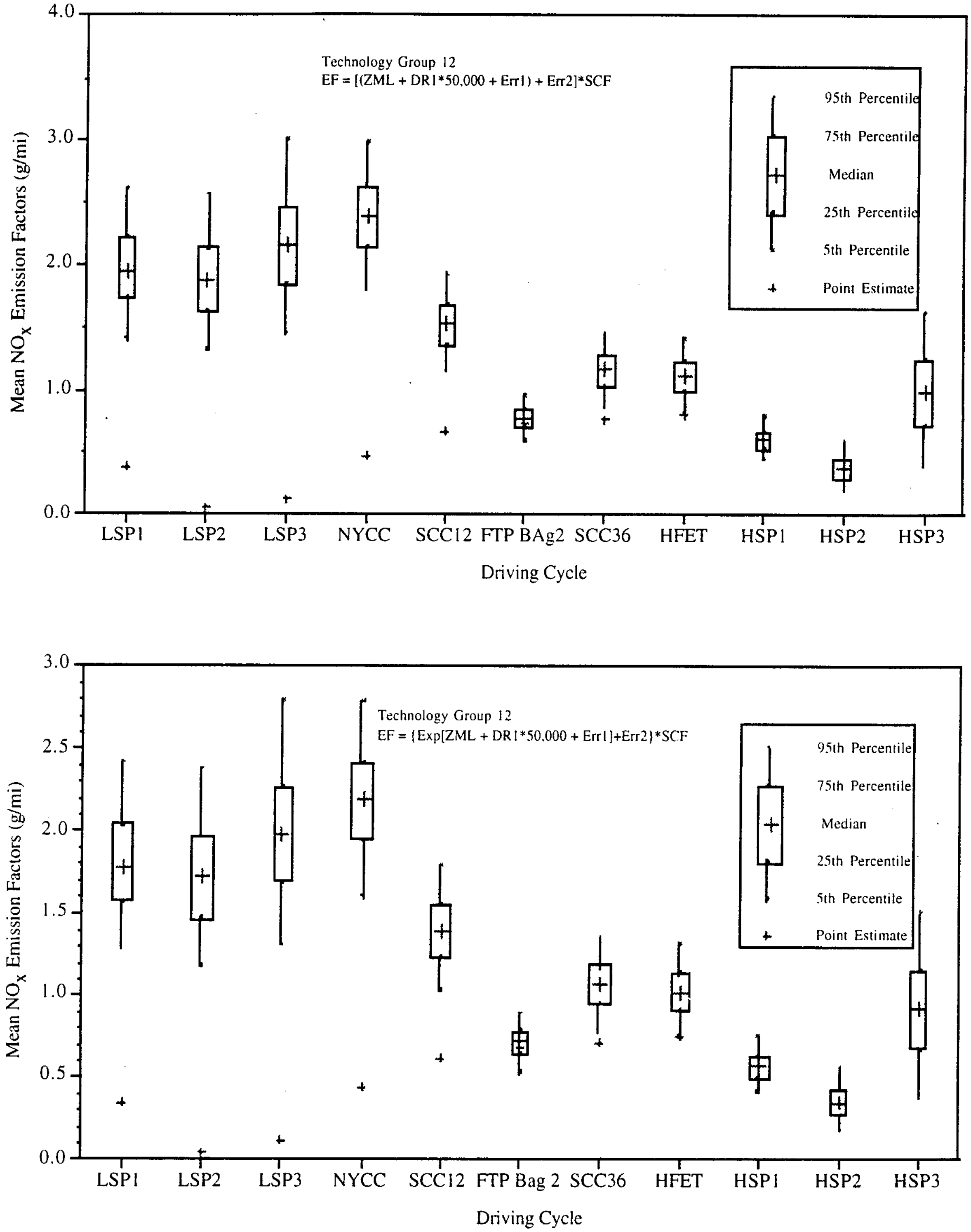
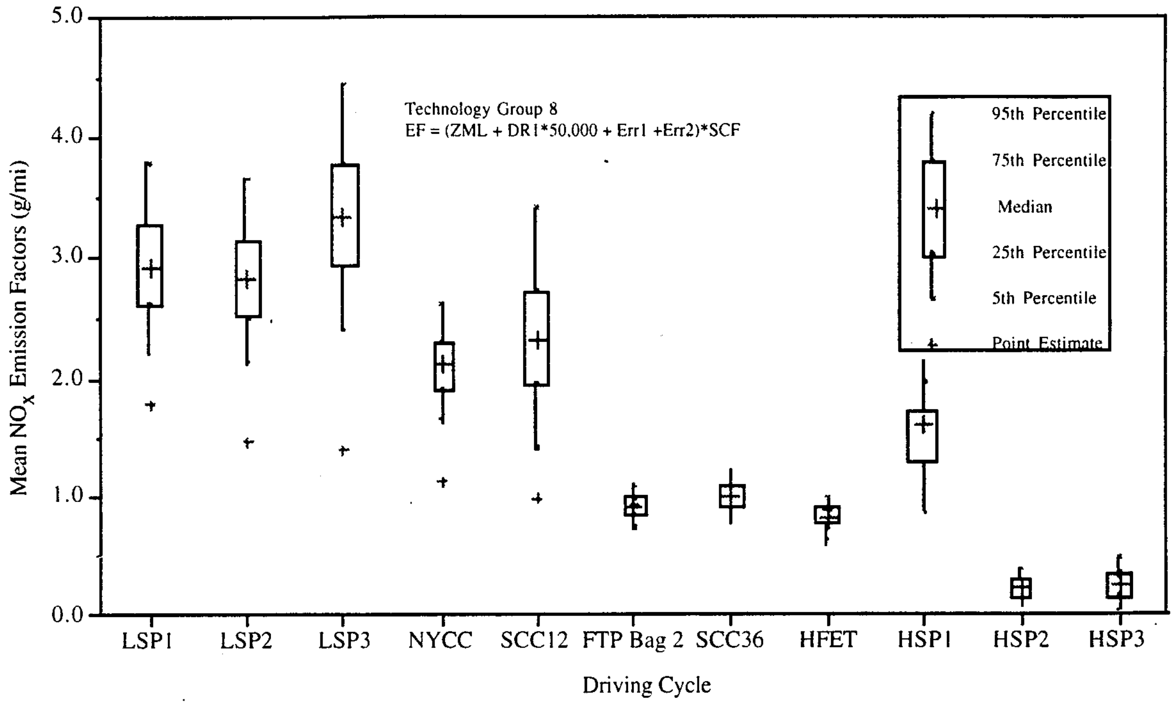


Figure 49. Predicted Uncertainty in the Mean NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 12 Using a Linear and a Log-Linear Model.



