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Methodology for Developing Modal Emission Rates for EPA's Multi-Scale Motor Vehicle and Equipment Emission System

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Methodology for Developing Modal Emission Rates for EPA's Multi-Scale Motor Vehicle and Equipment Emission System

Assessment and Standards Division
Office of Transportation and Air Quality
U.S. Environmental Protection Agency

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1 INTRODUCTION

EPA is undertaking an effort to develop a new set of modeling tools for the estimation of emissions produced by on-road and off-road mobile sources. The product of this effort will be the **M**ulti-scale m**O**tor **V**ehicle & equipment **E**mission **S**ystem, referred to as MOVES. The design of MOVES is guided by the following four considerations:

1) the model should encompass all pollutants (e.g., HC, CO, NO_x, particulate matter, air toxics, and greenhouse gases) and all mobile sources at the levels of resolution needed for the diverse applications of the system;
2) the model should be developed according to principles of sound science;
3) the software design of the model should be efficient and flexible; and
4) the model should be implemented in a coordinated, clear, and consistent manner.

A critical element of MOVES is the use of data gathered using on-board emissions measurement devices. To explore this issue, in Fall 2001 EPA issued an on-board emission analysis "shootout" contract in order to solicit several approaches for incorporating on-board emissions into moves. Three shootout contracts were issued to three organizations that worked independently on the same general statement of work. These organizations were NCSU, University of California at Riverside (UCR), and Environ. Each contractor had the flexibility to choose any approach they preferred. NCSU pursued a modal "binning" approach in which operational bins were defined based on speed, acceleration, and power demand, and refined the estimates within each modal bin using regression analysis. UCR pursued a database approach, deriving separate emissions for macroscale, mesoscale and microscale based on a database lookup of individual vehicle and trip results. Environ based their approach on a calculation of vehicle specific power (power per unit mass, or vehicle specific power - VSP), aggregating results over "microtrips" (20 or more seconds, defined by endpoints of stable operation). EPA also developed a conceptual approach based upon binning of data with respect to VSP bins.

The shootout results from NCSU, UCR, Environ, and EPA, revealed several promising approaches for using on-board data in the development of MOVES exhaust emission rates. In particular, the development of modal emission rates using a "binning" approach was successfully demonstrated by NCSU and EPA in the shootout analysis. NCSU directly tackled the time series nature of the on-board data and illustrated methods for dealing with the data to reduce the influence of the time series. The work by Environ illustrated potential benefits to averaging or smoothing the data. As a result of this work, the proposed design of MOVES is predicated on emission rates defined by vehicle and modal operation "bins," and the development of emission rates for these bins in MOVES is the ultimate purpose of the methodology that will be developed in this project.

The philosophy for MOVES is that it should be as directly data-driven as possible. The advantages of a data driven methodology are manifold and include the following:

- Emission rates can be developed from raw data
- Emissions estimates can be developed based upon summaries of actual data within given bins

- Emissions estimates from multiple bins can be weighted to represent any combination of trip and vehicle characteristics.
- Inter-vehicle variability and fleet average uncertainty can be easily estimated based upon appropriate averaging times
- Similar conceptual approaches can be used for different types of vehicles (e.g., on-road gasoline and diesel, nonroad gasoline and diesel)
- Similar conceptual approaches can be used for different pollutants (i.e. HC, CO, NO_x, particulate matter, air toxics, and greenhouse gases)
- The development of bins can be based upon empirical evidence regarding combinations of factors that have the most influence on aggregate emissions
- A modal/binning approach can easily support meso-scale and macro-scale analysis, and can also support micro-scale analysis depending on how the approach is actually implemented.
- A modal/binning approach for light duty gasoline vehicles (LDGV), heavy duty diesel vehicles (HDDV) and nonroad diesel vehicles has been demonstrated by NCSU and EPA
- The NCSU approach for on-road vehicles is an intuitive and easy to explain one based upon bins that correspond to idle, acceleration, cruise, and deceleration behaviors for onroad vehicles. The ability to easily explain the approach to policy makers and the public is an important consideration in gaining acceptance for a new modeling approach.
- A statistical data-driven statistical approach for developing bins, using Hierarchical Tree-Based Regression (HTBR) has been demonstrated and proven by NCSU and can be used in the identification of appropriate binning criteria.
- Methods have been demonstrated by NCSU for handling cold start emissions as part of the modal/binning approach.
- Methods have been explored and recommended by NCSU regarding estimation of modal emission rates from aggregate data (e.g., dynamometer driving cycle data).
- The modal/binning approaches have been evaluated by validating the approaches in comparison to real-world emission measurements.
- Time series analysis already performed by NCSU as part of the shoot-out establish a credible scientific basis for determining appropriate averaging times for the modal/binning approach to be developed in this project.
- The general framework for developing databases, analyzing the data, and developing modal models has already been established at NCSU, both as part of the shootout project and in other previous work.

A key goal of the binning methodology is to develop modal emission rates in a manner that does not require additional modeling analysis, such as regression modeling, and that eliminates the need for many correction factors common to existing models such as Mobile5 and Mobile6. Ideally, the emission rates estimated for a specific bin should be based directly on the sample of raw data falling into that bin.

On-board data is a promising means for developing tailpipe emissions estimates. However, as noted by EPA and as explained in the NCSU final report from the shootout (Frey, Unal, and Chen, 2002), in the short-term other sources of data will continue to play an important role in populating or evaluating MOVES. Thus, an important step in the development of MOVES is to evaluate the feasibility of techniques for applying the modal binning approach to data from other

sources, such as driving cycle dynamometer data and remote sensing device (RSD) data. For example, Frey *et al*. (2002) demonstrated an approach for estimating modal emission rates from aggregate data.

The key purpose of this project is to evaluate methods for developing modal emission rates from disparate data sources (e.g., on-board data, laboratory second-by-second data, aggregate driving cycle data, I/M data, and RSD data) for a relatively small "pilot" dataset of light duty vehicles. In the shootout, NCSU demonstrated that similar approaches can be applied to HDDV and to nonroad diesel vehicles; therefore, it is reasonable to focus resources on the example of LDGVs in this project. Furthermore, in previous work, NCSU demonstrated how to develop a bin for cold starts. Therefore, this project will focus on hot stabilized tailpipe emissions. This project will demonstrate at the proof-of-concept level the methodology for developing modal emission rates in MOVES using a wide variety of data sources, including an evaluation of the applicability of aggregate (bag) data and RSD data.

An important element of MOVES is the incorporation of uncertainty analysis as part of the emission estimation process. EPA has proposed to characterize emission rates for each vehicle/operating bin with a mean value, a distribution form, and standard deviation, to allow for the development of a utility in MOVES which would apply Monte Carlo analysis to generate uncertainty estimates of model final results. Moreover, this approach enables a change in how normal and high emitters are characterized. In previous models, EPA has stratified data into normal and high emitter categories. In the new approach, EPA proposes to treat all vehicles within a bin as a continuous distribution. Thus, for a given vehicle/operating bin, the distribution of emissions will reflect the variability of emissions among all vehicles within the bin, including what are now referred to as normal and high emitters. This approach sets the stage for estimation of the effect of I/M programs with respect to the characteristics of the distribution of inter-vehicle variability in emissions. For example, an I/M program would be expected to identify some portion of the vehicles with emissions above some value and to repair/modify the vehicles so as to reduce their emission rates. This, in turn, would change the distribution of inter-vehicle variability in emissions.

1.1 Objectives of this Project

The objectives of this project are as follows:

- Develop, demonstrate, and report an analytical approach for producing exhaust modal emission rates and emission rate disitributions for MOVES from a variety of data sources, possibly including aggregate (bag) data and RSD data.
- Develop, demonstrate, and report a methodology for estimation of model uncertainty and variability in emissions estimates
- Validate the developed approach against an independent dataset
- Develop a recommended step-by-step methodology for generating modal emission rates in MOVES.

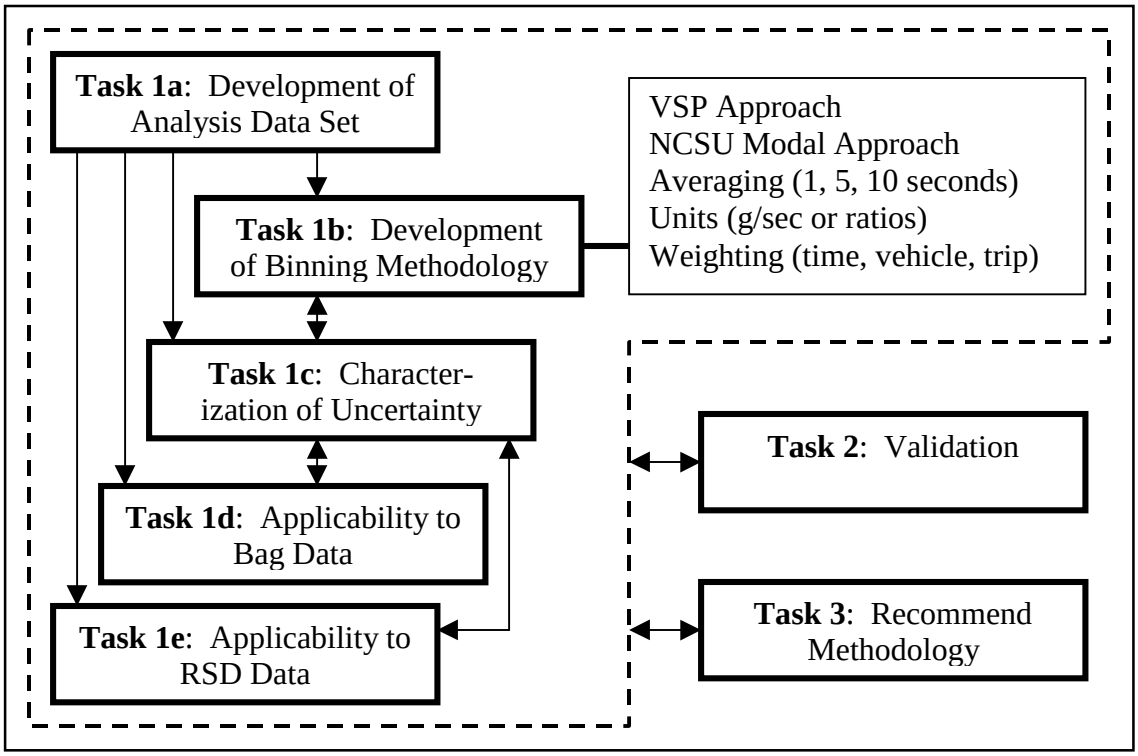

Figure 1-1. Simplified Schematic of Project Tasks and Their Inter-Relationships

1.2 General Technical Approach

In this section, an overview is provided of the technical approach of this project. This project was organized based upon three major tasks:

- Task 1. Develop Pilot Modal Emission Rates From Multiple Data Sources
- Task 2. Perform Validation of Developed Model Against Independent Dataset
- Task 3. Summarize Specific Methodologies for Developing Modal Emission Rates for MOVES

The first task is comprised of many specific subtasks. We subdivided Task 1 into subtasks as follows:

- Task 1a: Development of Analysis Dataset
- Task 1b: Development of Binning Methodology
- Task 1c: Characterization of Uncertainty
- Task 1d: Applicability to Bag Data
- Task 1e: Applicability to RSD Data

The relationship among the three major tasks, and among the subtasks of Task 1, is illustrated in Figure 1. The key starting point of the work was the development of an analysis data set in subtask 1a. The other subtasks in Task 1, including subtasks 1b, 1c, 1d, and 1e, were dependent upon the availability of the analysis data set, which included on-board data, second-by-second laboratory data, IM240 data, aggregate (bag) data, and RSD data. Task 1b included several

considerations that are illustrated by the tie-line to a box listing the binning approaches that were evaluated, the averaging times that were compared, the emission factor units that were compared, and the method for weighting of data. The uncertainty analysis method in Subtask 1c depended upon the binning approach selected as a result of Subtask 1b. However, a two-way arrow is shown between Subtasks 1b and 1c to illustrate the iterative nature of the selection of a binning approach and an uncertainty analysis approach. For example, the choice of averaging time and of weighting method in Subtask 1b influenced the results obtained for the uncertainty analysis method in Subtask 1c, and the availability of uncertainty analysis methods in Subtask 1c has implications regarding which types of weighting methods were chosen as preferred in Subask 1b. The applicability of bag and RSD data to the binning approach methodology also impact the uncertainty characterization. The specifics of these kinds of interactions among subtasks and trade-offs are addressed in more detail in the discussion of each specific subtask.

In the process of developing the tasks during the course of the project, the following key questions emerged and were addressed:

1. What dataset should be used for the final version of the conceptual model? (Task 1a, Chapter 2)

2. Which binning approach should be used? (Task 1b, Chapter 3)

3. How much detail should be included in the binning approach, in terms of how many explanatory variables and how many strata for each variable? (Task 1b, Chapter 3)

4. What averaging time is preferred as a basis for model development? (Task 1b, Chapter 4)

5. What emission factor units should be used? (Task 1b, Chapter 5)

6. What weighting approach should be used, when comparing time-weighted, vehicle weighted, and trip weighted? (Task 1b, Chapter 6)

7. How should variability and uncertainty be characterized? (Task 1c, Chapter 7)

8. How should aggregate bag data be analyzed to derive estimates of modal emission rates? (Task 1d, Chapter 8)

9. What is the potential role and feasibility of incorporating RSD data into the conceptual modeling approach? (Task 1e, Chapter 5)

10. How should the conceptual model be validated and what are the results of validation exercises? (Task 2, Chapter 9)

1.3 Organization of this Report

This report is organized on the basis of the ten motivating questions of the previous section. The development of an analysis data set is addressed in Chapter 2. Chapter 3 presents the empirical and statistical basis for development of modal emissions modeling approaches. The selection of

a preferred averaging time for model development is discussed in Chapter 4. Two major topics are addressed in Chapter 5: (1) what emission factor units should be used; and (2) evaluation of the role of RSD data with respect to model development or model validation. Three different data weighting approaches based upon time, trip, and vehicle averaging are compared in Chapter 6. Methods for quantifying variability and uncertainty are presented and compared in Chapter 7. Methods for estimating modal emission rates from aggregate driving cycle data are presented and evaluated in Chapter 8. The conceptual modal emissions model developed in this work is verified and validated in Chapter 9. Chapter 10 provides a brief summary of the specific methodology for developing modal emission rates that are recommended for future work.

2 DEVELOPMENT OF ANALYSIS DATASET

The objective of Subtask 1a is to develop a combined data set for running exhaust emission rates for LDGV based upon data provided by EPA. The dataset included the following data:

- Approximately 100,000 seconds of data from 17 on-board vehicles from the "shootout" analysis;
- Approximately 75,000 seconds of data on 25 vehicles tested at EPA's lab for the Mobile6 facility-specific driving cycles and other standard cycles;
- 82,800 seconds on 311 vehicles tested on the IM240 as part of the Colorado IM program;
- Bag-only and second-by-second data on 74 vehicles tested over FTP (i.e., Bag 2 and Bag 3) and US06 for development of UC Riverside's Comprehensive Modal Emission Model; and
- RSD data on 200,966 Tier 1 LDGVs collected as part of a Missouri's Gateway Clean Air Program.

The data sets typically contained the following information:

- The second-by-second datasets typically had the following data fields: time; vehicle speed; fuel consumption; HC, CO, NO_x, and CO_2 emissions; vehicle engine size; vehicle weight; vehicle age; vehicle technology; vehicle mileage; road grade (for on-board data); ambient temperature; and ambient humidity. Some datasets, such as from on-board data, typically also had data for more variables such as: engine RPM; latitude; longitude; altitude; mass air flow; intake air temperature; engine load; and other engine related variables.
- Bag data sets included total emissions for CO, HC, NO_x, and CO_2. The bag data were typically from standard driving cycles for which either the standardized or actual test second-by-second speed trace was available. Vehicle-related variables such as vehicle engine size, vehicle mileage, vehicle age, vehicle technology, and vehicle weight were available for "bag" data sets. Additional data were available for some "bag" data sets such as a/c usage, ambient temperature, and relative humidity.
- RSD data included instantaneous vehicle speed and emission rates for pollutants normalized to CO_2 emissions, such as the ratios of CO/CO_2, HC/CO_2, and NO_x/CO_2. In addition, vehicle-related data such as engine size and model year based upon the license plate number that was observed during data collection, identification of the VIN based upon registration data, and decoding of the VIN. However, information regarding vehicle mileage accumulation was not available. Additional variables such as road grade, ambient temperature, and relative humidity were available.

2.1 Development of a Combined Database

In performing the work for this study, our general philosophy was to make use of readily available software tools where possible. Therefore, we made use of Visual Basic, Excel, and SAS to a significant extent, consistent with our previous experience in working with similar datasets.

The combined second-by-second dataset, including on-board data, laboratory dynamometer data, and IM240 data, was created using programs written in Visual Basic and SAS. For this purpose,

Visual Basic programs that were prepared in previous studies (Frey *et al.*, 2001; Frey *et al.*, 2002) were utilized. The first step in developing a combined dataset was to make sure that each data file has the same data fields. Each data file represents a vehicle or a trip. A Visual Basic code was utilized to process the data and arrange the data fields such that each file has the same format. Formatting of the fields was conducted with Visual Basic programs that were written for this purpose in previous studies. After completing the processing of all data files, all of the data was in Excel with the same format. The Excel files were first exported to SAS and combined together in SAS using codes written specifically for this purpose.

For quality assurance purposes, the data were screened to check for errors or possible problems. A notable issue was that there were zero and negative numbers in the second-by-second emissions data. Specifically, 13 percent of the data were comprised of zero or negative values for CO, 12 percent for HC, 22 percent for NO_x, and 0.8 percent for CO_2. Since measurements errors could result in negative values that are not statistically significantly different from zero or a small positive value, the data were retained as is.