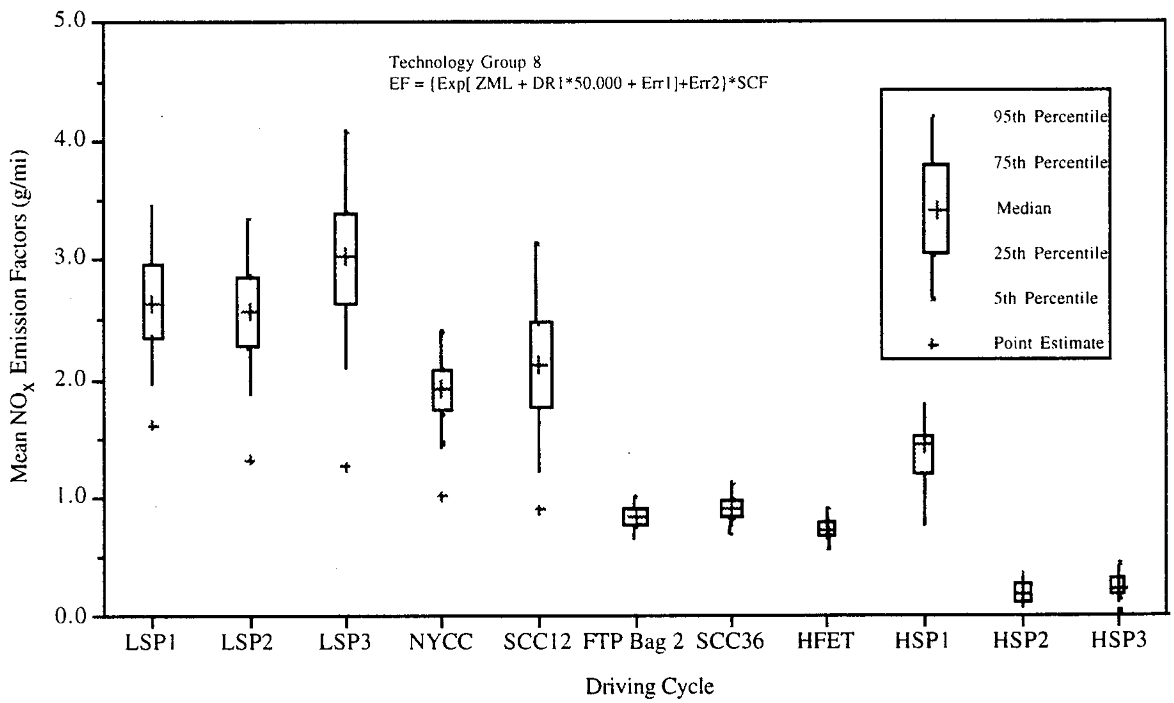


Figure 50. Predicted Uncertainty in the Mean NO_x Emission Factors for Different Driving Cycles for LDGV of Technology Group 8 Using a Linear and a Log-Linear Model.

9.0 RESULTS, CONCLUSIONS AND RECOMMENDATIONS

This Chapter provides a summary of all the results and conclusions based on the analyses carried out in this report. To improve emission estimates and develop more realistic emission inventories, recommendations have been made to modify the current modeling approach.

9.1 Results and Conclusions

The results of the analyses carried out here provide answers to the questions raised in Chapter 1. The variability analyses shows that the HC and CO emissions vary by up to three orders-of-magnitude from one vehicle to another, while NO_x emissions vary by up to two orders-of-magnitude. The results of the uncertainty analysis are summarized in Table 26. The summary indicates that in most cases, the point estimate is underestimated. Therefore, in-order to come up with a probabilistic mean of emissions, an analyst can multiply the point estimate obtained by using a deterministic model by the corresponding factor of underestimation shown in Table 26. The random error on the mean describes a 90 percent confidence interval range. That is to say that the fleet average emissions obtained after adjusting for systematic error would have a 90 percent probability of being enclosed by the mean plus or minus the random error shown in Table 26. For example, the point estimate for HC emissions of TG12 for the LSP1 cycle is 2.9 g/mi. Adjusting this for systematic error by a factor of 1.5, the fleet average would be reported as 4.35 g/mi. Furthermore, the random error on the mean is 25 percent of 4.35, which is equal to 1.08 g/mi. Therefore, an analyst can be 90 percent confident that the mean HC emissions for TG12 and the LSP1 cycle would be 4.35 ± 1.08 g/mi.

Confidence interval analysis is an important constituent of the uncertainty analysis. Faced with two alternate decisions to achieve the same emissions reduction, an informed decision maker needs to know the confidence intervals around the predicted value in order to know whether the alternatives actually differ. Furthermore, by characterizing uncertainties, decision makers can identify the key sources of uncertainty which, if reduced, might lead to different decisions and, therefore, prioritize additional data collection accordingly.

Uncertainty associated with the use of existing emission factor models should be quantified by revisiting the data used to develop each numerical algorithm in the models. In this report, the BERs and SCF data were analyzed. Other correction factor data such as the temperature correction factor and the operating mode correction factors should be analyzed. The mean emission factor uncertainty analysis shows that the means emissions for the three low speed cycles are not much different. Also as seen from the correlation tables in Appendix B, the three low speed cycles are highly correlated. Therefore, the use of three low speed cycles in the Mobile5a model is redundant. In most cases, the technology specific point estimate for SCF is not bounded by the uncertainty in the mean SCR distributions. This implies that the SCF model in Mobile5a needs to be re-analyzed. This is also justified by the rank correlations for uncertainty in the means shown by Table 25. The rank correlations describe the contributions of each model component leading to uncertainty in the predicted emissions. As seen from Table 25, the SCF contribution has a large contribution to the uncertainty in the model predictions in most cases. Further analyses on the distributions of the standard errors for emissions across different driving cycles can provide additional insight in to the uncertainties of model predictions at speeds other than the average speeds of the driving cycles. Once these uncertainties are quantified, they can be incorporated into policy analyses.

Potentially significant biases have been identified in the emission factors predicted by Mobile5a model. These findings are based upon analyses of only two of the technology groups for LDGV. The source of the bias is difficult to quantify, because insufficient documentation is available regarding the basis of the technology-specific point-estimates. One source of bias is the use of linear regression models in situations where a log-linear model would have been more appropriate.

Results from previous studies which examined the speed correction factors in detail (Guensler, 1993 ; NCHRP, 1995) have also indicated that application of speed correction factors and average speed modeling to analysis of emissions will yield highly uncertain results.

Because of the potential large amount of uncertainty associated with the emission factor estimates from Mobile5a, the numerical precision of the model should be viewed with caution. The findings in this study suggest that the precision of the model is not better than plus or minus 20 percent. The limitations of the precision of the model have to do with the large amount of inter-vehicle variability in emissions, which translates into uncertainty regarding fleet average emissions. This is a fundamental aspect of vehicle emissions estimation. The level of uncertainty can be reduced by collecting more data. The estimates of uncertainty can be used to help determine where data collection would be most beneficial, based upon the technology groups, pollutants, and driving cycles which are the most critical in emission inventory development or other environmental decision making contexts.

The accuracy of the model is more difficult to assess. However, our findings suggest that there may be biases in the model predictions. If so, these could have significant implications for development of emissions inventories and for various regulatory compliance analyses. The recommendations described below could help make the model predictions more realistic.

Our analysis has focused upon a trip-based emission factor model. It is likely that there are limits to the precision of alternative methods for emission factor estimation, such as modal emissions models. However, there are currently no estimates of uncertainty in these other methods available for comparison.

9.2 Recommendations

There are significant sources of uncertainty in average highway vehicle emission factor estimates. Many of these sources of uncertainty, such as variability in emissions from one vehicle to another and limited data set sizes, can and should be quantified. Knowledge of uncertainty enables decision makers to evaluate the degree of confidence that should be placed in the emission estimates. Furthermore, knowledge regarding key sources of uncertainty can be used to prioritize data collection.

The Mobile5a model is structured such that it is possible to misuse the data underlying the model by allowing the user to interpolate between emission estimates of different driving cycles driving cycles. Since the interpolations are done only on the basis of average driving cycle speed, whereas emissions are sensitive to the overall speed-acceleration profile of the driving cycle, this is actually a form of extrapolation. An additional concern is that the model is commonly used to predict on-road, link based emissions. However, Mobile5a is based on complete trip based driving cycles and use of the model to predict link-based emissions, which represent only segments of a complete trip, is inappropriate.

Instead of interpolating between driving cycles, or using a link-based approach to emission inventory development, we recommend the development of mixtures of diving cycles to better represent observed speed variations on transportation networks. We have illustrated an approach for developing mixture distributions of driving cycle emissions data. The uncertainty and variability analysis of the BER and SCF in Mobile5a have provided greater insights as to the appropriateness of the model algorithms and the model structure, as well as regarding the precision and accuracy of the model for the technology groups, pollutants, and driving cycles that we evaluated. The following recommendations can help address the limitations of the current model.

1. The current linear model for BERs in Mobile5a should be replaced by an appropriate log-linear model. As shown in Chapter 8, the HC and CO emissions vary by more than an order-of-magnitude. Therefore a log-linear model would be more appropirate model structure for the BER model.
2. The SCF equation in Mobile5a should be reanalyzed and replaced with a new more appropriate equation. The SCF module in Mobile5a predicts the emissions to be sensitive to speed at low speeds. However, the analysis in Chapter 8 shows that the emissions across the three low speed cycle do not vary significantly for the two technology groups that were studied. Also, in many cases, the point estimates for SCFs are not within by the 95 percent probability range for the mean of the probability distributions. This indicates that the current SCF module in Mobile5a does not adequately represent the driving cycle data in these cases.
3. Vehicles need to be tested on additional driving cycles to account for modal behaviors. However, we have shown that some of the driving cycles, such as LSP1, LSP2, and LSP3 provide redundant data. Thus, in some cases, it is possible to reduce the number of cycles used for testing without losing any significant information.

4. The Mobile5a model should be modified so as to enable the user to input data such as observed on-road variations in speed. Such data can be collected with traffic detectors such as double loop detectors, video-based systems, or pneumatic tube measurement systems such as Auto Poll. The on-road speed inputs should be used to generate mixture distributions of speeds and mixture distributions of emissions from each driving cycle as described in Chapter 7. The mean obtained from the mixture distribution for emissions can then be compared to the link-based average fleet emissions.

Recommendations 1 and 2 would account for model structure uncertainty by considering a different model structure. Recommendation 3 would provide additional and appropriate data for addressing model details. Recommendation 4 would make the model predictions more realistic in comparison to on-road measurements. This will enable the new emission factor model to be validated by on-road measurements such as tunnel studies.

In conclusion, a new model for emission factors based on the above recommendations would help make the emission inventories better and more realistic.

Table 26. Results of the Mean Emissions Uncertainty Analysis

Pollutant	Cycle Speed	Random Error	Systematic Error
HC	Low Medium High	25 percent 20 percent 40 percent	Underestimation by a factor of 1.5 to 3 Underestimation by a factor of up to 3
CO	Low Medium High	40 percent 20 percent 30 percent	Underestimation by a factor of upto 2 Underestimation by a factor of upto 2.5
NOx	Low Medium High	25 percent 30 percent 55 percent	Underestimation by a factor of 2 to 4 Underestimation by a factor of about 2

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APPENDIX A: Speed Time Profiles of Non-Standard Emissions Testing Driving Cycles