Several post-processing steps were applied to the dataset. The post processing steps included: (1) humidity corrections for NO_x emissions for the on-board data; (2) adjustments to the HC data for the on-board data; and (3) calculation of derived variables such as acceleration, power demand, and vehicle specific power. Since the dynamometer data was already corrected for humidity, a humidity correction was also applied to the on-board data. For this purpose, a humidity correction factor that was reported in the on-board dataset was utilized. The on-board measurements of HC emissions were made using NDIR, whereas the dynamometer measurements were made using FID. In other work, the measurements of the on-board instrument developed by Sensors that was used to collect the EPA on-board data were compared with measurements made with a laboratory dynamometer. By comparing the total HC emissions for specific vehicles and driving cycles, it was observed that the NDIR measurements resulted in lower values than did the FID measurements. Based upon the available comparison data, a correction factor of,1.65 was utilized to adjust the on-board HC measurements to an approximate equivalent basis. Because the adjustment factor was based upon an average of total trip emissions, the adjustment factor does not take into account possible variability in the ratio of FID to NDIR measurements on a second-by-second basis.

Variables such as acceleration, power demand and VSP were estimated from other variables such as vehicle speed. Acceleration is estimated from the observed speed by taking second-by-second differences in speed. However, to account for the effects of road grade, the estimate of acceleration was modified. As indicated by Bachman (1999), gravity exerts a force on a vehicle that must be counteracted. Therefore, the acceleration effect of road grade should be included in order to estimate the effective acceleration. The effect of road grade on acceleration can be quantified as:

$$\text{Acceleration (mph/sec)} = 22.15\,\text{(mph/sec)} \times \text{Gradient (\%)} \tag{2-1}$$

Power demand was estimated using the following equation:

$$P = v \times a \tag{2-2}$$

where:

P	=	Power Demand (mph^2/sec)
v	=	Vehicle speed (mph)
a	=	Vehicle acceleration (mph/sec)

Vehicle Specific Power (VSP) was estimated using an equation given by EPA, which is:

$$\text{VSP (kW/ton)} = v[1.1a + 9.81(a\tan(\sin(\text{grade}))) + 0.132] + 0.000302v^3 \qquad (2\text{-}3)$$

The coefficients given in Equation (2-3) are specific for on-board data. However, coefficients for dynamometer measurements were not available in this study, therefore, the same coefficients were used for dynamometer data as well. While it is recognized that the specific estimate of VSP is a function of vehicle weight and of the specific values of the parameters for each individual vehicle, it was beyond the scope of this study to develop detailed vehicle-specific estimates of VSP.

2.2 Organization of the Data for Analysis

The combined database was used to create specific databases for different analyses throughout the project. These databases included the following:

- A "Modeling" or "Calibration" database comprised of data for most of the on-board measurements, most of the EPA dynamometer data, and most of the NCHRP data. This database was also used as "Validation Data Set 1"
- "Validation Data Set 2" was comprised of a small sample of vehicles from the EPA on-board, EPA dynamometer, and NCHRP data that were excluded from the modeling database.
- IM240 data were used separately from the other data
- The NCHRP data were used in the analysis of methods for developing modal emission rates from aggregate bag data
- "Validation Data Set 3" was comprised of data obtained from the California Air Resources Board, and are also referred to as "ARB data."
- RSD data included approximately 2,000,000 seconds of data. Of this dataset, 200,966 data points were selected randomly for analysis, where each point represents measurement for one vehicle.

The data from on-board, EPA dynamometer and NCHRP dynamometer measurements were combined into the modeling data set, and included:

- 71,699 seconds of data from 13 on-board vehicles from the "shootout" analysis;
- 68,482 seconds of data on 33 vehicles tested at EPA's lab for the Mobile6 facility-specific driving cycles and other standard cycles; and
- 92,000 seconds of data on 49 vehicles tested over FTP and US06 for development of UC Riverside's Comprehensive Modal Emission Model.

Therefore, the combined database for modeling has a total of 232,181 seconds of data. The combined database has the following data fields: source for data (e.g., EPA dynamometer); vehicle make; vehicle model; VIN; number of vehicle tested; number of trip tested; speed; acceleration; ambient temperature; ambient humidity; road grade; power estimate, positive power estimate; Vehicle Specific Power (VSP) estimate; positive VSP estimate; CO, CO_2, HC,

NO_x emissions; vehicle model year; vehicle engine displacement; number of cylinders; air condition use; and vehicle net weight.

Validation Data Set 2 included the following data:

- 3 vehicles from EPA dynamometer data
- 3 vehicles from EPA On-board data
- 25 vehicles from NCHRP data

The validation dataset included 83,183 seconds of data. The data fields for this dataset were the same as for the Modeling dataset.

The NCHRP dataset included 8 high-emitter vehicles as reported in a User's Manual prepared by University of California at Riverside. In preparing Validation Dataset 1 and 2, data were selected randomly from NCHRP data. Six of the high emitter vehicles were included in Validation Dataset 1, and two of them were included in Validation Dataset 2.

Validation Data Set 3 included data for 17 vehicles from 11 different UCC cycles. The validation dataset included nominal speed profiles and total emissions for 15 of the vehicles, and actual speed profiles and second-by-second emissions for two of the vehicles. Detailed information regarding the Validation Datasets is given in the Appendix.

Data for IM240 were utilized for comparative purposes, as described in this report, including comparing average emission rates for the developed modes with respect to those obtained from the calibration data. The IM240 dataset included 311 vehicles tested on the IM240 cycle, for a total of 82,800 seconds of data. The data fields for this data set were the same as for the Modeling dataset.

EPA obtained an RSD database from the state of Missouri that contained approximately 2 million records. Of this dataset, 200,966 data points were selected randomly for analysis. This dataset included data fields similar to the modeling database. However, vehicle net weight was not available and engine displacement was only available for part of the dataset. Each data point in the RSD database used for analysis represents a unique vehicle.

2.3 Summary

Data from a variety of sources were reviewed and used to develop data bases for different components of this project. A modeling database comprised of approximately 232,000 seconds of data from on-board and laboratory dynamometer measurements was compiled for use in developing a conceptual modeling approach. A separate IM240 database was developed for comparison to the modeling data. A database comprised of RSD data was developed in order to answer key questions regarding the potential role of RSD data in model development or model interpretation. A database comprised of NCHRP dynamometer data was developed in order to evaluate methods for estimating modal emissions from aggregate driving cycle data. In addition to the modeling data set, two other databases were developed for model validation purposes, including an independent sample of on-board and dynamometer measurements for vehicles similar to those used in the modeling data base and a separate database obtained from CARB.

3 DEVELOPMENT OF A MODAL EMISSIONS MODELING APPROACH

The objective of this section is to demonstrate the modal "bin" approach on data for "running" hot-stabilized exhaust emission rates, and to determine the best binning approach based upon evaluation of alternative approaches. This chapter focuses upon the use of one second data in units of mass per time. Chapter 4 compare different averaging times and Chapter 5 compares different emission factor units. The two most promising binning approaches identified in the "shootout" were the VSP-based approach evaluated by EPA and the driving mode-based approach evaluated by NCSU. These two approaches were compared in this project. A key methodological component of this work was the use of Hierarchical Tree-Based Regression (HTBR), using S-Plus software. This chapter focuses on answering the second and third key questions of this project: (1) which binning approach should be used?; and (2) how much detail should be included in the binning approach, in terms of how many explanatory variables and how many strata for each variable? First, the methodology for developing bins based upon statistical methods is presented. Results of analysis of the modeling data set based upon each of the NCSU and VSP based approaches are presented. An evaluation of each approach is made, followed by a selection of a preferred approach.

3.1 Statistical Method for Developing Binning Criteria

HBTR is a forward step-wise variable selection method, similar to forward stepwise regression. This method is also known as Classification and Regression Trees (CARTs). Conceptually, HTBR seeks to divide a data set into subsets, each of which is more homogeneous compared to the total data set. At a given level of division, each of the subsets is intended to be different in terms of the mean value. Thus, HTBR is a statistical approach for binning data. More specifically, the method is based upon iteratively asking and answering the following questions: (1) which variable of all of the variables 'offered' in the model should be selected to produce the maximum reduction in variability (also referred to as deviance in HTBR methodology) of the response?; and (2) which value of the selected variable (discrete or continuous) results in the maximum reduction in variability (i.e., deviance) of the response? The method uses numerical search procedures to answer these questions. The HTBR terminology is similar to that of a tree; there are branches, branch splits or internal nodes, and leaves or terminal nodes (Washington *et al.*, 1997).

The iterative partitioning process is continued at each node until one of the following conditions is met: (1) the node of a tree has met minimum population criteria which is the minimum sample size at which the last split is performed; or (2) minimum deviance criteria at a node have been met (Frey *et al*., 2002; and Unal 1999).

In developing bins, vehicle-based variables such as vehicle class, mileage, age, engine size, vehicle weight, and technology were utilized. Vehicle operation variables such as vehicle speed, acceleration, and surrogate for power demand (i.e., Vehicle Specific Power) were included in this analysis. Based upon the availability of the data, external parameters such as road grade, air condition usage, ambient temperature, relative humidity were incorporated during HTBR analysis. S-Plus scripts that were written in previous studies were used in this study.

In developing bins both “unsupervised” and “supervised” techniques were utilized. In the “unsupervised” technique, data is provided to the HTBR with no prior specification of branches or nodes of the regression tree. In this situation, HBTR is allowed to create whatever bins result from direct application of HBTR. In contrast, for the “supervised” technique, HTBR is forced to start with pre-determined modes. A partially supervised technique can often be a better approach than a purely unsupervised technique. This is because HTBR can be sensitive to artifacts of variability in the data that may not be important from a practical perspective, and HBTR may give unexpected or difficult to interpret results if the unsupervised technique is used. Sometimes HBTR will repeatedly “split” on the same subset of variables (e.g., speed and acceleration) which may indicate the need for a new explanatory variable that is a function of the subset of variables. For example, if HBTR splits repeatedly on speed and acceleration, it may be better to remove speed and acceleration as criteria for creating bins and instead offer some variable that is a combination of both speed and acceleration, such as VSP or power demand.

The two binning approaches that were evaluated are the VSP approach demonstrated by EPA and the driving mode approach demonstrated by NCSU (Frey *et al*., 2002). VSP is a surrogate for power demand and is a function of vehicle speed, road grade, and acceleration. In an unsupervised approach, the selection of bins would be determined by the results of application of HBTR, rather than based upon arbitrary bin assignments, such as those made by EPA as part of the shootout (e.g., 1 kw/ton bins from –15 to +30).

The HBTR-based approach was also applied to the driving mode definitions developed by NCSU. As part of previous work (Frey *et al*., 2001; 2002), NCSU developed *a priori* driving mode definitions. Idle is defined as based upon zero speed and zero acceleration. The definition of the acceleration mode includes several considerations. First, the vehicle must be moving and increasing in speed. Therefore, speed must be greater than zero and the acceleration must be greater than zero. However, vehicle speed can vary slightly during events that would typically be judged as cruising. Therefore, in most instances, the acceleration mode is based upon a minimum acceleration of two mph/sec. However, in some cases, a vehicle may accelerate slowly. Therefore, if the vehicle has a sustained acceleration rate averaging at least one mph/sec for three seconds or more, that is also considered acceleration. Deceleration is defined in a similar manner as acceleration, except that the criteria for deceleration are based upon negative acceleration rates. All other events not classified as idle, acceleration, or decelerations are classified as cruising. Thus, cruising is approximately steady speed driving but some drifting of speed is allowed. It was shown by NCSU in previous studies (Frey *et al*., 2001; 2002) that emission estimates for these driving modes are statistically significantly different from each other. An example comparison of modal emission rates for hot stabilized driving is given in Figure 3-1.

In working with the NCSU-based approach, two specific applications of HBTR were made. In the first, the data set was modified to include a bin category for each data point. Unsupervised HBTR was applied to the modified database to determine whether HBTR will subdivide the data based upon the NCSU modal definitions preferentially compared to other possible binning criteria. Additional bins were developed using HBTR in order to further refine the binning approach. This type of approach was demonstrated briefly in the previous shootout project (Frey *et al*., 2002) and was expanded in its application in this project.

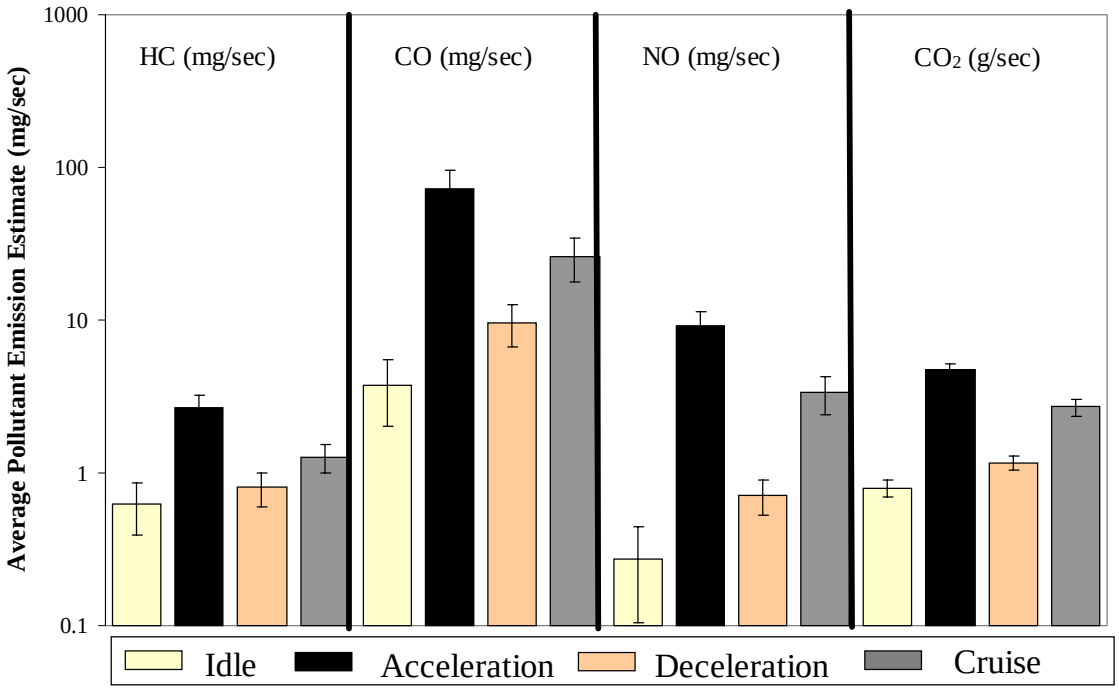

Figure 3-1. Average Modal Emission Rates for LDGVs (Source: Frey *et al*., 2002)

In developing modal "bins" in HTBR it should be kept in mind that there is a trade-off between the number of bins and the usefulness of the empirical model based upon the bins. While it is possible to obtain additional explanatory power by increasing the number of bins, there are diminishing returns associated with creation of an increasing number of bins. Furthermore, the HBTR determines bins based upon whether there are differences in the average emissions among the possible bins. It does not determine bins based upon what portion of trip or total emissions are explained by each bin. Therefore, it is possible to obtain a potentially large number of bins that do not help explain a significant portion of total trip or aggregate emissions. Supervised techniques are sometimes more useful than unsupervised techniques in helping to avoid a proliferation of relatively useless bins. Another method for dealing with the possible combinatorial explosion of bins is to "prune" a tree created using HBTR. For example, HBTR could be allowed to develop a large number of bins for purposes of determining a practical upper limit on the amount of deviance in the data set that can be explained by the bins. Then, the number of bins can be reduced to a point where there is still good explanatory power of the binning approach with a much smaller number of bins. This process requires some judgment and therefore would be considered to be a supervised technique. This approach has been demonstrated previously (e.g., Rouphail *et al*., 2000; Frey *et al*., 2002).

Another important issue regarding bin development is that bins that are formed under different branches of the tree (see Figure 3-2) may not be statistically significantly different from each other

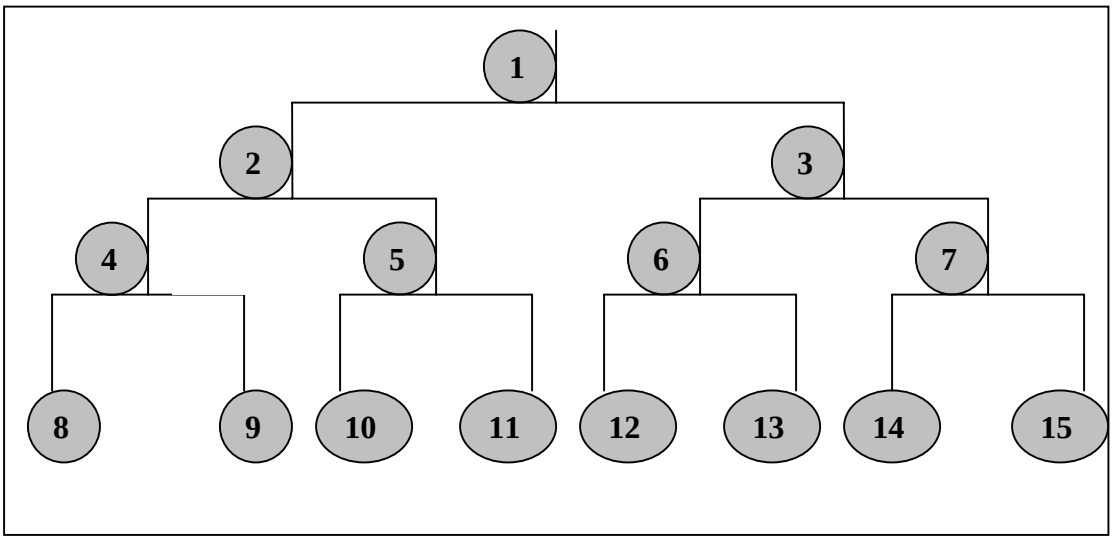

Figure 3-2. Sample Regression Tree Diagram (Numbers represent Node Numbers of the Tree)

when the number of bins increases. All of the data are "fed" into the HBTR process as Node 1. HBTR will divide into separate data sets at each branch in the tree. Thus, the first split of the data is into bins represented by Nodes 2 and 3. Then, another split is made in which the data are further subdivided into four nodes, Nodes 4, 5, 6, and 7. A third split results in eight modes, which are Nodes 8 through 15. Each time a split is made, the two nodes that are subdivided based upon a higher level node are statistically significantly different from each other with respect to the mean value. Thus, for example, Nodes 8 and 9 will have significantly different mean values. However, Nodes 9 and 10, which result from different branches, are not guaranteed to have significantly different means. Thus, it is possible that a larger number of nodes could result in some overlap with respect to mean values. In other words, the creation of a large number of bins or nodes may not substantially increase explanatory power compared to a smaller number of bins or nodes. We evaluated the statistical significance of differences in the average value of emissions associated with different bins and considered lack of statistical significance of average values as a stopping criteria pertaining to the creation of additional branches of the regression tree.