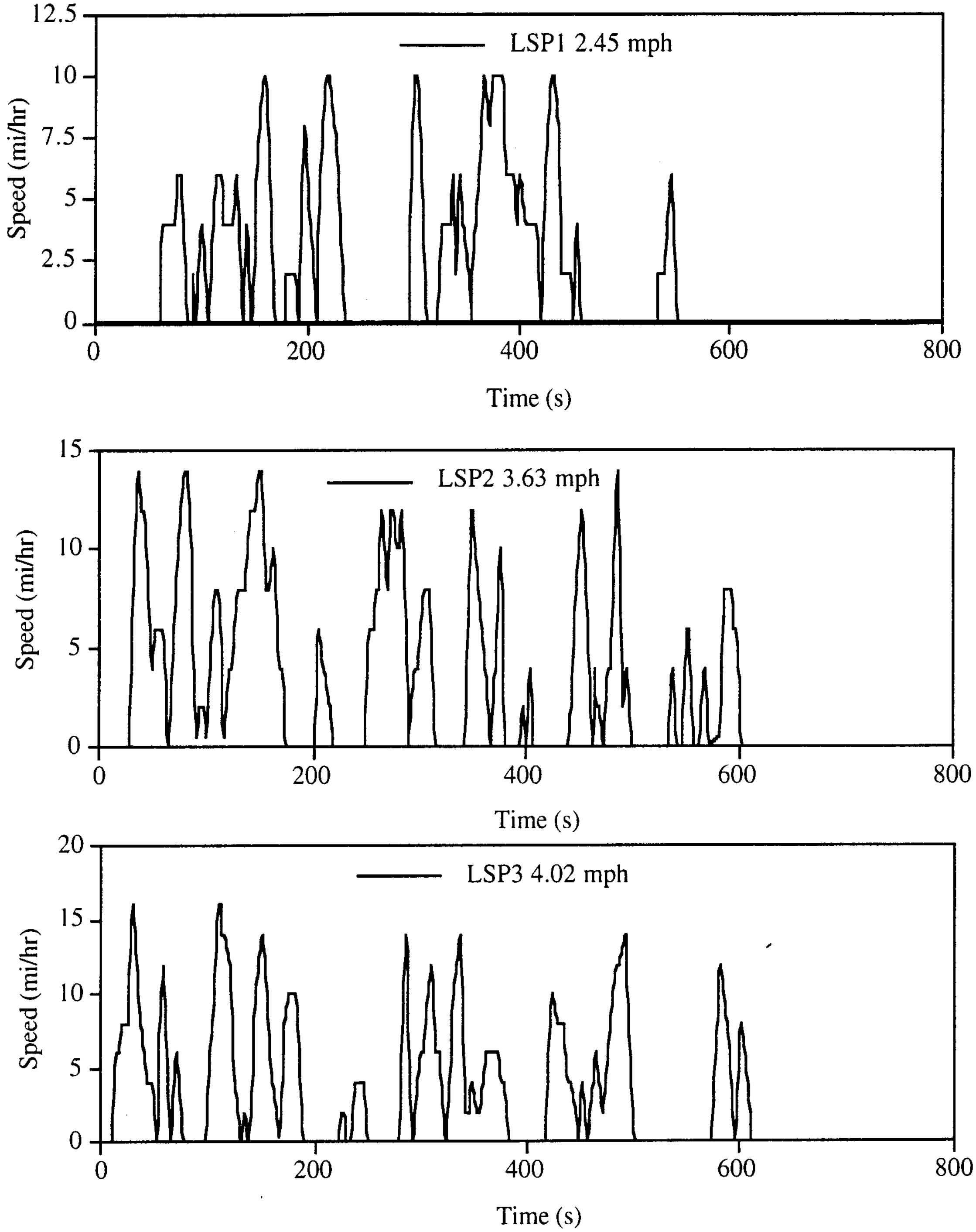

Figure 51. Speed Time Profiles of LSP1, LSP2 and LSP3 Driving Cycles

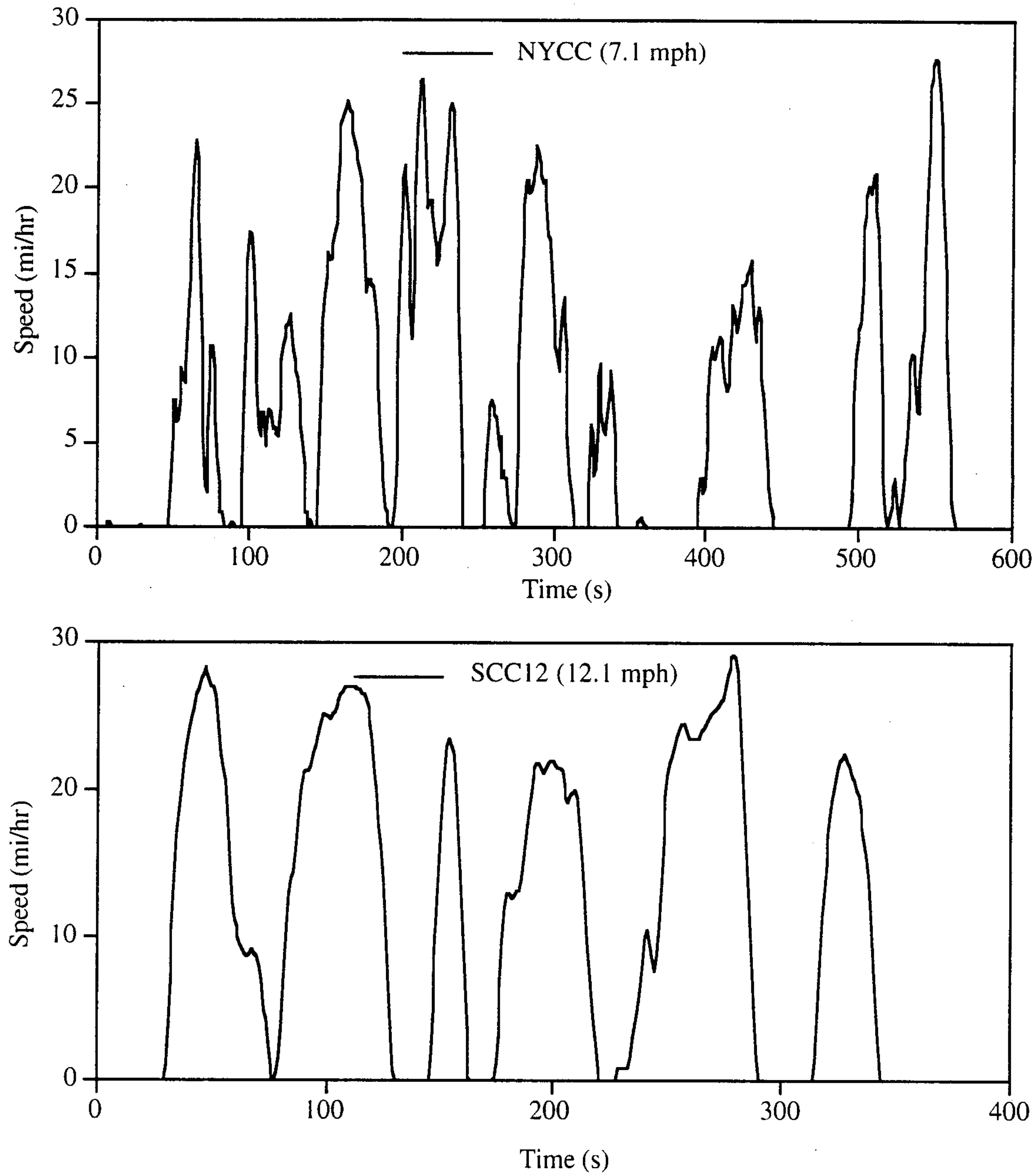

Figure 52. Speed Time Profiles of the NYCC and SCC12 Driving Cycles

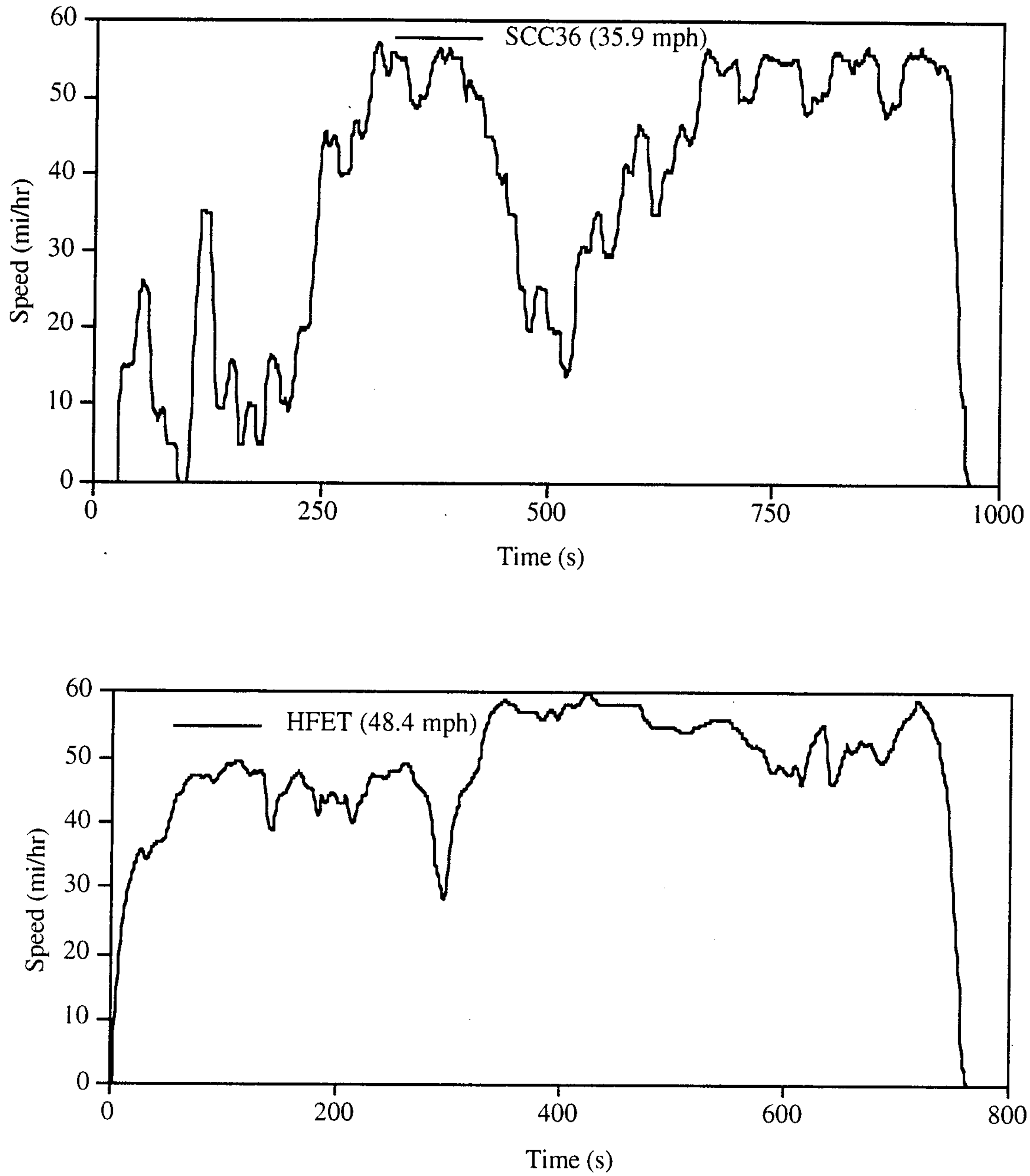

Figure 53. Speed -Time Profile of the SCC36 and HFET Driving Cycles

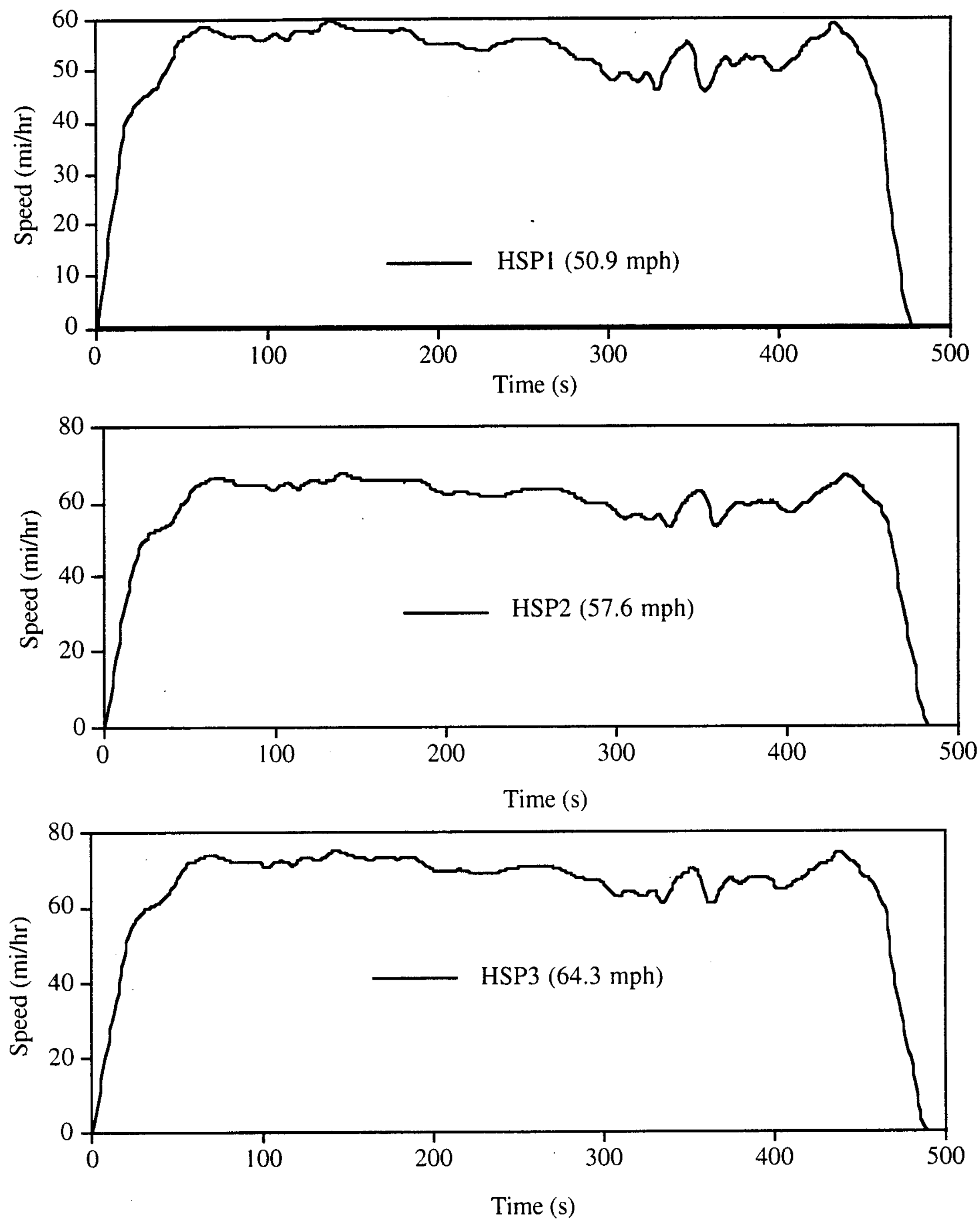

Figure 54. Speed time Profiles of the HSP1, HSP2 and HSP3 Cycles.

Appendix B: The SCF Data for Technology Group 12 and Technology Group 8 andthe Correlation Coefficients of Emissions at Different Driving Cycles

Table 27. Emissions for LDGV of Technology Group 12 Across Different Driving Cycles

Poll.	Driving Cycle	Average Cycle Speed	Min (g/mi)	Median (g/mi)	Mean (g/mi)	95th % C.I.	Max (g/mi)	No. of Vehicles Tested
HC	LSP1	2.50	0.05	0.58	1.17	0.35	13.18	91.00
	LSP2	3.60	0.05	0.43	0.87	0.30	12.11	91.00
	LSP3	4.00	0.07	0.55	1.44	0.64	27.89	91.00
	NYCC	7.10	0.02	0.23	0.39	0.11	5.33	111.00
	SCC12	12.10	0.01	0.23	0.45	0.11	3.47	111.00
	FTP Bag 2	16.10	0.02	0.07	0.17	0.08	4.43	111.00
	SCC36	36.00	0.00	0.06	0.09	0.02	0.67	111.00
	HFET	48.00	0.00	0.05	0.08	0.02	0.89	111.00
	HSP1	50.00	0.03	0.05	0.06	0.02	0.11	12.00
	HSP2	57.00	0.01	0.07	0.07	0.02	0.18	26.00
	HSP3	64.00	0.01	0.09	0.14	0.07	0.85	26.00
CO	LSP1	2.50	0.00	4.30	9.34	4.54	202.80	91.00
	LSP2	3.60	0.00	3.00	7.48	4.16	188.30	91.00
	LSP3	4.00	0.00	2.10	8.47	6.74	313.10	91.00
	NYCC	7.10	0.00	4.00	8.31	2.18	82.60	111.00
	SCC12	12.10	0.00	2.60	4.49	1.27	51.80	111.00
	FTP Bag 2	16.10	0.00	1.70	3.02	1.44	77.20	111.00
	SCC36	36.00	0.00	1.00	1.69	0.65	30.60	111.00
	HFET	48.00	0.00	0.60	1.01	0.34	17.40	111.00
	HSP1	50.00	0.09	0.54	0.58	0.17	1.19	12.00
	HSP2	57.00	0.01	0.07	0.07	0.02	0.18	26.00
	HSP3	64.00	0.01	0.09	0.14	0.07	0.85	26.00
NOx	LSP1	2.50	0.01	0.46	0.52	0.07	1.74	91.00
	LSP2	3.60	0.01	0.40	0.47	0.06	1.69	91.00
	LSP3	4.00	0.00	0.38	0.45	0.07	1.75	91.00
	NYCC	7.10	0.00	0.73	0.78	0.09	2.60	111.00