Not all modes are equally important. Some modes are more important than others since they represent a larger share of total emissions than others. For example, in a previous study by NCSU it was found that acceleration and cruise modes are the most important modes in terms of total trip emissions. Figure 3-3 illustrates the distribution of time spent in each driving modes (i.e., cold-start, idle, acceleration, deceleration, and cruise) and the corresponding percentage contribution of each mode to total trip emissions for each of four pollutants. One key finding is that the idle and deceleration modes contribute relatively little to total emissions for any of the

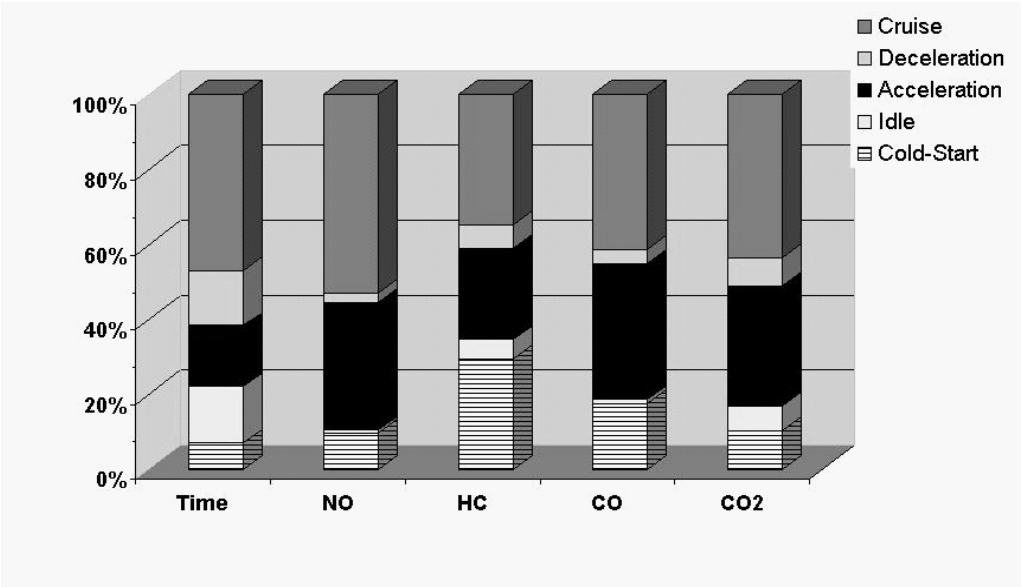

Figure 3-3. Example of Average Distribution of Time and Emissions with Respect to Modes (Source: Frey *et al*., 2002)

four pollutants compared to cruise, acceleration, and cold start emissions. Therefore, there is likely to be little to be gained by spending resources to improve the explanatory power of the idle and deceleration modes. In contrast, cruising, acceleration, and cold start, in a general descending order, are the most important contributors to total emissions. Therefore, an iterative approach was taken to develop bins. First bins were developed using the HTBR method. The percent contribution of each mode total emissions was estimated. Based upon these results, the definitions of the modes were revised so that no single mode contributes disproportionately to the total emissions represented in the database.

3.2 Development of the VSP-Based Modal Approach

In developing bins based upon VSP, first step was to explore the relationship between VSP and emissions with the help of scatter plots. Based upon exploratory analysis of the sensitivity of emissions to VSP and other explanatory variables, a recommended approach was developed for a modal model.

3.2.1 Exploratory Analysis

Figure 3-4 shows the relation between VSP and emissions for HC, NO, CO, and CO_2. VSP data were binned into 1kw/ton bins from -50 to +50 and the average within each bin is shown.
It is observed from these scatter plots that there is an approximately monotonic increase in emissions for all four pollutants for positive VSP. Emissions tend to be very low for negative VSP bins and tend to increase as VSP increases above zero. For very high values of VSP (i.e., VSP bins higher than 45) there is an apparent decrease for CO_2 and NO_x especially. The number of data points in these bins are small, typically less than 100. Thus, the reliability of the estimates for the very high VSP bins in question. However, one reviewer of this work indicated that there is the possibility that emissions may actually decrease on average in the very high VSP range.

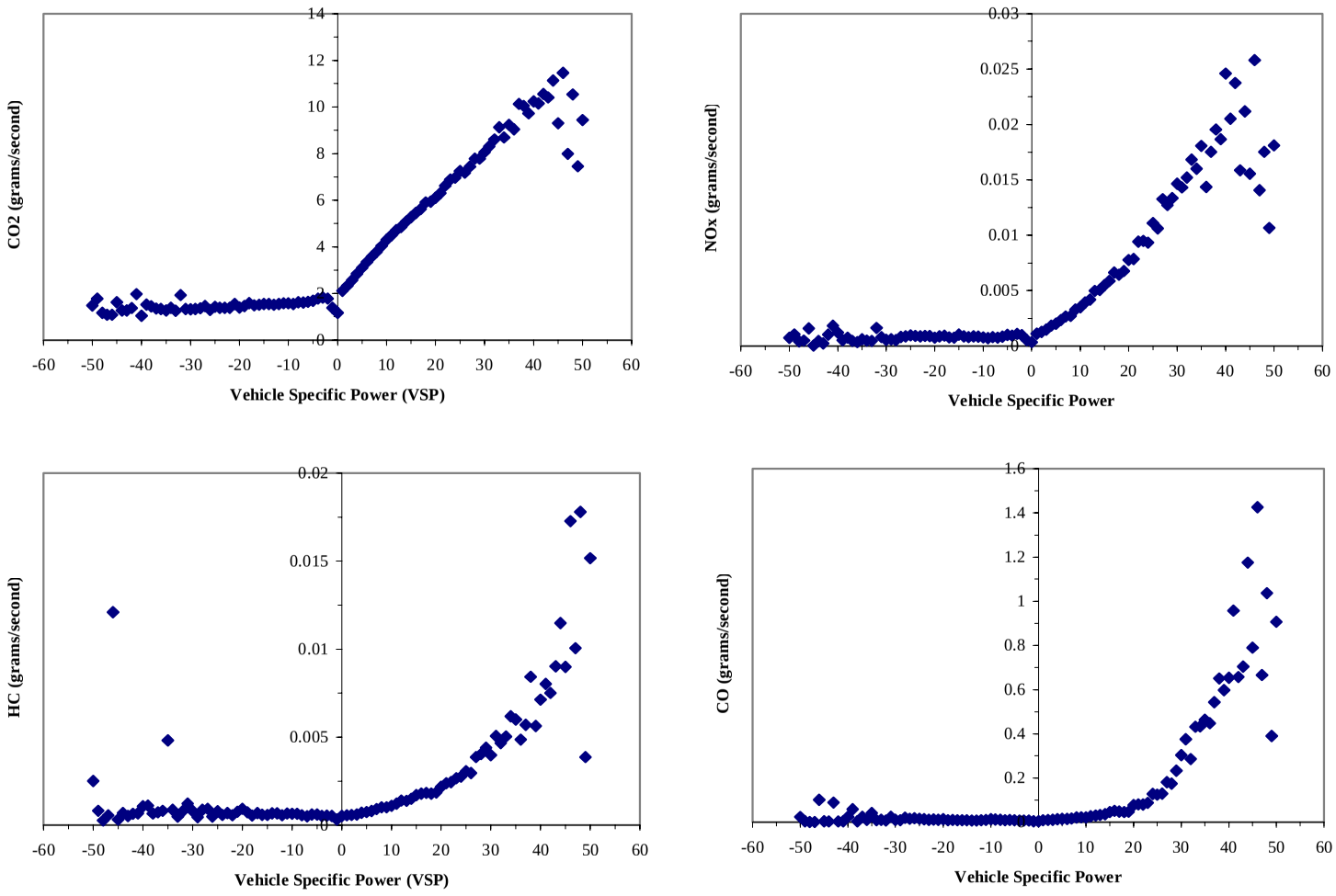

Figure 3-4. Exploratory Analysis of Average Emissions of CO_2, NO_x, HC, and CO versus Vehicle Specific Power (VSP) Based Upon the Modeling Database.

HBTR was applied to the modeling dataset in order to see whether VSP would be selected by HTBR as the mot important explanatory variable. An example for this analysis is given for NO emissions in Figure 3-5. Vehicle operating parameters as well as vehicle technology parameters were used as possible explanatory variables. These parameters are: speed; acceleration; VSP; temperature; engine displacement; number of cylinders; a/c usage; temperature, odometer reading; model year; and net weight. Of all these parameters VSP was selected as the first split by HTBR. The vertical distance depicted for each branch is proportional to the reduction in deviance associated with each explanatory variability. In this specific case, splitting the data set into two strata based upon a VSP criteria of 13.2 lead to a substantial reduction in deviance. Under the second branch of the tree, a second split was made based upon vehicle net weight. However, the reduction in deviance based upon further stratification by net weight is less than the reduction in deviance from the first split based upon VSP. At the lowest portion of the tree, a second split based upon VSP is observed for the smaller net weight category of data. When a variable occurs repeatedly in the tree, such as VSP does in this case, that is evidence that the variable plays an important role. In this case, VSP alone helps explain a substantial portion of deviance in the data. When the data are further stratified, VSP explains additional deviance for vehicles with a net weight less than 4,400 pounds. This result illustrates that VSP is the most important variable and therefore could be selected as the first criteria for developing bin definitions. Qualitatively similar results were obtained for other pollutants.

A judgment was made that it would be useful to separately analysis the role of vehicle operating parameters (e.g., VSP) as distinct from vehicle characteristics (e.g., net weight, odometer reading, engine size). When only vehicle operating parameters were utilized in HTBR, VSP was again found to be the most important explanatory variable.

Because VSP was consistently identified as the most important explanatory variable, modal bins were developed using VSP. HBTR was not used to develop the actual definitions of the bins. While useful in identifying which variables offer the most capability to explain deviance in the data set, an “unsupervised” approach to HBTR does not provide optimal bin definitions. For example, it is possible that nodes that occur under different branches of the tree may have similar average emission rates. From a practical perspective, it is not useful to have bins with similar average emission rates, since the objective is to explain variability in emissions. Therefore, a “supervised” approach was adopted. In the supervised approach, two key considerations were taken into account. The first is that ideally each mode should have a statistically significantly different average emission rate than any other mode. The second is that no single mode should dominate the estimate of total emissions for a typical trip as represented by the database. Therefore, to guide the selection of modal definitions, it was decided that no mode should explain more than approximately 10 percent of total emissions. Based upon these two considerations, VSP modes were defined. It should be noted that same modes were defined for all the pollutants. Table 3-1 gives the VSP modal definitions.

Figure 3-6 shows average modal rates for these bins for all four pollutants. The average modal rates are significantly different from each other for all four pollutants. In all four pollutants the average modal rates for the first two modes, Modes 1 and 2, are higher than average rate for Mode 3. There is an increasing trend in emissions with increase in VSP bins for Modes 4

Table 3-1. Definitions for VSP Modes

VSP Mode	Definition
1	VSP<-2
2	-2<=VSP<0
3	0<=VSP<1
4	1<=VSP<4
5	4<=VSP<7
6	7<=VSP<10
7	10<=VSP<13
8	13<=VSP<16
9	16<=VSP<19
10	19<=VSP<23
11	23<=VSP<28
12	28<=VSP<33
13	33<=VSP<39
14	39<=VSP

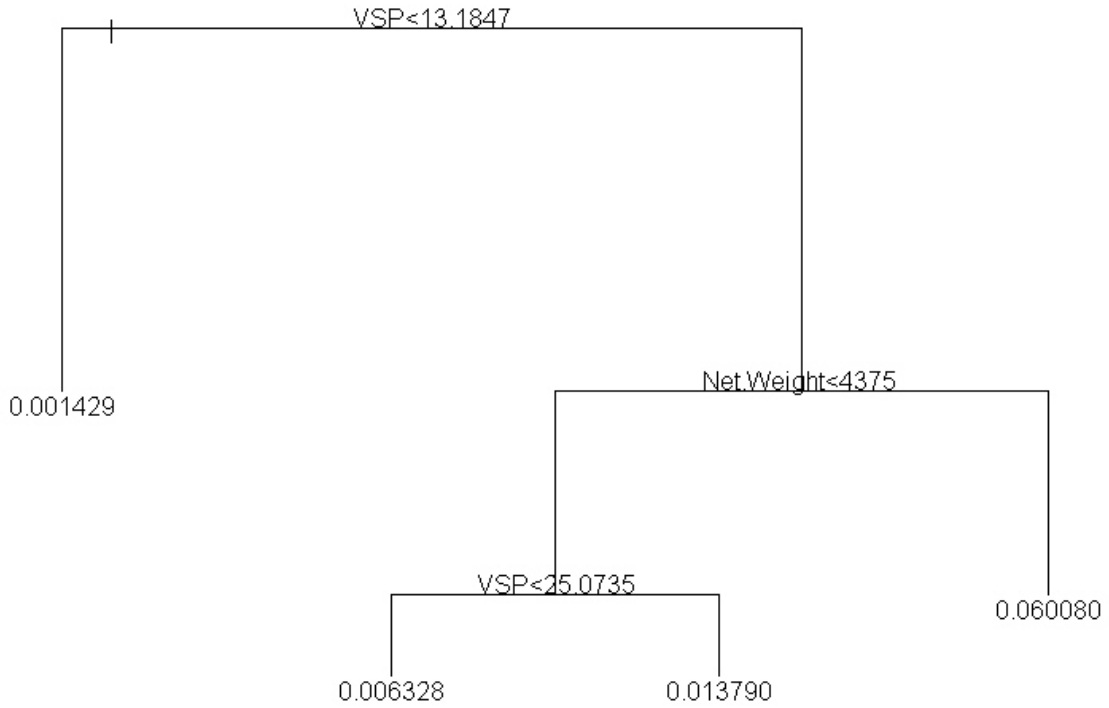

Figure 3-5. Example of Unsupervised HTBR Tree Results for the Modeling Data Set for NO_x Emissions (g/sec)
Note: The vertical distance of each branch indicates the proportional explanatory benefit of each particular split, and the numbers at the bottom of the branches are the average emission rates for the stratified data.

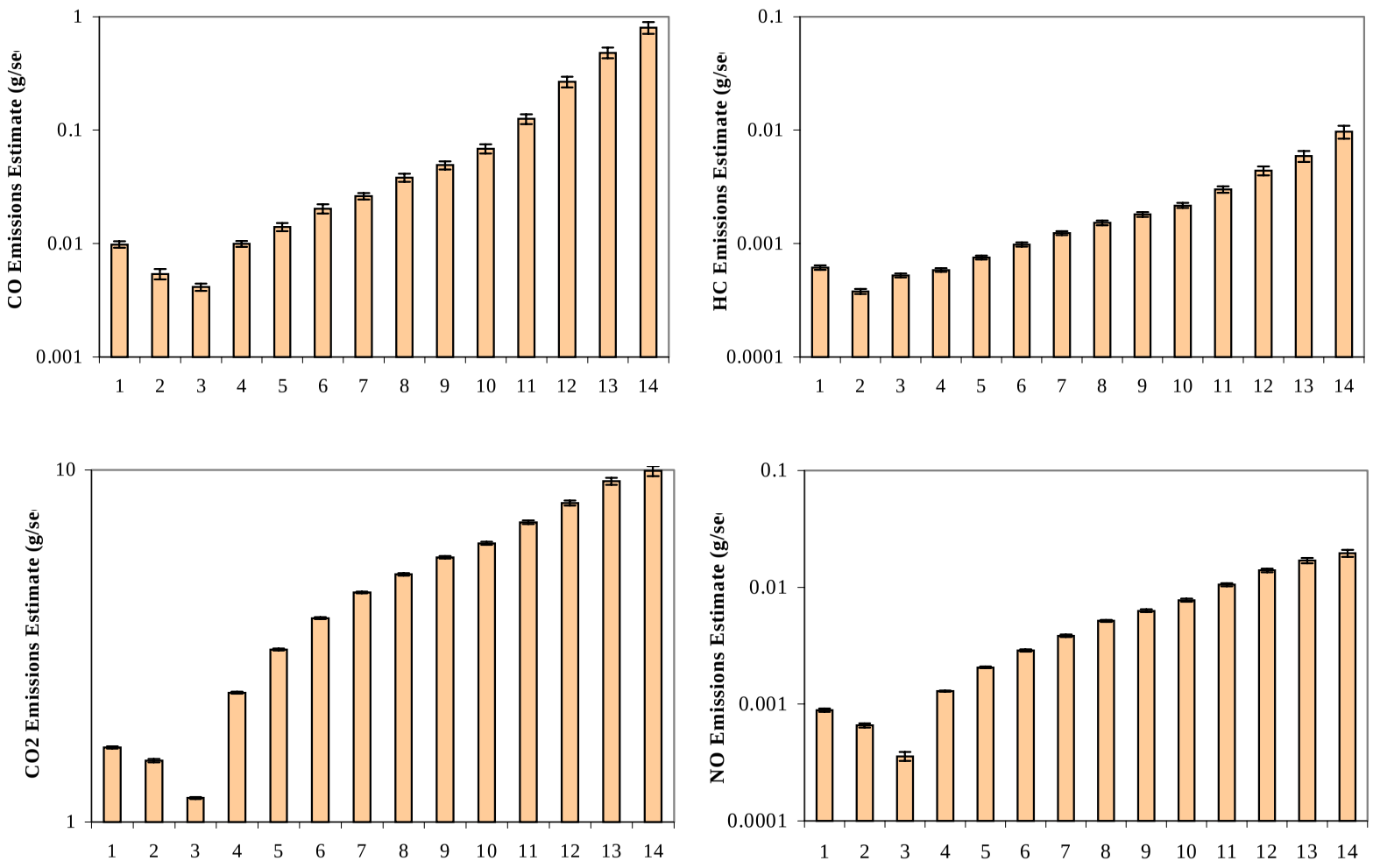

Figure 3-6. Average Modal Emission Rates (g/sec) for VSP Bins for CO, HC, CO_2, and NO_x Based Upon the Modeling Dataset.

through 14 for all of the pollutants. For CO, the range in average modal emissions is more than two orders-of-magnitude, when comparing Mode 3 and Mode 15. A similar comparison for NO_x, HC, and CO_2 implies a range of approximately one to two orders-of-magnitude.