	SCC12	12.10	0.01	0.42	0.59	0.10	3.42	111.00
	FTP Bag 2	16.10	0.01	0.27	0.31	0.05	1.76	111.00
	SCC36	36.00	0.03	0.34	0.38	0.05	2.14	111.00
	HFET	48.00	0.02	0.30	0.37	0.06	2.38	111.00
	HSP1	50.00	0.03	0.29	0.26	0.10	0.55	12.00
	HSP2	57.00	0.01	0.07	0.07	0.02	0.18	26.00
	HSP3	64.00	0.01	0.09	0.14	0.07	0.85	26.00

Table 28. Emissions for LDGV of Technology Group 8 Across Different Driving Cycles

Pollutant	Driving Cycle	Average Cycle Speed (mi/hr)	Min (g/mi)	Median (gm/mi)	Mean (g/mi)	95th % C.I.	Max (g/mi)	No. of Vehicles Tested
HC	LSP1	2.50	0.22	0.69	1.62	1.06	7.49	14.00
	LSP2	3.60	0.19	0.70	1.73	1.18	8.76	14.00
	LSP3	4.00	0.25	1.27	2.74	1.65	11.78	14.00
	NYCC	7.10	0.06	0.33	0.50	0.19	3.21	35.00
	SCC12	12.10	0.07	0.29	0.48	0.17	2.19	35.00
	FTP Bag 2	16.10	0.04	0.13	0.16	0.04	0.69	35.00
	SCC36	36.00	0.02	0.08	0.09	0.02	0.33	35.00
	HFET	48.00	0.02	0.06	0.08	0.02	0.23	35.00
	HSP1	50.00	0.10	0.14	0.14	0.04	0.19	4.00
	HSP2	57.00	0.09	0.15	0.17	0.06	0.39	8.00
	HSP3	64.00	0.08	0.12	0.18	0.09	0.49	8.00
CO	LSP1	2.50	0.80	4.35	15.56	14.93	113.90	14.00
	LSP2	3.60	0.60	3.70	18.47	18.57	140.70	14.00
	LSP3	4.00	0.40	4.15	25.38	23.86	173.30	14.00
	NYCC	7.10	1.30	8.50	11.52	4.09	77.20	35.00
	SCC12	12.10	0.30	3.60	5.33	2.28	42.80	35.00
	FTP Bag 2	16.10	0.30	2.70	3.44	1.18	22.30	35.00
	SCC36	36.00	0.50	1.70	1.89	0.29	4.30	35.00
	HFET	48.00	0.40	1.10	1.24	0.21	3.60	35.00
	HSP1	50.00	0.66	0.81	0.83	0.17	1.05	4.00
	HSP2	57.00	0.03	0.05	0.06	0.02	0.13	8.00
	HSP3	64.00	0.03	0.04	0.06	0.03	0.16	8.00
NOx	LSP1	2.50	0.58	0.89	1.05	0.27	2.38	14.00
	LSP2	3.60	0.28	0.84	1.02	0.24	1.84	14.00
	LSP3	4.00	0.18	1.06	1.19	0.35	2.65	14.00
	NYCC	7.10	0.10	0.71	0.70	0.09	1.30	35.00
	SCC12	12.10	0.10	0.55	0.77	0.23	3.32	35.00
	FTP Bag 2	16.10	0.06	0.32	0.34	0.05	0.66	35.00
	SCC36	36.00	0.06	0.31	0.35	0.06	0.76	35.00
	HFET	48.00	0.07	0.24	0.29	0.05	0.70	35.00
	HSP1	50.00	0.24	0.52	0.59	0.32	1.09	4.00
	HSP2	57.00	0.03	0.05	0.06	0.02	0.13	8.00
	HSP3	64.00	0.03	0.04	0.06	0.03	0.16	8.00