Because each pollutant has a different sensitivity to the modal definitions, there are some cases in which a mode may contribute approximately 10 percent to the total emissions of one pollutant but a far lower percentage of total emissions for another pollutant, as shown in Figure 3-7. For example, for the high VSP bins, such as Modes 12, 13, and 14, approximately 10 percent of the total CO emissions in the calibration data set are accounted for, for a total of over 30 percent of the total CO emissions. These four modes account for less than three percent of total travel time in the database. Furthermore, these modes account for only approximately 15 percent or less of total NO_x, HC, and CO_2 emissions. The implication is that high VSP has a more substantial impact upon CO emissions than for the other pollutants. This seems plausible, in that high VSP is likely to be associated with an increased frequency and duration of command enrichment, which tends to have more effect on CO emissions than, for example, NO_x emissions. Because pollutants respond differently to activity captured by each mode, it was necessary to have 14 modes in order that no individual mode represent more than approximately 10 percent of the emissions of any single pollutant. Of course, the proportion of emissions in each mode is conditional on the database used to estimate the modal emission rates.

3.2.2 Considerations in Refinement of the VSP-Based Modal Approach

In order to further improve modal definitions, parameters related to vehicle technology were included in an analysis to determine which ones are most useful in further explaining variability in emissions. These parameters included were: engine displacement; number of cylinders; odometer reading; model year; and net weight. Some of these parameters are correlated with each other. For example, odometer reading and model year tend to have a positive dependence, and engine displacement, number of cylinders, and net weight tend to have a positive dependence. The correlation analysis for these parameters is given in Appendix. Therefore, in the final model, it is not expected to be necessary to include all of these. Separate HTBR trees were fit to data in each mode for each pollutant separately. Tables 3-2 through 3-5 summarize the results of these analyses for CO, CO_2, HC, and NO_x respectively.

One of the observations from Tables 3-2 through 3-5 is that both net weight and engine displacement are important variables for all of the pollutants for most of the modes. Engine displacement is an important variable especially for CO and CO_2, whereas odometer reading is important especially for HC. Based upon the results given in Tables 3-2 through 3-5, improvements in the VSP modal definitions were considered based upon comparison of based upon net weight or engine displacement. In addition, the effect of stratification of VSP bins with respect to odometer reading was also considered.

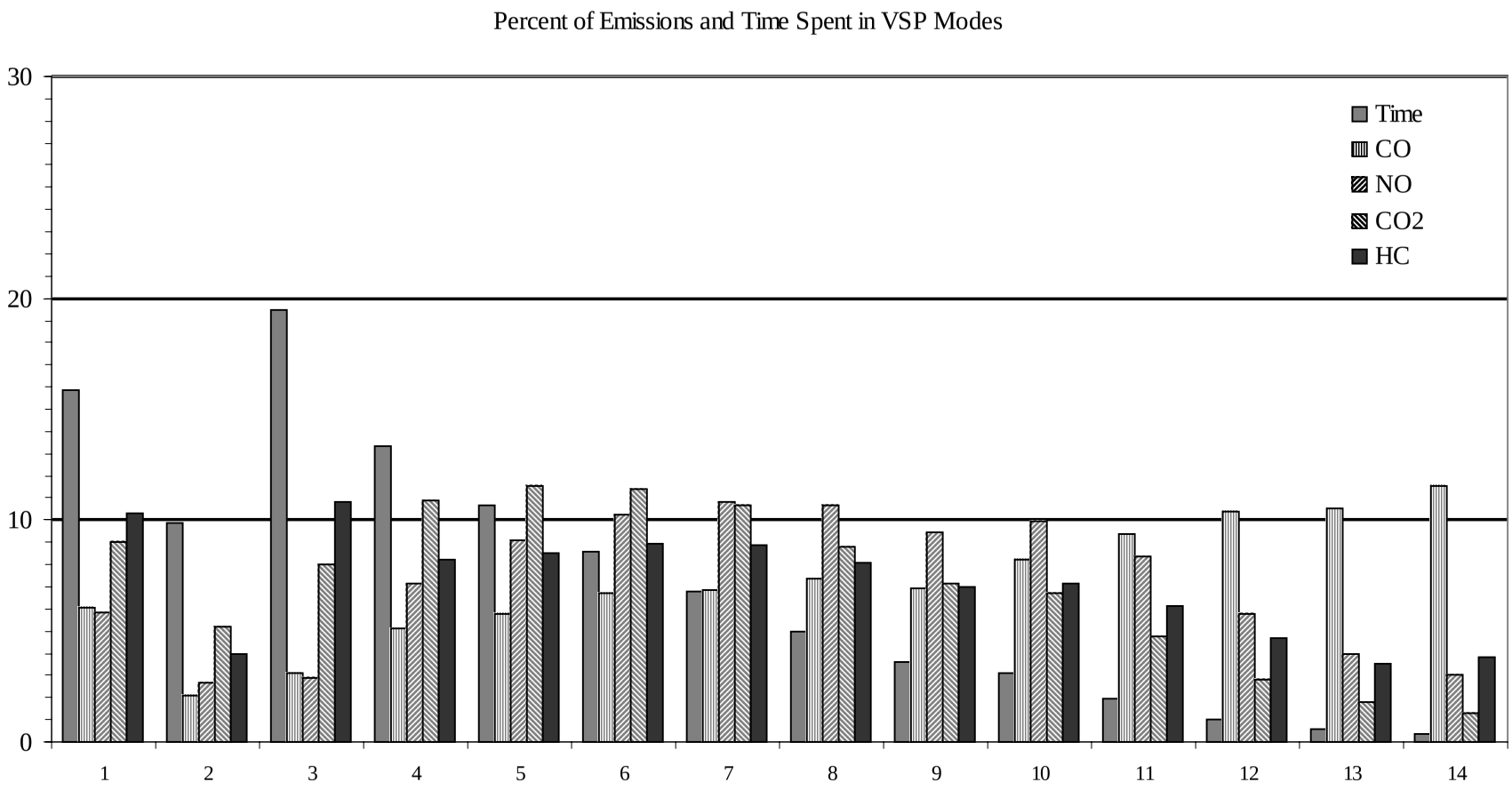

Figure 3-7. Percent of Time Spent in VSP Modes and Percentage of Total CO, NO_x, CO_2, and HC Emissions Attributable to Each VSP Mode, Based Upon the Modeling Data Set.

Table 3-2. Unsupervised HBTR Regression Tree Results for CO for Each of 14 VSP Modes

Mode	**1st Cut point**	**2nd Cut point**	**3rd Cut point**
1	E* 5.3	NW 4400	NW 3600
2	E 5.3		
3	E 5.3		
4	E 5.3		
5	E 5.3		NW 3600
6	NW** 4400	O 15000	
7	NW 4400	NW 3600	
8	NW 4200	O 15000	O 24000
9	NW 4200	C**** 5	
10	NW 4200	C 5	
11	NW 4200	C 5	
12	NW 3800	NW 3200	
13	O*** 15000		O 79000
14	NW 3300	O 45000	O 79000

Table 3-3. Unsupervised HBTR Regression Tree Results for CO_2 for Each of 14 VSP Modes

Mode	**1st Cut point**	**2nd Cut point**	**3rd Cut point**
1	NW 3200	C 5	O 25000
2	NW 3200		
3	C 5	NW 3200	
4	C 5	NW 2700	NW 3600
5	E 2.3	NW 2800	NW 3700
6	E 2.3	E 1.95	C> 7
7	NW 3700	E 1.95	E 3.9
8	NW 3700	E 1.95	E 3.5
9	E 3.5	O 46000	
10	E 3.5	O 44000	
11	E 3.5	O 46000	
12	E 3.5	O 37000	
13	E 3.5	O 23000	
14	E 3.5		O 60000

Note: “NW” means “Net Vehicle Weight (lbs)”, “O” means “Odometer Reading (miles)”, “C” means “Number of cylinders”, “E” means “Engine Displacement (liters)”. The number following the variables is the value of the cut point.
Results are not shown in cases where sample size was small

Table 3-4. Unsupervised HBTR Regression Tree Results for HC for Each of 14 VSP Modes

Mode	**1st Cut point**	**2nd Cut point**	**3rd Cut point**
1	O 77000		
2	O 77000		O 98000
3	O 79000		
4	O 79000		O 98000
5	O 78000		O 98000
6	O 78000		O 98000
7	O 78000	O 30000	O 98000
8	O 78000	O 26000	
9	O 78000	O 33000	O 95000
10	O 78000	O 32000	
11	O 43000		O 95000
12	O 43000		NW 2800
13	O 43000	O 15000	NW 3000
14	O 46000		NW 3000

Table 3-5. Unsupervised HBTR Regression Tree Results for NO_x for Each of 14 VSP Modes

Mode	**1st Cut point**	**2nd Cut point**	**3rd Cut point**
1	NW 3600	O 23000	NW 3800
2	O 66000		O 83000
3	O 30000		O 43000
4	NW 4400	O 66000	
5	NW 4400	O 66000	
6	NW 4400	O 66000	
7	NW 4400	O 66000	
8	O 70000	NW 2800	NW 3800
9	NW 4200	O 38000	
10	NW 4200	O 38000	
11	NW 4200	O 38000	
12	O 13000		
13	O 14000		O 95000
14	NW 3800	NW 3600	NW 2800

Note: “NW” means “Net Vehicle Weight (lbs)”, “O” means “Odometer Reading (miles)”, “C” means “Number of cylinders”, “E” means “Engine Displacement (liters)”. The number following the variables is the value of the cut point.
Results are not shown in cases where sample size was small

Figures 3-8 and 3-9 present the effect of net weight and engine displacement, respectively, on emissions as applied to the VSP modal bins. For Figure 3-8, the data were stratified based upon a vehicle weight of 4,000 pounds, and for Figure 3-9, the data were stratified based upon an engine displacement of 3.5 liters. These cut-offs were chosen based upon the results of Tables 3-2 through 3-5 and were intended to be representative values. Although for some pollutant/mode combinations there is no significant or substantial difference in average emissions, for other combinations there are statistically significant differences based upon either net weight or engine displacement. For example, for the higher VSP modes (e.g., Modes 10 to 14), average emissions are larger for all four pollutants for the larger weight category. In the case of CO_2, the trend of higher emissions for heavier vehicles is systematic among all of the positive VSP modes (i.e. Modes 3 to 14); this difference is expected since heavier vehicles typically have lower fuel economy and, hence, higher CO_2 emissions than lighter vehicles. For CO and NO_x, for the most part emissions of heavier vehicles are higher for the positive VSP modes. For HC, the trend is slightly different than other pollutants. For the first eight modes, lighter vehicles have higher emissions; however, for Modes 10 to 14, heavier vehicles have significantly higher emissions. These results confirm that vehicle net weight is an important variable. The differences in emissions between the weight categories is on the order of a factor of two to five in most cases.

The relationship between emissions and engine displacement is shown for all pollutants and modes in Figure 3-9. Although there are some exceptions, particularly for the negative VSP modes (e.g., Modes 1 and 2), typically vehicles with larger engine size have significantly higher emissions by a factor of two to five. Thus, engine displacement is also shown to be a potentially important explanatory variable. Since engine displacement and net vehicle weight are highly correlated, there is little benefit to including both as criteria for stratification of the data. Engine displacement was selected as the criteria for further model development, although it is likely that similar results would be obtained if net vehicle weight were selected instead.

Aside from either engine displacement or vehicle weight, it is clear from the results of Tables 3-2 through 3-5 that odometer reading is also an important explanatory variable. The range of cutpoints for odometer reading obtained from HBTR varies substantially from one pollutant to another, and in some cases multiple cutpoints for odometer reading were obtained from the analysis. However, for simplicity and for consistency with other models and analyses, a single cutpoint of 50,000 miles was selected. This cutpoint is within the range of values obtained from HBTR.

The average modal emission rates, and the 95 percent confidence intervals for the averages, are shown in Figure 3-10 for the 14 VSP modes stratified with respect to two engine displacement categories and two odometer reading categories. The sample sizes for each mode for each strata of engine displacement and odometer reading are shown in Figure 3-11.

For the lower engine displacement category of less than 3.5 liters, represented by Strata 1 and Strata 3 in Figure 3-10, respectively, it is typically the case that the higher mileage vehicles have higher emissions of HC and NO, only marginally higher emissions of CO, and comparable emissions for CO_2. Similarly, for the larger engine displacement category of greater than 3.5 liters, the higher mileage vehicles have substantially higher HC and NO_x emissions, marginally

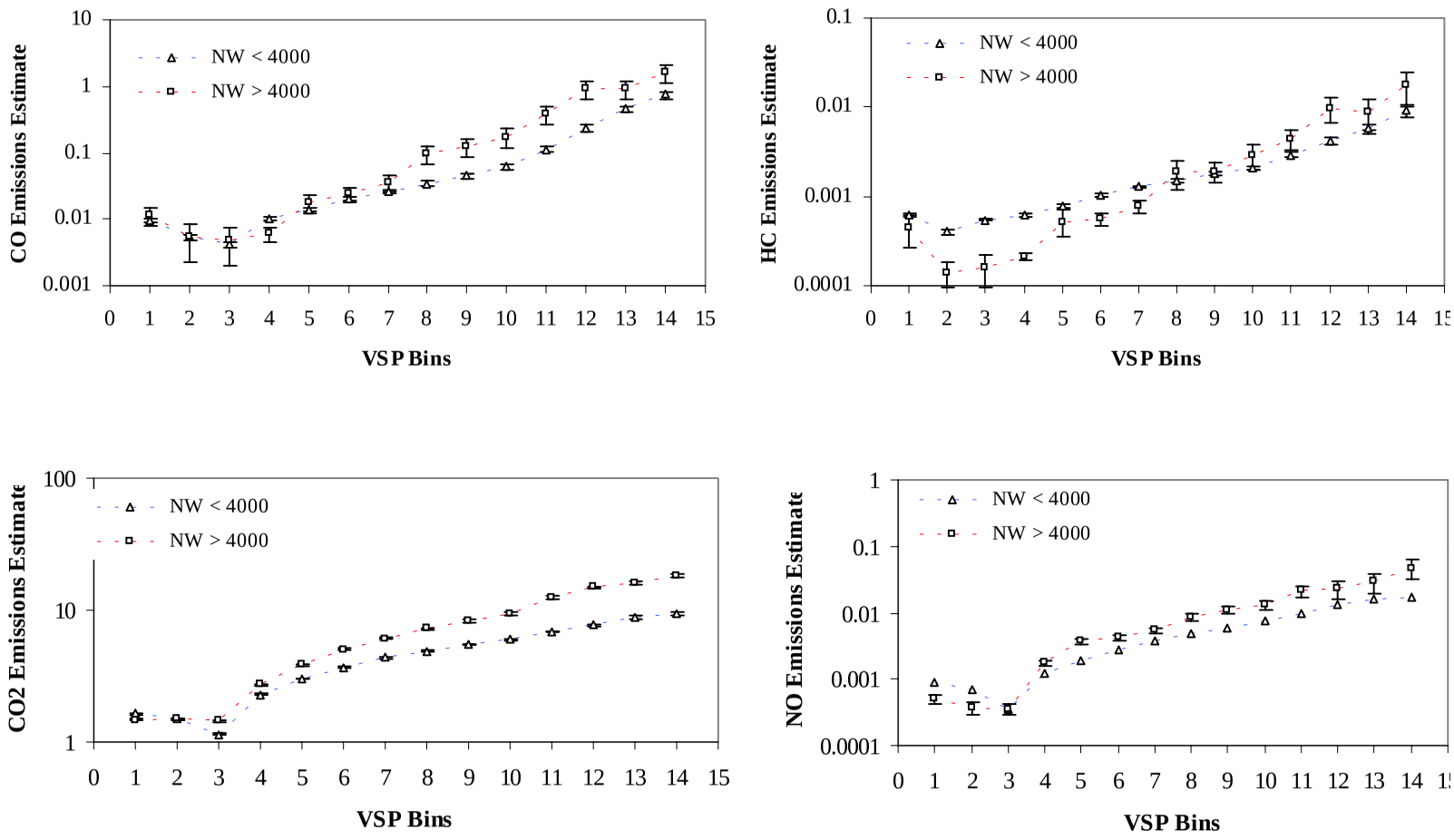

Figure 3-8. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for 14 VSP Bins for Vehicles with Net Weight < 4,000 lb to Vehicles with Net Weight > 4,000 lb.

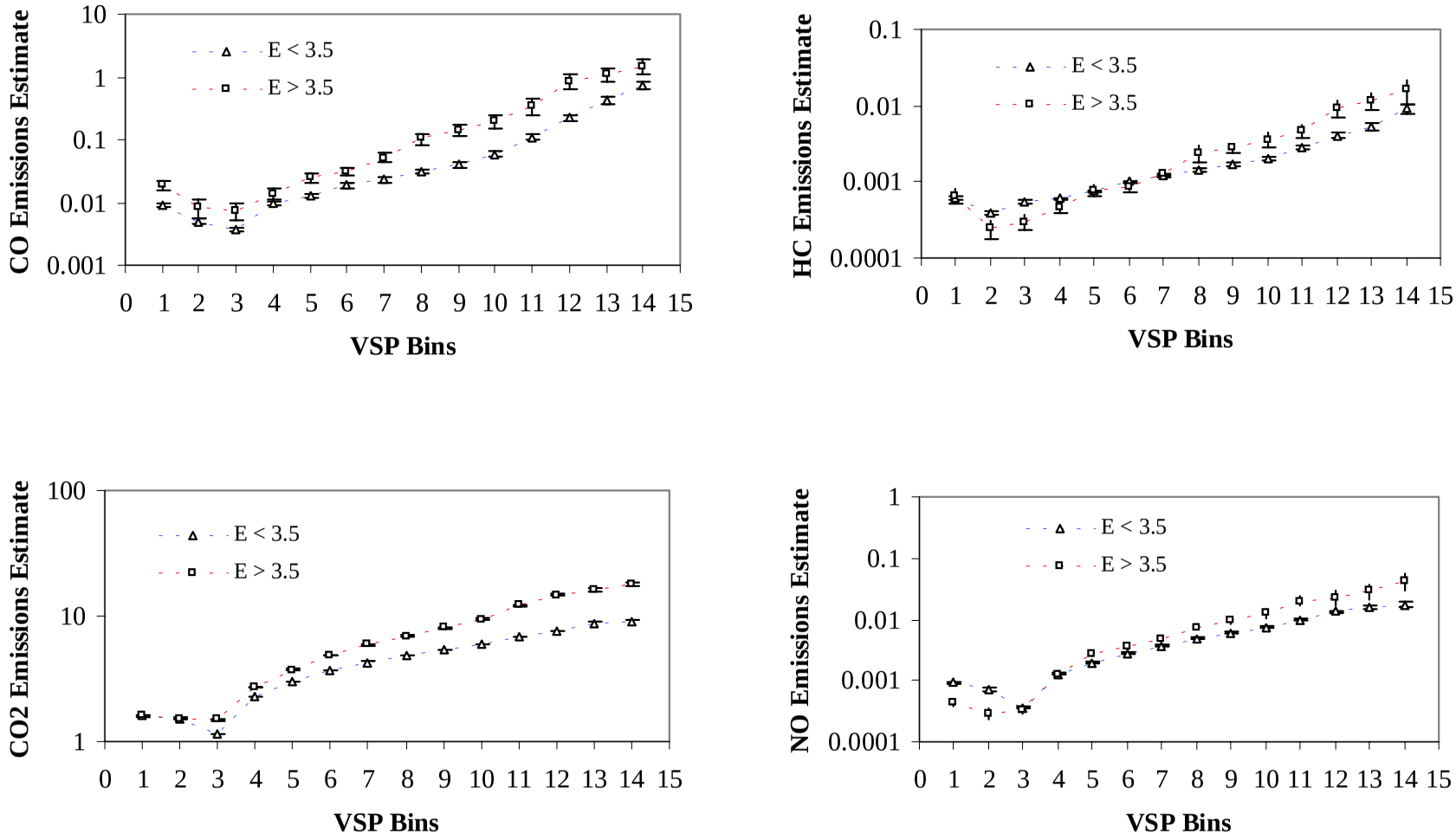

Figure 3-9. Comaparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for 14 VSP Bins for Vehicles with Engine Displacement < 3.5 liters to Vehicles with Engine Displacement > 3.5 liters.

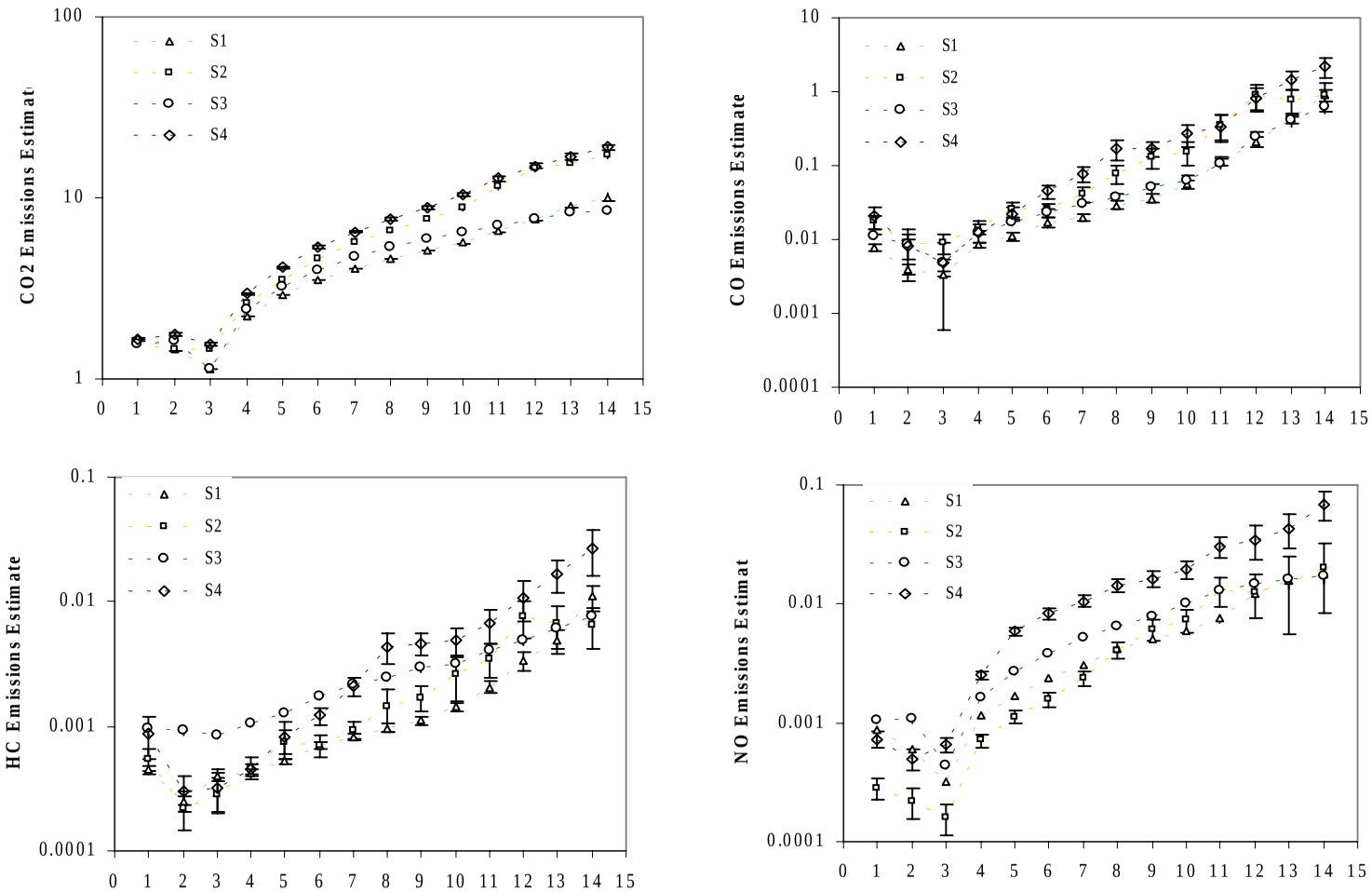

Figure 3-10. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for 14 VSP Bins Stratified by Engine Displacement and Odometer Reading.

S1: Engine Displacement <3.5 liters and Odometer < 50K miles; S2: Engine Displacement >3.5 liters and Odometer < 50K miles;
S3: Engine Displacement <3.5 liters and Odometer > 50K miles; S4: Engine Displacement >3.5 liters and Odometer > 50K miles.

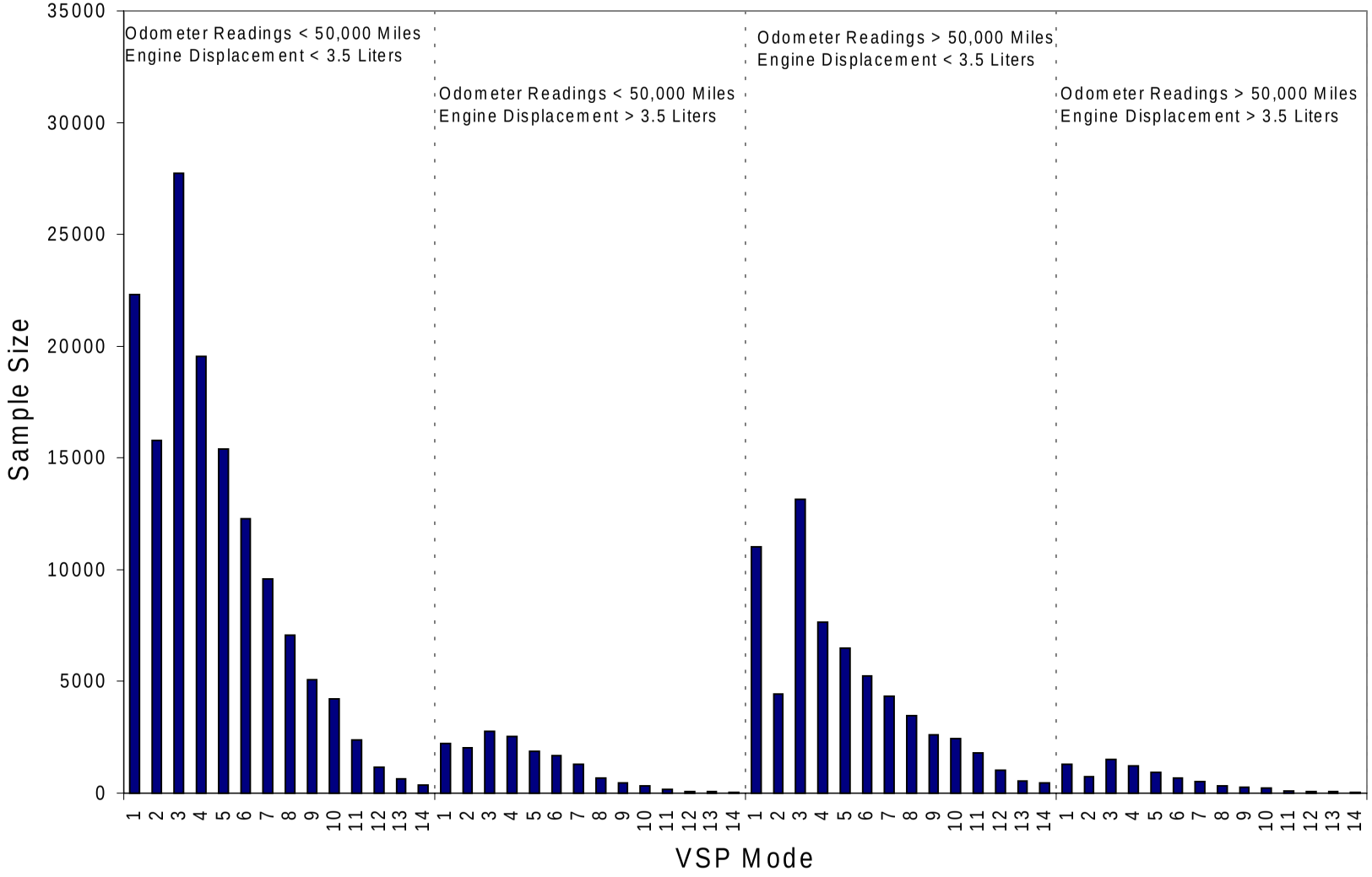

Figure 3-11. Sample Sizes for Each VSP Mode for Each Odometer Reading and Engine Displacement Strata.

higher CO emissions, and comparable CO_2 emissions for most modes. Thus, it is clearly important to compare emissions for different odometer reading categories, especially for HC and NO_x.

When comparing engine displacement categories for a given odometer category, it is typically the case that the larger engine size category has higher CO_2, CO, HC, and NO_x emissions than the lower engine size category. However, there are some exceptions to this trend. For example, the lower mileage vehicles with larger engines tend to have lower NO_x emissions for Modes 1 through 7 compared to any other strata, and for the higher VSP modes, the NO_x emissions for the larger engines are not substantially higher than that for the smaller engines for lower mileage vehicles. However, among the higher mileage vehicles, those with larger engines have substantially higher NO_x emissions than those with smaller engines.

The fact that there are important differences in emissions based upon engine size and odometer reading for many modes for each of the pollutants confirms that engine size and odometer reading are useful explanatory variables. Therefore, the modal approach based upon 14 VSP bins, each divided into four strata representing two engine size and two odometer reading categories, was adopted for further analysis. This approach is referred to as the "56-bin" approach because of the 56 bins required (14 VSP bins x 2 engine displacement strata x 2 odometer reading strata = 56 bins in total).

3.2.3 Comparison of Modeling and IM240 Datasets

In this section comparison of modal results based upon the calibration dataset and the IM240 dataset is given based upon the preliminary VSP approach. For this purpose, the VSP bins that were segregated via net weight are given. The IM240 data were not used in the initial calibration activity because IM240 data are for a smaller range of VSP than the calibration data and because of concern that there may be significant differences in fuel characteristics. An objective in comparing the two data sets is to determine whether the results obtained based upon the modeling data set are robust when the same binning criteria are applied to a different data set. In order to make this comparison, it is important to first stratify both datasets as much as possible to correct for variability in key factors. Based upon appropriate stratification, a more direct comparison can be made between the data sets.

Figure 3-12 presents a comparison of modeling data and IM240 data based upon VSP bins where vehicle net weight is less than 4,000lb. For CO_2, the results from the modeling data set and the IM240 data are very similar, both in terms of general trends among all modes and in terms of comparisons of mean emission rates for individual modes. The only exception is an apparent anomaly for Mode 1. Aside from the anomaly, the comparison suggests that on average the vehicles in the two data sets have similar CO_2 emission rates, which also indicates that they have similar fuel economy, since the vast majority of carbon in the fuel is emitted as CO_2. For the other three pollutants, there are similarities in average emission rates for the highest VSP modes, such as Modes 10 to 14, especially for CO and HC emissions. For NO_x, the emissions appear to differ by a factor of approximately two for these modes. The similarities for the higher modes for CO and HC may suggest that vehicles emit similarly for these two pollutants under conditions of high power demand and, presumably, increased occurrence and frequency of

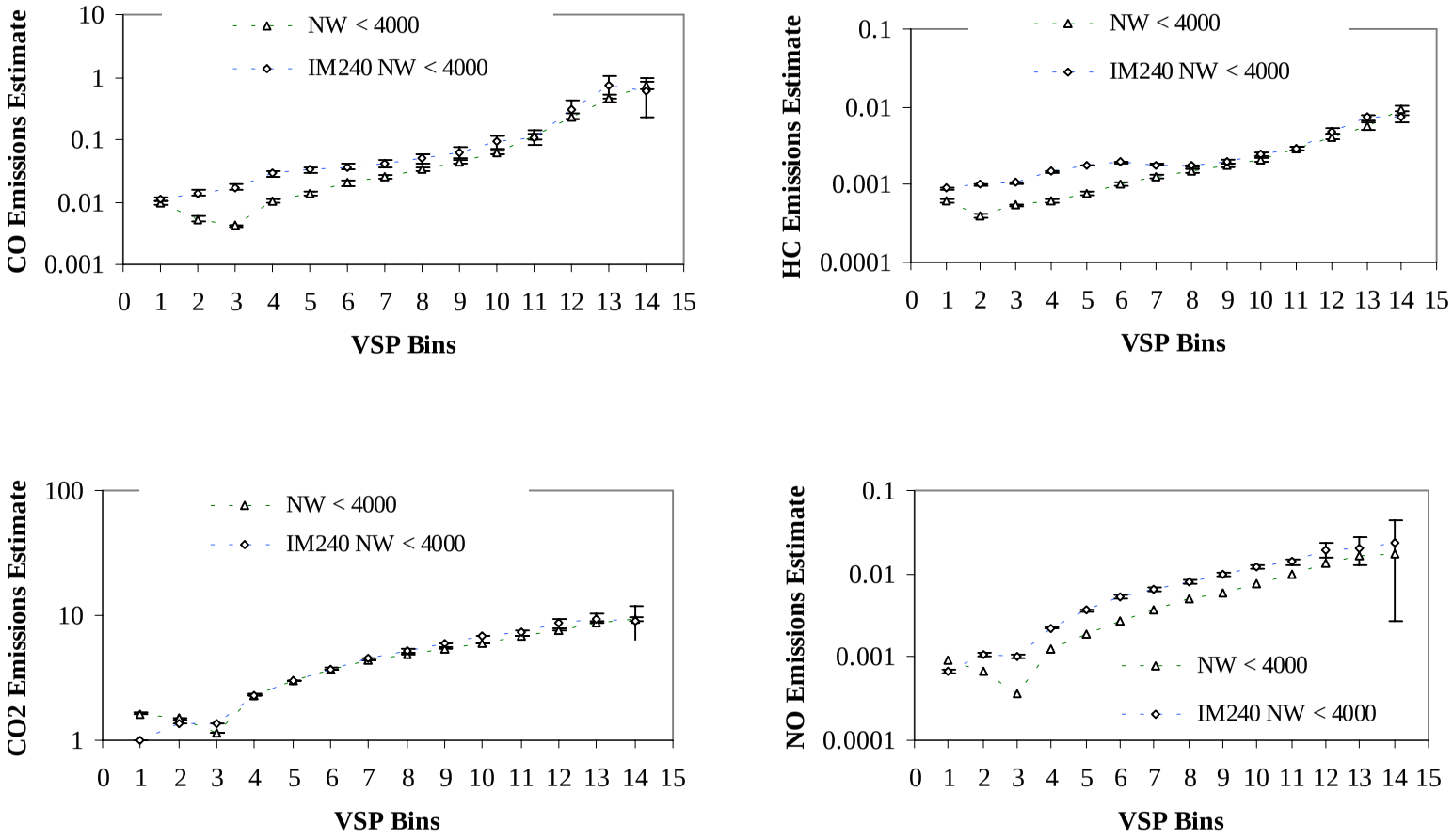

Figure 3-12. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates based upon the Modeling Data versus IM240 Data for 14 VSP Bins for Net Vehicle Weight < 4,000 lb.

enrichment. For all other modes, it is generally the case that the IM240 database reveals higher average emission rates than does the calibration database. This could be perhaps because there is a higher proportion of high emitting vehicles, a different activity pattern of the vehicles, or perhaps different fuel or ambient characteristics.

Figure 3-13 shows the comparison between the IM240 and the calibration data for net weight greater than 4000lb. There are not many data points in several of the VSP bins for the IM240 data. For Modes 11 and 12 there are less than 20 data points and for Modes 13 and 14 there are no data points. Thus, the results for Modes 11 and 12 are subject to considerable random sampling error. Similar to the case for the lower weight vehicles, for CO_2 there are generally not significant differences between average modal rates for the IM240 and calibration datasets. For other pollutants, the IM240 database tends to have higher average modal rates than the calibration data, especially for the first seven modes.