Table 29. Correlation Coefficients for HC Emissions at Different Driving Cycles for Technology Group 12.[a]

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.93	1.00									
4.00	0.88	0.97	1.00								
7.10	0.38	0.40	0.31	1.00							
12.10	0.41	0.25	0.19	019	1.00						
16.10	0.31	0.23	0.16	0.22	0.64	1.00					
36.00	0.39	0.37	0.26	0.59	0.56	0.67	1.00				
48.00	0.28	0.35	0.23	0.22	0.38	0.56	0.63	1.00			
50.00						-0.36	0.57	0.72	1.00		
57.00						-0.39	0.41	0.87	0.74	1.00	
64.00						-0.60	-0.61	0.49	-0.14	0.33	1.00

Table 30. Correlation Coefficients for CO Emissions at Different Driving Cycles for Technology Group 12[a].

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.99	1.00									
4.00	0.96	0.97	1.00								
7.10	0.30	0.28	0.16	1.00							
12.10	0.22	0.16	0.07	0.32	1.00						
16.10	0.19	0.14	0.08	0.28	0.81	1.00					
36.00	0.22	0.23	0.11	0.58	0.40	0.40	1.00				
48.00	0.08	0.08	0.04	0.21	0.42	0.51	0.47	1.00			
50.00						0.54	0.63	0.80	1.00		
57.00						-0.49	-0.42	0.03	0.09	1.00	
64.00						0.32	0.08	0.67	0.38	0.33	1.00

a : For LSP1, LSP2, and LSP3, 91 vehicles were tested.
For NYCC, SCC12, FTP Bag 2, SCC36 and HFET, 111 vehicles were tested, of which 91 were also tested on the low speed cycles.
The correlation coefficients for the high speed cycles are for a combination of vehicles of Technology Groups 12 and 13.
12 vehicles were tested for the HSP1 cycle while 26 vehicles were tested for the HSP2 and HSP3 cycles. The same vehicles were also tested on the FTP Bag 2, SCC36 and HFET cycles.

Table 31 Correlation Coefficients for NO_x Emissions at Different Driving Cycles for Technology Group 12[b].

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.87	1.00									
4.00	0.71	0.84	1.00								
7.10	0.63	0.60	0.41	1.00							
12.10	0.63	0.53	0.35	0.68	1.00						
16.10	0.57	0.51	0.29	0.79	0.80	1.00					
36.00	0.49	0.48	0.26	0.71	0.71	0.82	1.00				
48.00	0.39	0.36	0.17	0.54	0.64	0.71	0.91	1.00			
50.00						0.94	0.94	0.98	1.00		
57.00						-0.58	0.55	-0.68	-0.74	1.00	
64.00						-0.59	-0.65	-0.65	-0.68	0.33	1.00

b : For LSP1, LSP2, and LSP3, 91 vehicles were tested.
For NYCC, SCC12, FTP Bag 2, SCC36 and HFET, 111 vehicles were tested, of which 91 were also tested on the low speed cycles.
The correlation coefficients for the high speed cycles are for a combination of vehicles of Technology Groups 12 and 13.
12 vehicles were tested for the HSP1 cycle while 26 vehicles were tested for the HSP2 and HSP3 cycles. The same vehicles were also tested on the FTP Bag 2, SCC36 and HFET cycles.

Table 32. Correlation Coefficients for HC Emissions at Different Driving Cycles for Technology Group 8[d].

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.99	1.00									
4.00	0.99	0.99	1.00								
7.10	0.96	0.93	0.94	1.00							
12.10	0.92	0.90	0.94	0.85	1.00						
16.10	0.95	0.97	0.94	0.87	0.85	1.00					
36.00	0.71	0.78	0.69	0.59	0.57	0.86	1.00				
48.00	0.67	0.73	0.63	0.54	0.49	0.82	0.98	1.00			
50.00						-0.10	0.93	0.75	1.00		
57.00						0.01	0.49	0.59	0.45	1.00	
64.00						0.88	0.42	0.54	0.12	-0.26	1.00

Table 33. Correlation Coefficients for CO Emissions at Different Driving Cycles for Technology Group 8[d]

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.99	1.00									
4.00	0.98	0.98	1.00								
7.10	0.56	0.56	0.68	1.00							
12.10	0.70	0.69	0.74	0.83	1.00						
16.10	0.75	0.73	0.80	0.82	0.87	1.00					
36.00	0.18	0.17	0.17	0.24	0.30	0.40	1.00				
48.00	0.37	0.35	0.34	0.22	0.30	0.63	0.62	1.00			
50.00						0.18	-0.74	0.85	1.00		
57.00						0.75	0.42	-0.24	0.29	1.00	
64.00						0.41	-0.41	0.19	0.16	-0.26	1.00

d : For LSP1, LSP2, and LSP3, 14 vehicles were tested.
For NYCC, SCC12, FTP Bag 2, SCC36 and HFET, 35 vehicles were tested, of which 14 were also tested on the low speed cycles.
The correlation coefficients for the high speed cycles are for a combination of vehicles of Technology Groups 8 and 9.
4 vehicles were tested for the HSP1 cycle while 8 vehicles were tested for the HSP2 and HSP3 cycles. The same vehicles were also tested on the FTP Bag 2, SCC36 and HFET cycles.

Table 34. Correlation Coefficients for NO_x Emissions at Different Driving Cycles for Technology Group 8[d].

Cycle Name	LSP1	LSP2	LSP3	NYCC	SCC12	FTP Bag 2	SCC36	HFET	HSP1	HSP2	HSP3
Cycle Speed	2.50	3.60	4.00	7.10	12.10	16.10	36.00	48.00	50.00	57.00	64.00
2.50	1.00										
3.60	0.84	1.00									
4.00	0.56	0.88	1.00								
7.10	0.04	0.45	0.59	1.00							
12.10	0.33	0.38	0.25	0.61	1.00						
16.10	0.52	0.71	0.64	0.63	0.64	1.00					
36.00	0.34	0.60	0.56	0.79	0.48	0.67	1.00				
48.00	0.43	0.57	0.46	0.61	0.30	0.56	0.91	1.00			
50.00						0.93	0.98	1.00	1.00		
57.00						-0.16	-0.07	-0.01	-0.04	1.00	
64.00						-0.51	-0.64	-0.79	-0.78	-0.26	1.00

d : For LSP1, LSP2, and LSP3, 14 vehicles were tested.
For NYCC, SCC12, FTP Bag 2, SCC36 and HFET, 35 vehicles were tested, of which 14 were also tested on the low speed cycles.
The correlation coefficients for the high speed cycles are for a combination of vehicles of Technology Groups 8 and 9.
4 vehicles were tested for the HSP1 cycle while 12 vehicles were tested for the HSP2 and HSP3 cycles. The same vehicles were also tested on the FTP Bag 2, SCC36 and HFET cycles.