Overall, these comparisons suggest important similarities between the modeling and the IM240 datasets. The general trend of an increase in emissions from Modes 3 to 14 is common to all pollutants and for both vehicle size categories. The results for CO_2 agree very well, especially for the smaller vehicle size category for which there is more IM240 data. The results for NO_x are comparable in terms of general trend and relative variation in emissions among the modes, but the average emissions are systematically higher for the IM240 data than for the modeling data. For HC, the average modal emissions from the IM240 data are substantially higher than for the modeling data for Modes 1 through 7, but are statistically similar for the highest VSP modes. For CO, the average modal emissions based upon the IM240 data are higher than those based upon the modeling data set for the lower VSP modes for both vehicle size categories. For the smaller vehicle size category, for which there are more data, the CO emissions are similar for the higher VSP modes. Since the IM240 is based upon potentially different fuel than the modeling data set, it is possible that differences in fuel may be important. However, it is also likely that the IM240 data set contains high emitting vehicles, and that the lower VSP modes may be more susceptible to differences between normal and high emitting vehicles than the higher VSP modes, which also typically represent higher emissions.

A more thorough comparison of different data sets is shown in Figures 3-14 through 3-17 for the four engine displacement and odometer reading strata, respectively. The data sets compared include the EPA on-board data, the EPA dynamometer data, NCHRP data, and the IM240 data. The first three are the constituent data of the modeling database. Not all databases could be compared for all four strata because of lack of data in some of the strata. Generally, the CO_2 results are comparable among the databases, although it appears that the NCHRP database represents higher average CO_2 emissions than does the IM240 database for higher mileage vehicles with larger engines. There tends to be more agreement regarding NO_x emissions estimates compared to CO and HC. Both the on-board and dynamometer data from EPA tend to be similar. For example, for the smaller engines and lower mileage vehicles, the CO emissions agree well for most of the modes, and for NO_x the trends are very similar even though the averages are similar primarily only for the lower VSP modes. The on-board hydrocarbon emissions values tend to be much higher than those of the other data sets except for the high VSP modes, although the difference is not as pronounced for the larger engine size range. Even though emissions are not similar when comparing some of the datasets, a likely reason for such

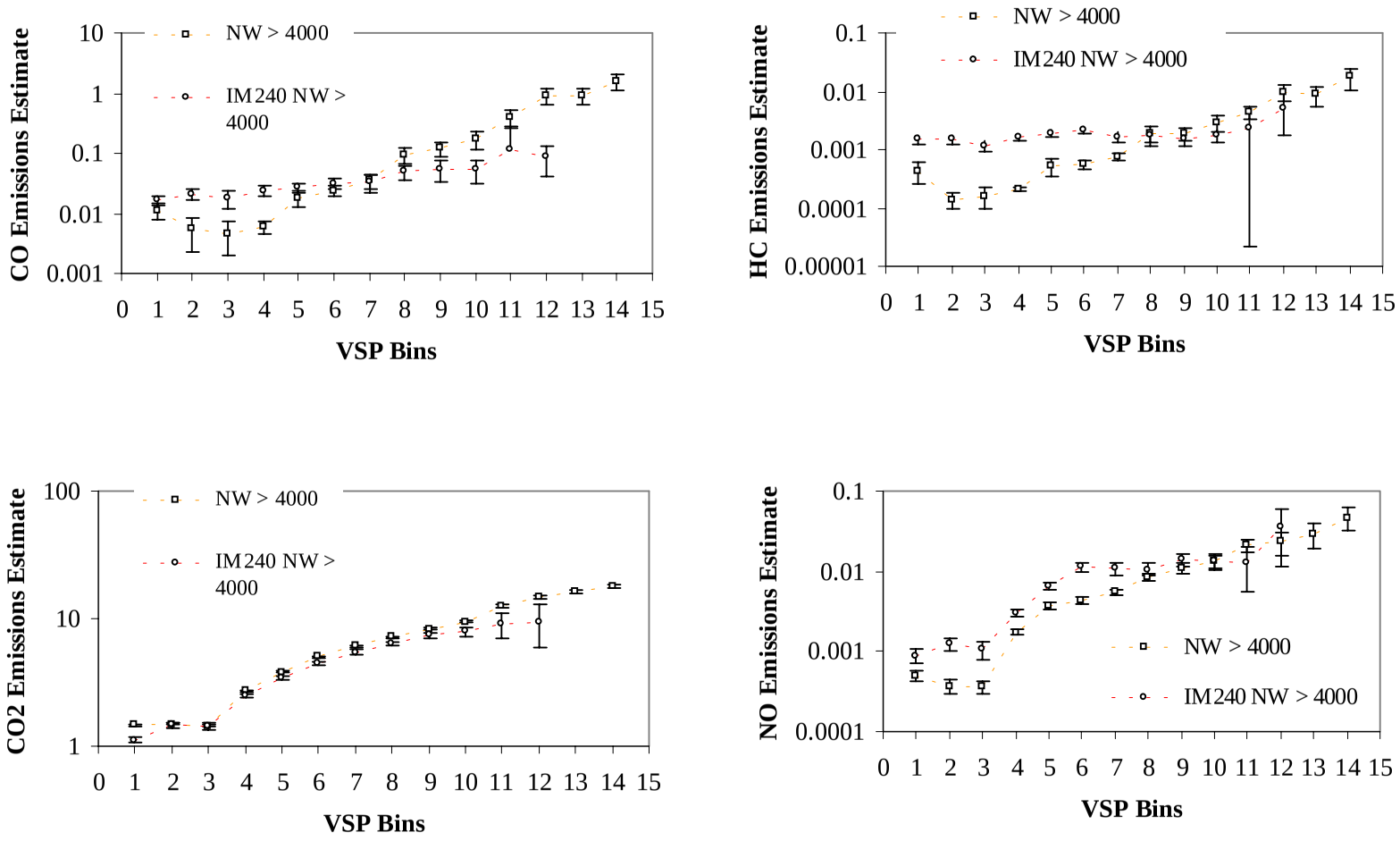

Figure 3-13. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates based upon the Modeling Data versus IM240 Data for 14 VSP Bins for Net Vehicle Weight > 4,000 lb.

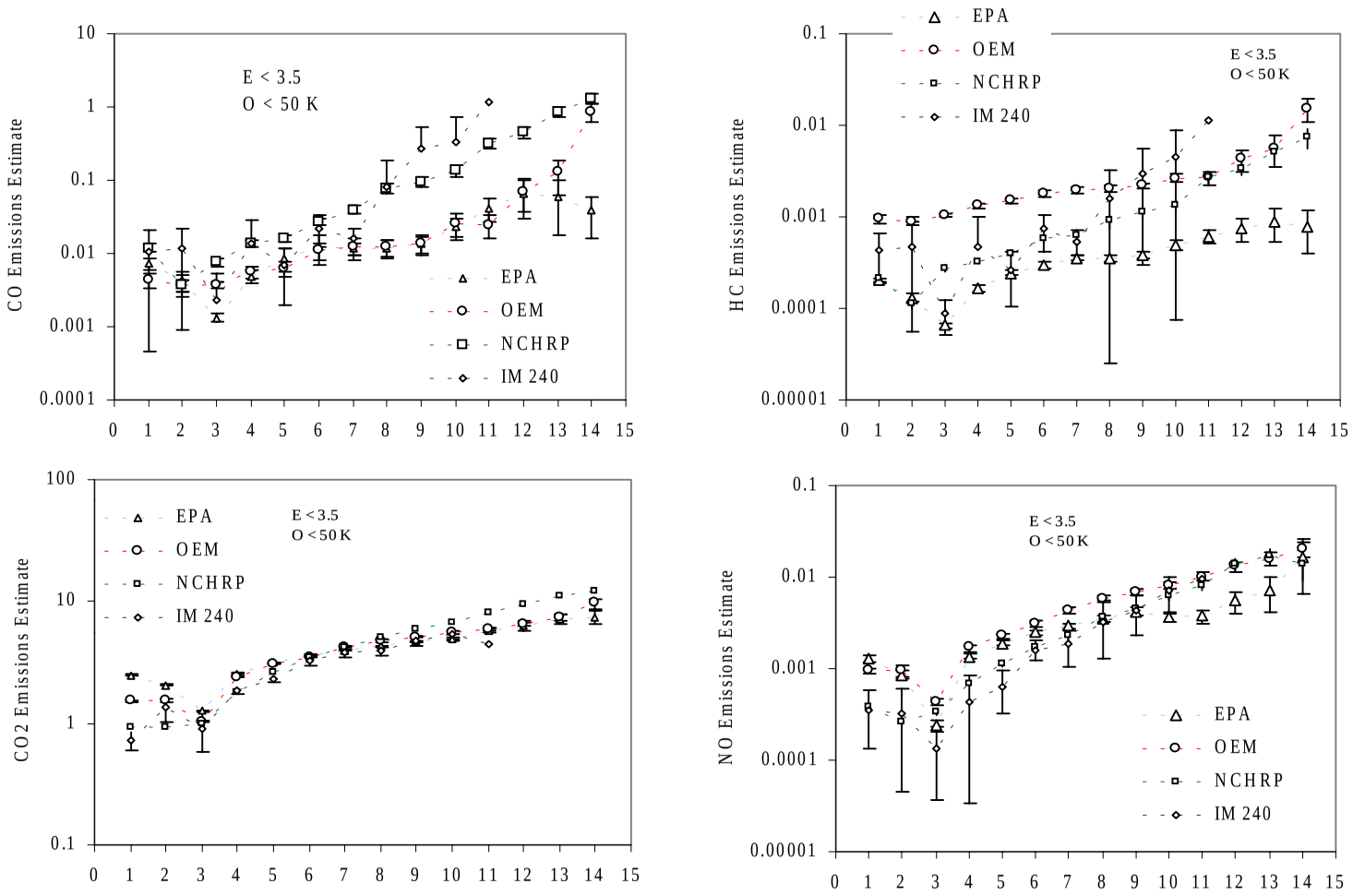

Figure 3-14. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for Engine Displacement < 3.5 Liters and Odometer Reading < 50,000 miles for EPA dynamometer, EPA on-board, NCHRP, and IM240 Databases.

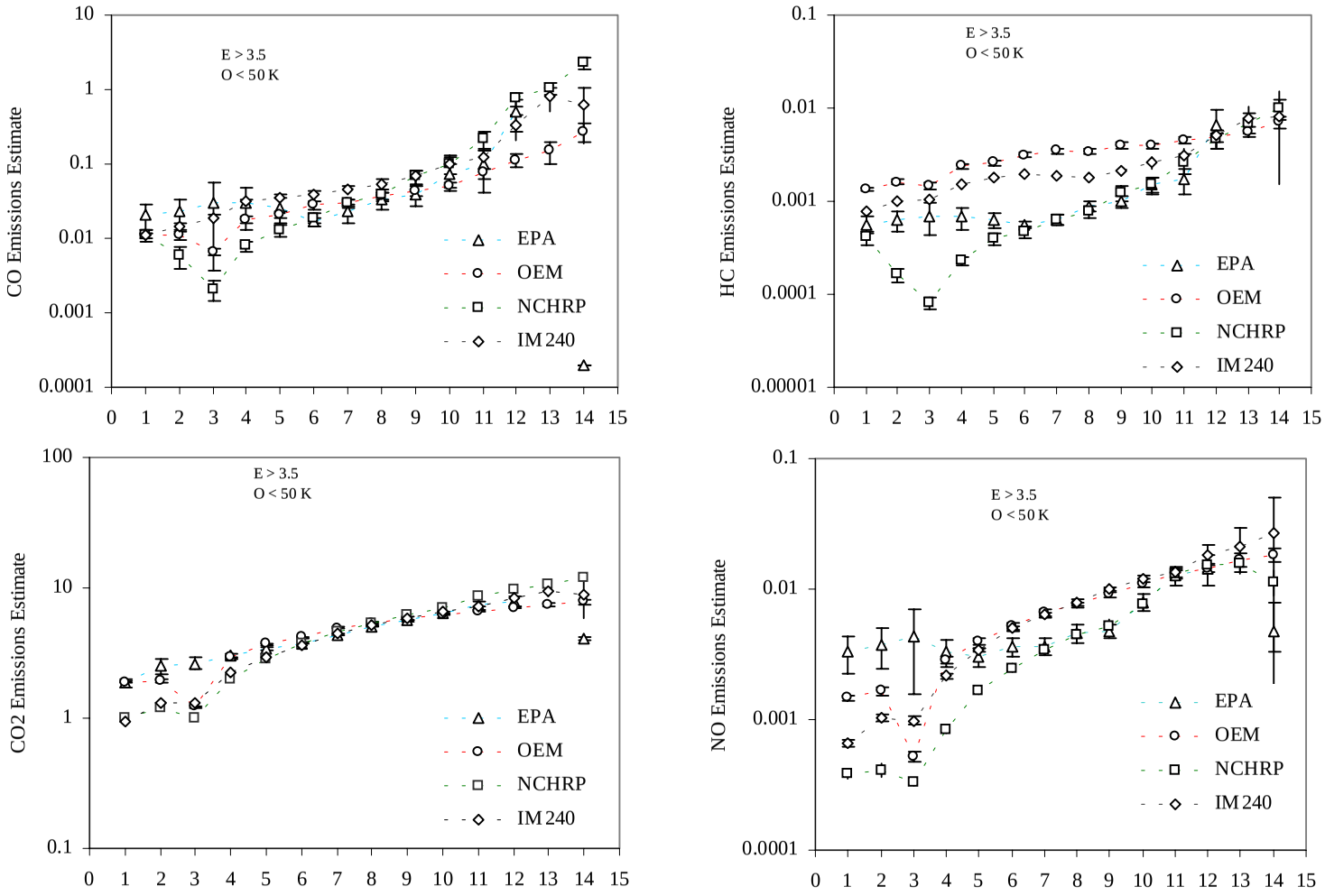

Figure 3-15. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for Engine Displacement > 3.5 Liters and Odometer Reading < 50,000 miles for EPA dynamometer, EPA on-board, NCHRP, and IM240 Databases.

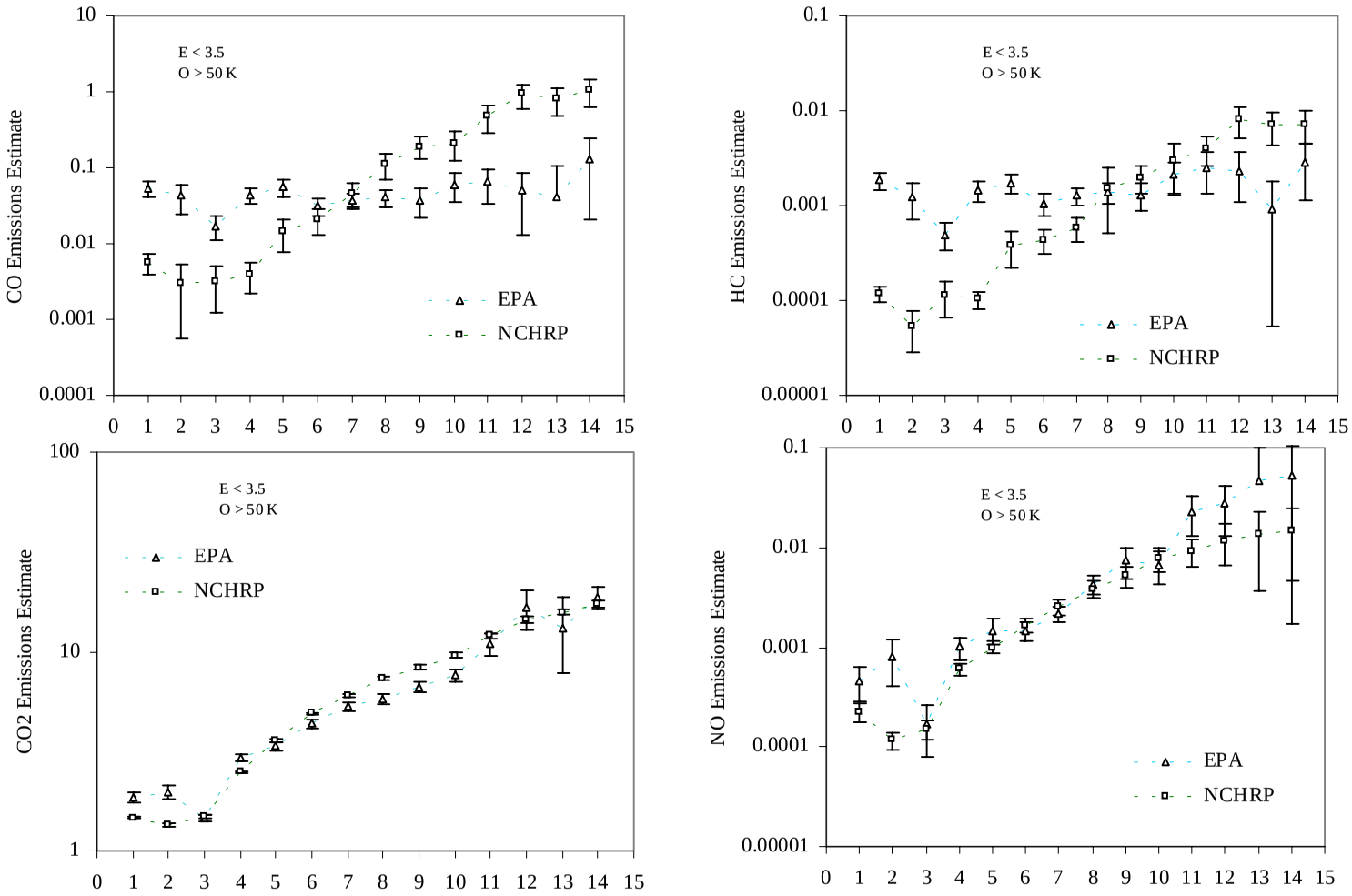

Figure 3-16. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for Engine Displacement < 3.5 Liters and Odometer Reading > 50,000 miles for EPA dynamometer and NCHRP Databases.

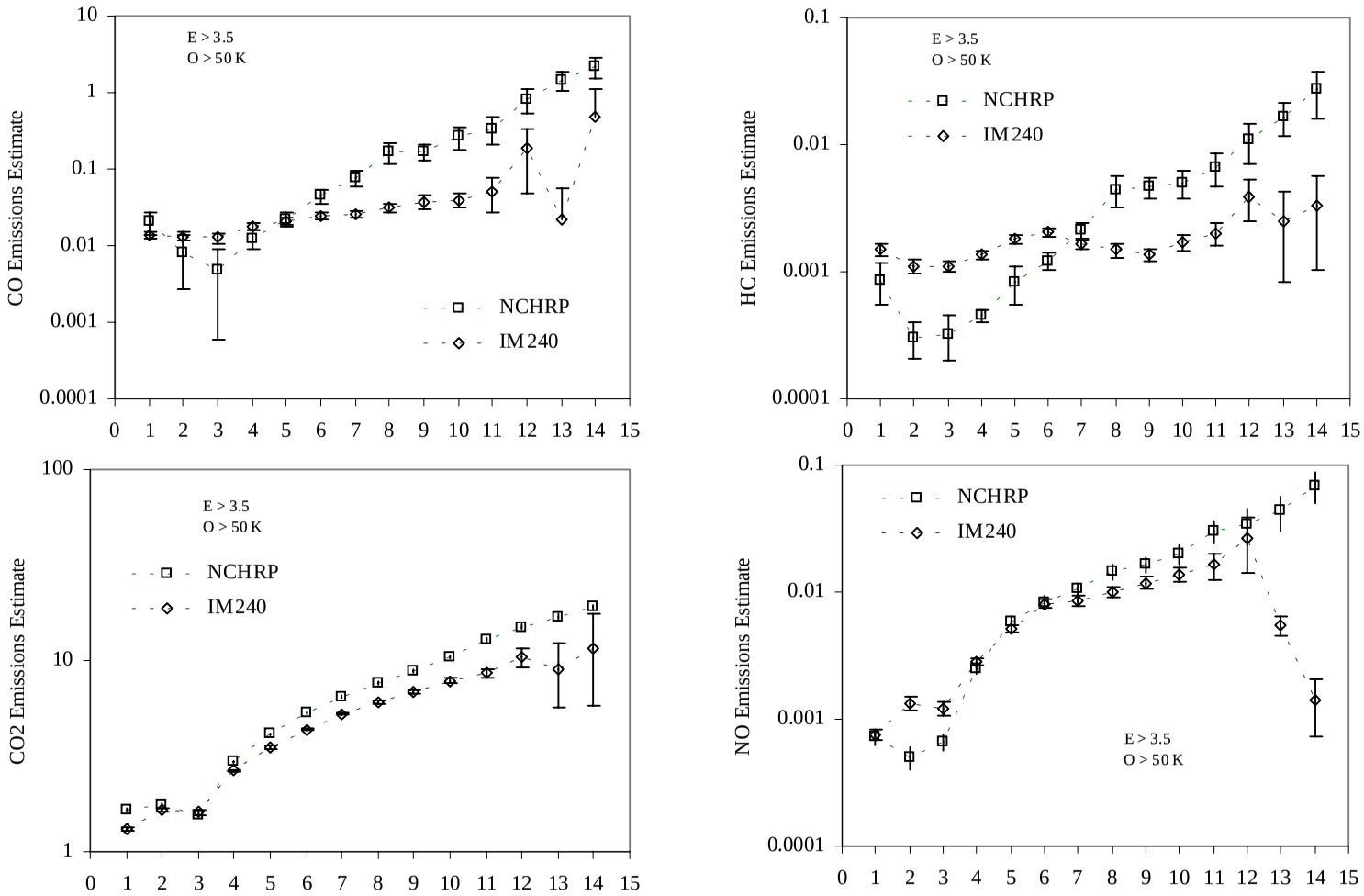

Figure 3-17. Comparison of Average Modal CO, HC, CO_2, and NO_x Emissions Rates for Engine Displacement > 3.5 Liters and Odometer Reading > 50,000 miles for IM240 and NCHRP Databases.

differences is a different mix of vehicles. The differences among the data sets suggest that it is important to obtain a good representative sample of vehicles so that the combined database will adequately capture and represent variability in emissions. The comparison also suggests that the VSP definitions are useful in explaining variability in emissions within any of the data sets individually.

3.3 NCSU Modal Approach: Idle, Acceleration, Deceleration, and Cruise

This approach is based on the NCSU modal definitions that are given in previous reports. The vehicle operating conditions were categorized into NCSU modes, which are idle, acceleration, deceleration and cruise. In order to refine the NCSU modes, HBTR was run for each of the NCSU modes for all pollutants. When both operating and vehicle technology parameters were included in HBTR, VSP was typically selected as the most important explanatory variable, except as noted below. In a refined HBTR analysis based upon only operating parameters of speed, acceleration and VSP, VSP was again selected as the most important explanatory variable in most cases.

It was found that for the acceleration mode, VSP is most powerful in explaining the variability in the emission rate. For example, Figure 3-18 shows the HBTR results for the acceleration mode for NO. The first cut point is VSP, and it accounts for a large portion of the reduction of deviance. VSP also is used for some additional stratification, along with speed. However, the portion of deviance explained by speed is very small compared to that explained by VSP. Thus, VSP is identified as the single most important variable to further improve the NCSU Acceleration mode. Therefore, data within the acceleration mode were subdivided into addition modes based upon VSP cut-offs. The cut-offs were selected based upon the same criteria as described for the VSP approach: (1) ideally, each newly defined mode should have a significantly different average emission rate compared to other modes; and (2) each mode should account for not more than approximately 10 percent of the total emissions of a single pollutant. Based upon these criteria, six modes were defined, as summarized in Table 3-6.

For the NCSU Cruise mode, it was found that VSP and Speed are both important variables that are picked by HBTR. For example, Figure 3-19 shows the regression tree cruise mode results for NO. The data are first stratified with respect to VSP, resulting in a large reduction in deviance, as indicated by the vertical length of the branches under the first split. For the high VSP data, the data are further stratified into smaller VSP categories, suggesting that VSP alone is useful in explaining emissions as long as the VSP is above a cut-off (in the example, the cut-off is approximately VSP=12). For the lower VSP data, speed was found to be the most important variable for further stratification of the data. Therefore, in defining new modes within the cruise mode, consideration was giving to using speed to stratify data for low VSP cases, and VSP alone was used to discriminate among the high VSP data. The specific criteria for the bins shown in Table 3-6 were developed based upon judgment after reviewing HBTR results for all pollutants.

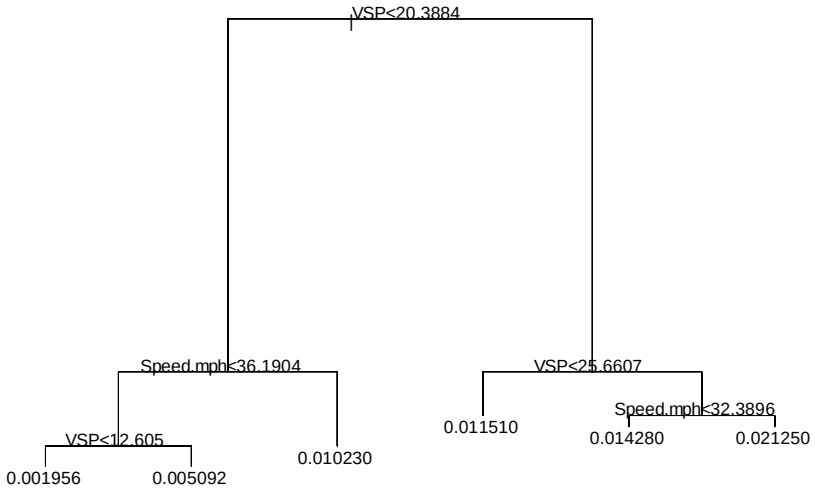

Figure 3-18: Unsupervised HBTR Results for NCSU Acceleration Mode for NO_x Emissions (g/sec).

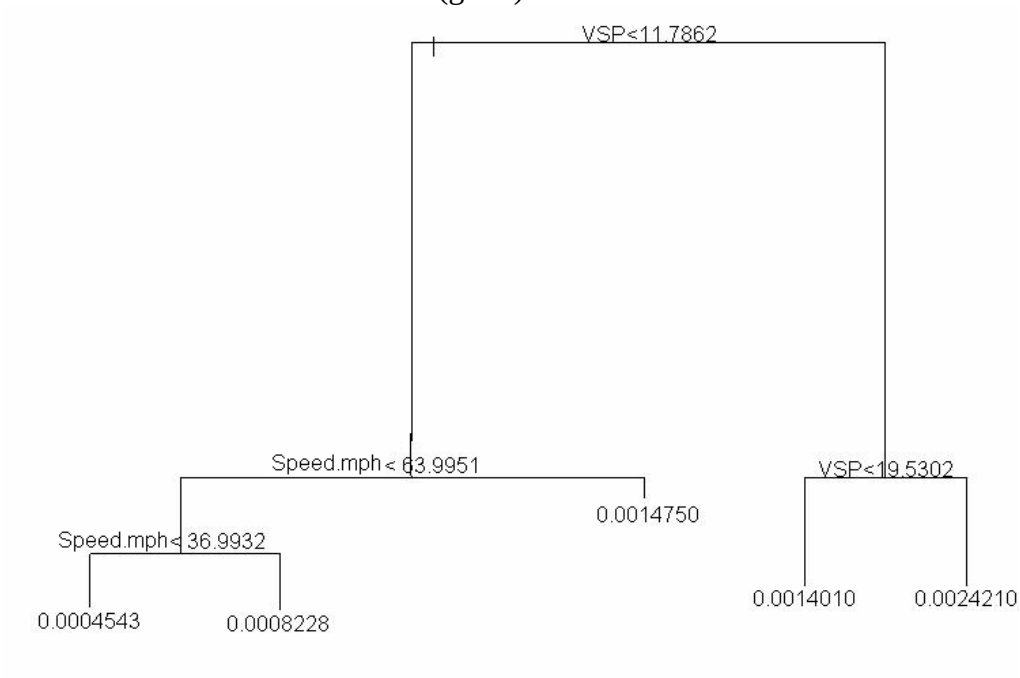

Figure 3-19. Unsupervised HBTR Results for NCSU Cruise Mode for NO_x Emissions (g/sec).

Notes for Figures 3-17 and 3-18: The vertical distance of each branch indicates the proportional explanatory benefit of each particular split, and the numbers at the bottom of the branches are the average emission rates for the stratified data

Table 3-6. Definition of NCSU Driving Modes

ID	Definition
1	NCSU Idle
3	NCSU Deceleration
21	NCSU Acceleration & VSP<8
22	NCSU Acceleration & 8≤VSP<15
23	NCSU Acceleration & 15≤VSP<25
24	NCSU Acceleration & 25≤VSP<33
25	NCSU Acceleration & 33≤VSP<40
26	NCSU Acceleration & VSP≥40
41	NCSU Cruise & VSP≤12 and Speed≤30
42	NCSU Cruise & VSP≤12 and 30<Speed≤55
43	NCSU Cruise & VSP≤12 and Speed>55
44	NCSU Cruise & 12<VSP≤16
45	NCSU Cruise & 16<VSP≤22
46	NCSU Cruise & VSP>22

For the deceleration mode, speed was the most important explanatory variable picked by HBTR analysis. However, considering that the total emission contributed by the deceleration mode is less than 10 percent for all four of the pollutants, it was deemed not necessary to further divide deceleration into submodes. The idle mode was also not further refined, since idle contributes only a small portion of total emissions.

In total, 14 modes were identified, including one idle mode, one deceleration mode, six acceleration modes, and six cruise modes. The definition of these modes is given in Table 3-6. The time spent in each of the 14 modes, and the emissions contributed by these 14 modes is shown in Figure 3-20. The average emission values for each of the 14 modes for the four pollutants are given in Figure 3-21,and the sample size for each mode is shown in Figure 3-22. Figure 3-20 indicates that CO emissions were the binding consideration in determining the need for six acceleration modes. Specifically, the high VSP acceleration modes (i.e. Modes 24, 25, and 26) each represent approximately 10 percent of the total CO emissions in the database, but a far smaller percentage of emissions of the other three pollutants. On the other hand, NO_x emissions were the binding constraint on determining the need for six cruise bins, since NO_x contributes approximately 10 percent to total NO_x emissions for the high VSP cruise modes (Modes 44, 45, and 46) and other pollutants contribute less than this percentage to their respective totals.

The comparison of average emission rates in Figure 3-21 reveals that the lowest emission rates for a given pollutant typically occur for idle, deceleration, and low speed cruising. As cruising speed increases for low VSP values, as represented by Modes 41, 42, and 43, the average emission rate increases for all pollutants. High VSP cruising results in higher average emissions than low VSP cruising. These results tend to confirm intuitive *a priori* assumptions that emissions during cruising will typically be higher at higher speeds or under conditions of higher engine load. The ability to distinguish emissions for different types of cruising illustrates the intuitive appeal of this particular modal binning approach: it is relatively easy to explain the relationship between vehicle activity and emissions with this approach.

For the acceleration mode, emissions for any of the pollutants increase with VSP, as illustrated by comparing Modes 21, 22, 23, 24, 25, and 26. For CO and HC, there is a significant increase in emissions when comparing one mode with the next mode that has higher VSP. For both NO_x and CO_2 emissions, the average emissions increase substantially with VSP for the lower VSP modes (i.e. Modes 21, 22, 23). For Modes 24, 25, and 26, there are small increases in average emissions as VSP increases. These results suggest that CO and HC emissions are very sensitive to VSP throughout the entire range of acceleration events, whereas NO_x and CO_2 emissions are sensitive to lower ranges of VSP of less than about 25. Above VSP=25, NO_x and CO_2 emissions are less sensitive to VSP. Thus, it appears to be the case that once a VSP threshold is reached, NO_x and CO_2 emissions will not change much, but that CO and HC emission rates are more sensitive to high (or perhaps aggressive) accelerations.

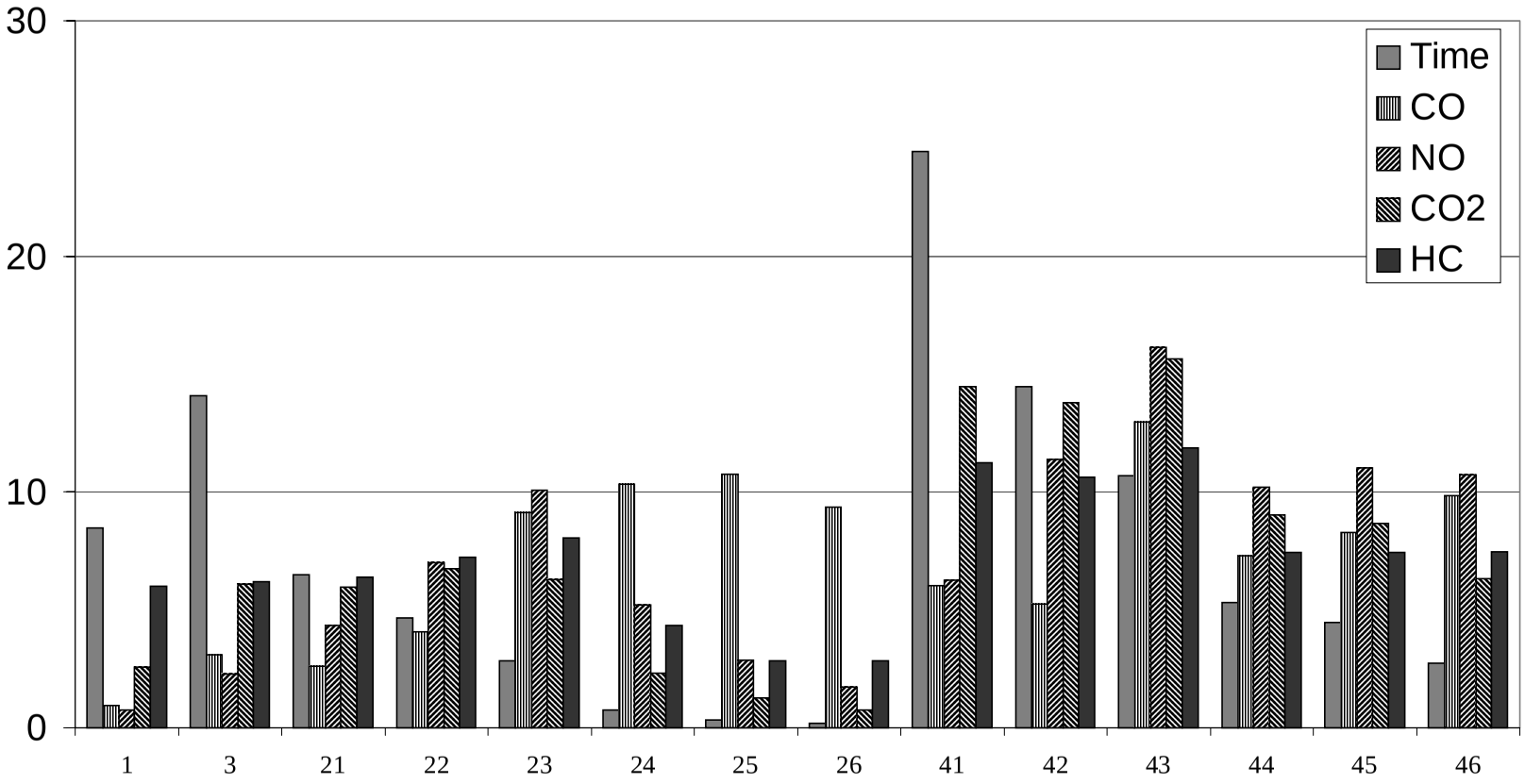

Figure 3-20. Percent of Time Spent in NCSU Modes and Percentage of Total CO, NO_x, CO_2, and HC Emissions Attributable to Each NCSU Mode, Based Upon the Modeling Data Set.