APPENDIX C: An Overview of Automobile Emissions

C.1 Sources of Automobile Emissions

Emissions from vehicles with conventional, gasoline powered, internal combustion engines arise from three sources: the crankcase, the fuel system and the exhaust. The crankcase and fuel system are sources of hydrocarbons, whereas the exhaust contains hydrocarbons, carbon monoxide and nitrogen oxides (Horrowitz, 1982).

To understand the formation and control of emissions it is necessary to have a rudimentary understanding of the operation of the internal combustion engines. In conventional, gasoline powered engines, the motion of the pistons is transmitted through connecting rods to a crankshaft and ultimately to the wheels. Each piston operates in a four stroke cycle consisting of an intake stroke, a compression stroke, a power stroke, and an exhaust stroke. In the intake stroke, the piston moves downward in the cylinder. This causes a mixture of air and fuel to be drawn in to the cylinder through the open intake valve. The air and fuel are mixed together in the carburetor, which controls the air to fuel (A/F) ratio. At the bottom of the intake stroke, the intake valve closes and the piston begins to move upward in the cylinder, compressing the mixture of air and fuel. This is the compression stroke. An electrical current causes the spark plug to create a spark in the cylinder near the top of the compression stroke. The spark ignites the compressed air-fuel mixture, and the expansion of the burning gases forces the piston to move downward, thereby delivering power to the crankshaft. This is the power stroke. At the end of the power stroke the exhaust valve opens, and the piston begins to rise in the cylinder, forcing the combustion products out through the exhaust valve. Following this exhaust stroke, the four stroke engine repeats itself (Horowitz, 1982).

The exhaust emissions account for all of the CO and NO_x emissions and 60 percent of HC emissions in automobiles without emission controls. The organic constituents of the exhaust include aldehydes and traces of alcohols and other products of partial oxidation of hydrocarbons, in addition to pure hydrocarbons. If the fuel supplied to the cylinders burned completely, it would be oxidized to carbon dioxide CO_2 and water. Then there would be no exhaust HC or CO emissions. However, as described above, an automobile engine operation involves a very rapid batch-burning process. After ignition, the flame progresses in the combustion chamber, but fails to propogate in the vicinities of the cylinder walls. This effect, known as wall quenching, is caused partly by the chemical reactions that occur in the layers of the A/F mixture adjacent to the walls and partly by cooling of these layers by the wall. As a result of the wall quenching, the A/F mixture near the wall does burn completely. This process leaves a layer of unburned hydrocarbons next to the wall, a portion of which subsequently mixes with the burned charge and escapes with the exhaust gas. This can occur during transient conditions such as warm up, when the fuel entering the cylinders may be inadequately atomized and mixed with air, or during idle or deceleration, when the cylinders contain excessive quantities of residual exhaust gas from previous piston cycles. Incomplete combustion can also be caused by engine malfunctions or maladnustments. For example, if an ignition system malfunction prevents one or more spark plugs from producing a spark at a proper time or if a carburetor malfunction causes the A/F to be too high or too low, the combustion will be incomplete and HC emissions will be excessive (Horrowitz, 1982).

CO is formed when the carbon containing substances such as gasoline are burned with an inadequate supply of oxygen. In an internal comnustion engine, low A/F ratios tend to produce high CO emissions, where as CO emissions are lower at high A/F ratios.

The exhaust emissions rates are sensitive to a variety of the engine adjustments and design parameters, including Air/fuel (A/F) ratio, spark timing, compression ratio etc. The A/F ratio is an important variable in determining emissions. In actual operations the A/F ratio is not the optimum theoretical mixture since the flow is not homogeneously distributed throughout the combustion chamber. Thus combustion is not complete, particularly when the mixture is fuel rich. As a result the exhaust gas emitted from the tailpipe consists of a complex mixture of CO and unburned or partially burned HC's, NO_x, various particulate matter and sulfur compounds.

The engine emits different amounts of pollutants depending upon the driving mode. Air rich mixtures will tend to produce minimal CO but will produce considerable NO. The combustion temperatures will also affect the pollutant formation. At low temperatures CO and NO concentrations will be lower but the concentration of unburned HC's in the exhaust will increase (Johnson,1988).

During the compression and the power strokes, some of the gases in the cylinders escape past the pistons and in to the crankcase. This escape of gases is a source of crankcase, or blowby, emissions. The crankcase is the space underneath the pistons that contains the connecting rods and the crankshaft, among other engine parts. The escaping gases consist mostly of unburned A/F mixture. Since gasoline is largely a mixture of HCs, these emissions have high HC concentrations. The crankcase emissions account for roughly 20 precent of the HC emissions of uncontrolled automobiles (Horowitz, 1982).

In addition to the engine, the other source of emissions are from the fuel systems. The emissions from the fuel tank are due to evaporation of the fuel when the automobile is sitting after use (hot soak) or when the tank gets heated during the day or during refueling operations. The heating on warm days causes the fuel and the fuel vapors in the tank to expand. Some of these vapors spill out of the tank into the air. The resulting emissions are called diurnal emissions and are independent of any use that the vehicle receives during a day. In refueling, the entering fuel displaces the gasoline vapor that are in the fuel tank and forces them in to the air. Emissions from the carburetor occur mainly while the engine is hot after having been turned off at the end of a trip. The fuel left in the carburetor at this time is hot and the volatile costituents evaporate rapidly. These emissions are called hot soak emissions. The evaporative emissions from the fuel tank and the carburetor consist mainly of HC's and account for roughly 20 percent of HC emissions from automobiles without emission controls.

An obvious way to reduce CO emissions is to increase the A/F ratio. The NO emissions are also governed by the availability of oxygen for the reaction and high temperatures to promote the reaction. The time for NO to form is longer than the time available so that equilibrium at peak temperature conditions is not obtained. The maximum NO levels are formed with an A/F ratio about 10 percent above stoichiometric ratio. The stoichiometric ratio of 14.7:1 is necessary in the control technology using a three way catalyst since the A/F ratio must be within 0.05 of the stoichiometric ratio to achieve high HC, CO and NO_x control efficiencies. However, the uncontrolled concentrations of all these pollutants are not minimum at the optimum A/F ratio. When CO and HC concentrations are a minimum at an A/F ratio of 16:1, NO_x production is maximum. More air than this reduces the peak temperature, since the excess air must be heated for energy to be released during combustion. Hence the NO concentration falls off with additional excess oxygen. This is the lean burn region where A/F ratio exceeds 17.5 :1. Lean burn regions are potential sources of improved fuel economy although they give rise to increased HC concentration due to low flame temperatures. Therefore they would require adequate emission control with oxidation catalysts (Johnson, 1988).

C.2 Exhaust Emission Controls

Since 1960 automobile emissions have been significantly lowered by improved design of the engine and fuel systems. These reductions were a result of a A/F ratio control, cylinder to cylinder distribution of the air and fuel, choke operations, combustion chamber designs, fuel injection, exhaust gas recirculation (EGR), ignition systems, spark and valve timings along with the addition of emission control devices such as catalytic converters, evaporative emission storage canisters, purge control valave, fuel filler neck restricter etc.

The first emission control device was the positive crankcase ventilation (PCV) which draws clean air through the crankcase in to the inlet manifold, providing a path for the blowby gases to be drawn in to the cylinders and be burnt. Engine modifications include elimination of nooks and crevices in the combustion chamber that inhibited complete combustion, changes in the design of the inlet manifolds, cylinder head assemblies and addition of the air injection reactor (AIR), which pumps air in to the hot engine to promote the oxidation of unburned fuel. Exhaust gas recirculation, in which a small amount of the hot exhaust gases are allowed to flow in to the inlet manifold to reduce combustion temperature, allowed a reduction in NO_x concentrations in the tailpipe emissions. Retarding the spark decreased the wall quench effect and raised the exhaust gas temperature so the completion of hydrocarbon reaction in the exhaust could occur. This also reduced NO emissions significantly. Closed loop fuel control allowed the operation of the engine at stoichiometric ratio.

C.3 Catalyst Control Systems

Two additional approaches, namely the three way catalyst and the dual catalyst systems, have gained application with the microprocessor control systems to provide necessary control. The three way catalytic convertor yeilds optimal performance in reducing exhaust emissions with the engine operating at stoichiometric ratio. Therefore, the use of a three way catalytic convertor with a closed loop fuel control in which an oxygen sensor is used in conjunction with the microprocessor makes this technology more effective. In a dual catalyst, two catalysts are used in series: a three way catalyst followed by an oxidizing catalyst to operate more efficiently. Air is injected in to the exhaust gas between the two catalysts to provide the oxygen necessary for the oxidizing catalyst to operate efficiently.

Precise A/F ratio control is required for the efficient functioning of the catalyst control systems. Air supplied to the oxidised catalyst can be diverted to the exhaust ports. This facilitates the addition of oxygen to the combustion products of a rich start-up mixture for faster catalyst light-off. It also helps to achieve higher HC and CO control efficiencies in the three way catalyst. The dual bed converter is more complex than the single bed three way catalyst, because it requires an extensive air management system. A closed loop control, which has a feedback control of the fuel delivery based upon the oxygen level in the exhaust, is used to maintain the A/F ratio control. The key element in the closed loop system is the oxygen sensor which is inserted in the exhaust pipe ahead of the catalyst. It measures the exhaust oxygen concentration and signals an electric controller to adjust the fuel rate continuously so that the mixture is maintained at stoichiometric ratio.

C.4 Current Approaches and Future Trends in Emission Controls

The current trend is to use heated oxygen sensors to initiate closed loop operations faster and to maintain them during long idling periods. The heated sensor also deteriorates less with extended mileage. The three-way catalyst system can be modified to reduce NO_x emissions by using larger amounts of noble metals in the catalytic converter. Introduction of an electrically heated catalyst to improve effectiveness during cold starts and recycling the exhaust gas to lower the peak temperatures in the cylinder would effectively reduce NO_x emissions (NRC, 1993).

Lean Burn Combustion Systems are under development . These use a closed loop microprocessor in conjuction with a lean mixture sensor and an oxidation catalyst. The catalysts are temperature sensitive and under exhaust conditions typical of high speed operations, they tend to deactivate. Therefore they would require increased control of the exhaust temperature. The catalysts are also sensitive to the oxygen and sulfur. Because of their oxygen sensitivity, the catalysts would be of limited value for diesel exhaust systems where the particulates are likely to accumulate on the catalyst thereby lowering its effectiveness. In lean operating region, the engine needs a different sensor design to provide feedback and also a highly turbulent fast burn combustion system so that the slow flame speed and misfires do not cause emission and driveability problems. However this system require a large volume of catalyst which restricts the use of the lean burn system to cars under 2500-3000 pounds because NO_x increases with vehicle weight. An electrically heated catalyst would increase the weight of the vehicle and reduce fuel economy. Cost effective approaches for controlling the emissions would be to have the catalyst heated initially by briefly igniting a mixture of fuel and air in an after-burner, slightly upstream of the catalyst. Fuel could be supplied by calibrating the engine to run with excees fuel. Air could be supplied by an electrically driven pump. By controlling the fuel to the individual cylinders, a mixture with both excess air and excess fuel could be supplied to the catalyst. However, this approach would be effective only after the catalyst has reached the initial start-off temperature (Jhonson, 1988).

C.4.1 Alternate Fuels

One of the potential long term solutions to reduce ozone precursors from automobile emissions is the use of alternate fuels. The role of VOCs in formation of tropospheric ozone suggests that changing the fuels could be effective in reducing the reactivity of the VOC emissions. Exhausts from conventionally fueled gasoline vehicles are highly reactive in the atmosphere because they are rich in aromatics and alkenes. Alternatively fueled vehicles such as those which run on methanol or natural gas would have less reactive emisions and hence would reduce ozone formation. Electric vehicles would run virtually without emissions. Reformulated gasoline, methanol, natural gas and electricity are likely candidates to replace gasoline and diesel as vehicle fuels. Environmental attributes of each fuel need to be studied for their effect on air quality and the relative effectiveness of each fuel in lowering ozone (NRC, 1992).

C.4.2 Reformulated Gasoline

The composition of gasoline is altered by modifying the refining process and by adding oxygenates to obtain a fuel lower in aromatics and olefins. The oxygenates enhance the fuels octane rating and improve the efficiency of combustion. The presence of fuel oxygen tends to decrease the CO emissions. The potential for using reformulated gasoline to improve air quality is uncertain. There is the possibiity of reducing the total mass emissions of VOCs and NO_x by using different blends of reformulated gasoline but at the same time it needs to be determined to what degree automobile control systems and the fuels match to reduce emissions. Reformulated gasolines offer the easiest transition to a cleaner fuel and studies in progress indicate that properly reformulated gasolines can meet or surpasss reductions in emission reactivity of methanol-gasoline blends (e.g., M85) (NRC, 1992).

C.4.3 Natural Gas

Natural gas is primarily methane, with other light HCs such as ethane, ethene, propane, etc. as impurities. For use as an automotive fuel it is either compressed and is called as compressed natural gas (CNG) or it is liqified and called as liqified natural gas (LPG).

VOC emissions from natural gas vehicles (NGVs) largely consist of methane, which has low atmospheric reactivity. The NGVs usually operate under lean burn conditions and the CO emissions are much less than those from gasoline powered vehicles. The emission satndards for NO_x limit the use of lean burn engines in NGVs. However, the engine-out emissions (Engine out emissions are those released prior to the catalyst reduction by a catalytic converter) of VOCs, CO and NO_x from NGVs are substancially lower than from conventional vehicles. Also the evaporative emissions are very small and only slightly reactive (NRC, 1992).

C.4.4 Methanol

Methanol fuel is primarily methanol although a significant amount of other compounds are added for safety and performance. Methanol has a high heat of vaporisation and this makes it difficult to start a vehicle running on pure methanol. Therefore additives which raise vapor pressure and help cold start, are added to methanol. The resulting blends are designated by an "M" followed by fraction of methanol (e.g., M85).

Unburned methanol is the largest component of methanol-fueled vehicle (MFV) exhaust. However it is the second most abundant speceis of MFV exhaust, which is formaldehyde (HCHO), that is toxic and highly photochemically reactive. Cold starts provide bulk of the emissions from MFVs. Electrically heated catalysts reduce the tailpipe emissions of HCHO by about 55 percent although these reulsts can not be sustained in vehicles wirh higher mileage. The heated catalyst also decreases methanol emissions, although NO_x emissions increase. CO emissions from MFVs are lower than their conventionally-fueled counterparts. NO_x emissions could be catalytically controlled to meet emission standards. Evaporative emissions from MFVs would be less reactive and the mass emission rate would also be lower (NRC, 1992).

C.4.5 Electricity

Electricity powered vehicles will have virtually no on-road emissions. The use of electric vehicles would eliminate all smog producing emissions. However fossil fuel power plants producing electricity would emit NO_x, oxides of sulfur, and small quantities of VOCs and CO. These plants would contribute to ozone formation. The VOC and CO emissions from these power plants are very small in comparision to internal combustion engines. The NO_x emissions depend on the type of fuel and control technology used. According to a study by Krupnick *et al.* (1990), using electric vehicles would lead to almost three times the reduction in peak ozone concentrations as compared to that obtained from using M85 vehicles. The expected change in NO_x emissions is an important consideration, given that mobile sources are a dominant sources of NO_x. Concentrations of particulate matter and organic nitrates can be effectively reduced by lowering NO_x emissions.

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