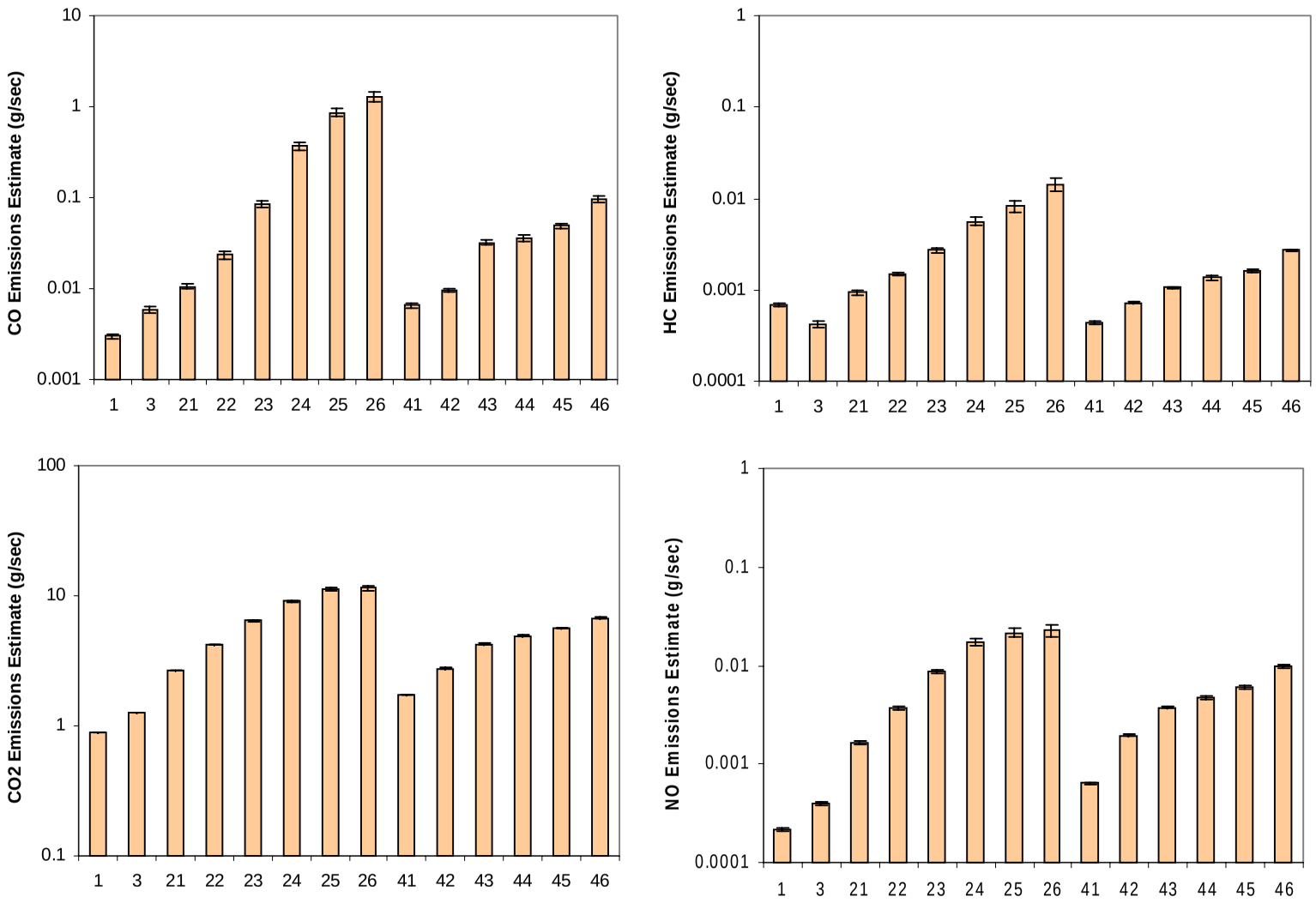

Figure 3-21. Average Modal Emission Rates (g/sec) for NCSU Modes for CO, HC, CO_2, and NO_x Based Upon the Modeling Dataset

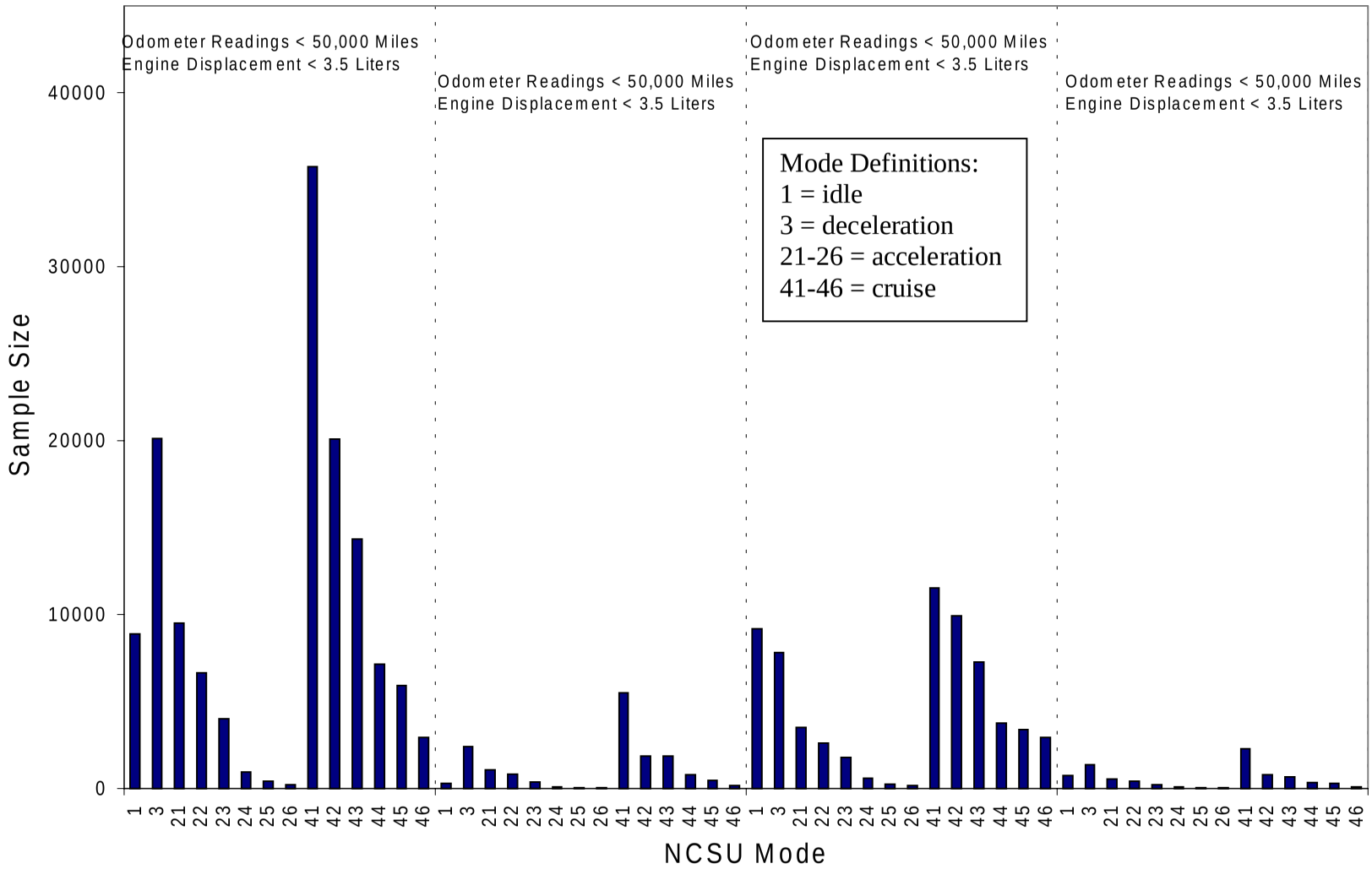

Figure 3-22. Sample Sizes for Each NCSU Mode for Each Odometer Reading and Engine Displacement Strata.

After defining the 14 modes shown in Table 3-6, unsupervised HBTR was applied to data for each pollutant and each mode to identify vehicle characteristics useful in further explaining the variability in the emission rate. The vehicle characteristics considered included net weight, number of cylinders, odometer readings and engine displacement. Tables 3-7 through 3-10 summarize which variable was chosen for the first, second, and third cut-points in the regression tree and also display the numerical values of the cut-offs.

There is variation regarding which variables were selected for the first stratification of the data, implying that the choice of a preferred explanatory variable is conditional on the mode. However, since the objective of this work is to develop modes that are both technically rigorous but also sufficiently simple for practical application, it is preferred to identify one explanatory variable that works well for all modes. In reviewing the results of Tables 3-7 through 3-10, it is apparent that the odometer reading is typically the most frequently selected variable for use in the first stratification of the data. The second most frequently selected variable for the first cut-point is the net vehicle weight. Odometer reading and net vehicle weight are also frequently selected as the basis for the second and third cut-points. These results suggest that both odometer reading and net vehicle weight are important variables. Therefore, both variables were selected as the basis for further refinement of the modal definitions.

The selection of specific cutpoint values for odometer reading and net vehicle weight was made based upon judgment. The specific cutoffs from the HBTR analysis are different for different modes and pollutants. However, in order to keep the modal definitions as simple as possible, only one representative cutpoint was selected for each variable. The cutpoints for odometer readings obtained from HBTR range from typically 12,000 to 80,000 miles. However, many values are within a range of plus or minus 15,000 miles compared to a chosen cutpoint of 50,000 miles. The cutpoint of 50,000 miles was selected because it is representative of results from the statistical analysis and is consistent with previous cutpoints used in other modeling work. For net vehicle weight, a representative cutpoint of 3,500 pounds was selected, which is representative of many of the cutpoints in the range of 3,300 to 3,800 pounds identified in the statistical analysis.

Using the same modal definitions as given in Table 3-6, the data were further binned into four categories:

Net Weight <= 3,500 pounds	AND	Odometer Reading <= 50,000 miles
Net Weight <= 3,500 pounds	AND	Odometer Reading > 50,000 miles
Net Weight > 3,500 pounds	AND	Odometer Reading <= 50,000 miles
Net Weight > 3,500 pounds	AND	Odometer Reading > 50,000 miles

A comparison of average modal emission rates for these four categories is given in Figures 3-23, 3-24, 3-25, and 3-26 for CO, HC, NO_x, and CO_2 emissions, respectively. The figures suggest that at least for some pollutant/mode combinations that average emissions for these four categories are statistically significantly different from each other (e.g., NO emissions for acceleration modes 21, 22, 23, 24, and 25). In some cases, there is more sensitivity to odometer

Table 3-7. Unsupervised HTBR Regression Tree Results for CO Emissions Based Upon the NCSU Modal Approach.

Mode	1st Cut point	2nd Cut point	3rd Cut point
1 (Idle)	Net 3328	O 79901	Net 3482
3 (Deceleration)	E 4.1	N 5	O 17783
21 (Acceleration)	O 75432	O 15210	O 12325
22	O 66163	O 15210	
23	O 43433	O 15251	O 71964
24	E 3.9		
25	Net 3587		
26	O 43433		
41 (Cruise)	O 15210	O 12798	O 75432
42	O 15215	O 12789	O 56637
43	E 3.45	N 5	O 20892
44	E 3.45	N 5	Net 2862
45	Net 3659	N 5	
46	O 79022	O 50177	

Table 3-8. Unsupervised HTBR Regression Tree Results for NO_x Emissions Based Upon the NCSU Modal Approach.

Mode	1st Cut point	2nd Cut point	3rd Cut point
1 (Idle)	N 5	O 60158	E 3.45
3 (Deceleration)	O 8785		E 3.45
21 (Acceleration)	O 58057	O 29057	E 2.75
22	O 66163	O 38353	O 45900
23	O 63341	O 22195	O 43433
24	O 58560	O 12800	Net 3486
25	O 58057	Net 2813	E 2.3
26	O 58057	Net 2550	
41 (Cruise)	O 71964	E 0.75	Net 3754
42	Net 3611	O 57695	E 4.45
43	O 17220	E 3.05	
44	O 17220	O 11493	Net 2531
45	O 38353	E 3	O 83491
46	O 83490	O 61024	

Note: “Net” means “Net Vehicle Weight (lbs)”, “O” means “Odometer Reading (miles)”, “N” means “Number of cylinders”, “E” means “Engine Displacement (liters)”. The number following the variables is the value of the cut point.
Results are not shown in cases where sample size was small

Table 3-9. Unsupervised HTBR Regression Tree Results for HC Emissions Based Upon the NCSU Modal Approach.

Mode	1st Cut point	2nd Cut point	3rd Cut point
1 (Idle)	O 79022	O 48626	O 98129
3 (Deceleration)	O 74867	E 5.3	Net 3613
21 (Acceleration)	O 79022	O 37236	O 48465
22	O 74867	O 37238	O 48465
23	O 77495	O 37326	
24	O 43437	Net 2586	
25	O 43433	Net 2967	
26	O 45900	E 2.75	
41 (Cruise)	O 79022	E 5.3	O 10110
42	O 77495	Net 3611	E 4.9
43	O 77495	O 29949	
44	O 77495	O 79022	
45	O 77495	O 26082	
46	Net 4375	O 43433	O 90660

Table 3-10. Unsupervised HTBR Regression Tree Results for CO_2 Emissions Based Upon the NCSU Modal Approach.

Mode	1st Cut point	2nd Cut point	3rd Cut point
1 (Idle)	N 5	Net 2454	
3 (Deceleration)	Net 3264	O 25347	E 3.45
21 (Acceleration)	O 43433	E 3.45	N 5
22	O 43433	E 1.55	Net 3284
23	Net 3724	O 44035	Net 3568
24	Net 3724	E 1.95	Net 2688
25	Net 3724	E 2.1	O 22358
26	E 2.1	O 55582	
41 (Cruise)	Net 3034	Net 2246	E 1
42	Net 3551	Net 2788	E 2.5
43	E 2.45	Net 2983	Net 3626
44	Net 3724	E 1.95	O 45900
45	Net 3724	O 45900	O 37236
46	Net 3724	Net 2446	

Note: “Net” means “Net Vehicle Weight (lbs)”, “O” means “Odometer Reading (miles)”, “N” means “Number of cylinders”, “E” means “Engine Displacement (liters)”. The number following the variables is the value of the cut point.
Results are not shown in cases where sample size was small

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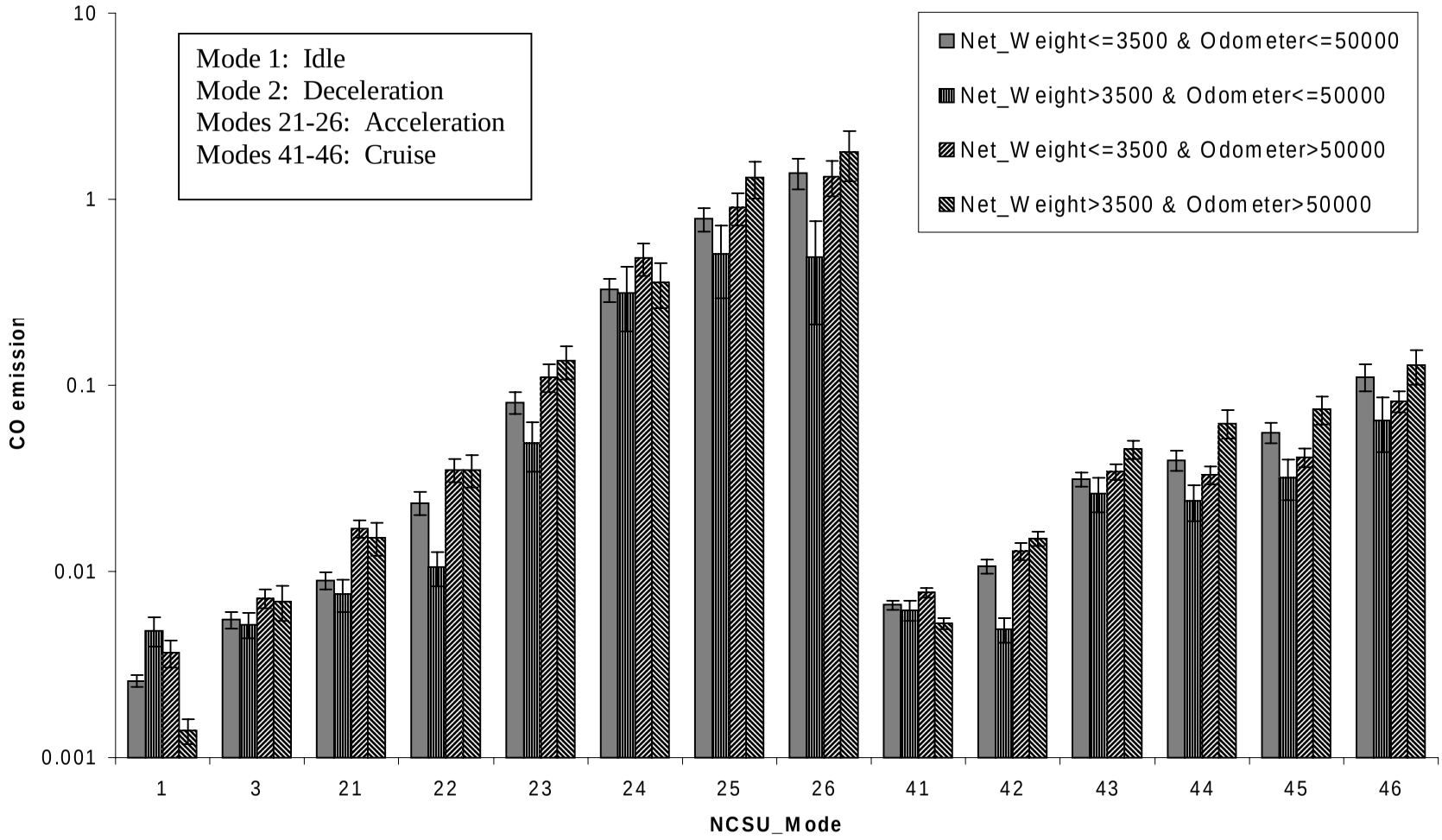


Figure 3-23. Average CO Emissions (g/sec) For the NCSU Idle, Deceleration, Acceleration, and Cruise Modes By Vehicle Weight and Odometer Reading Based Upon the Modeling Database.

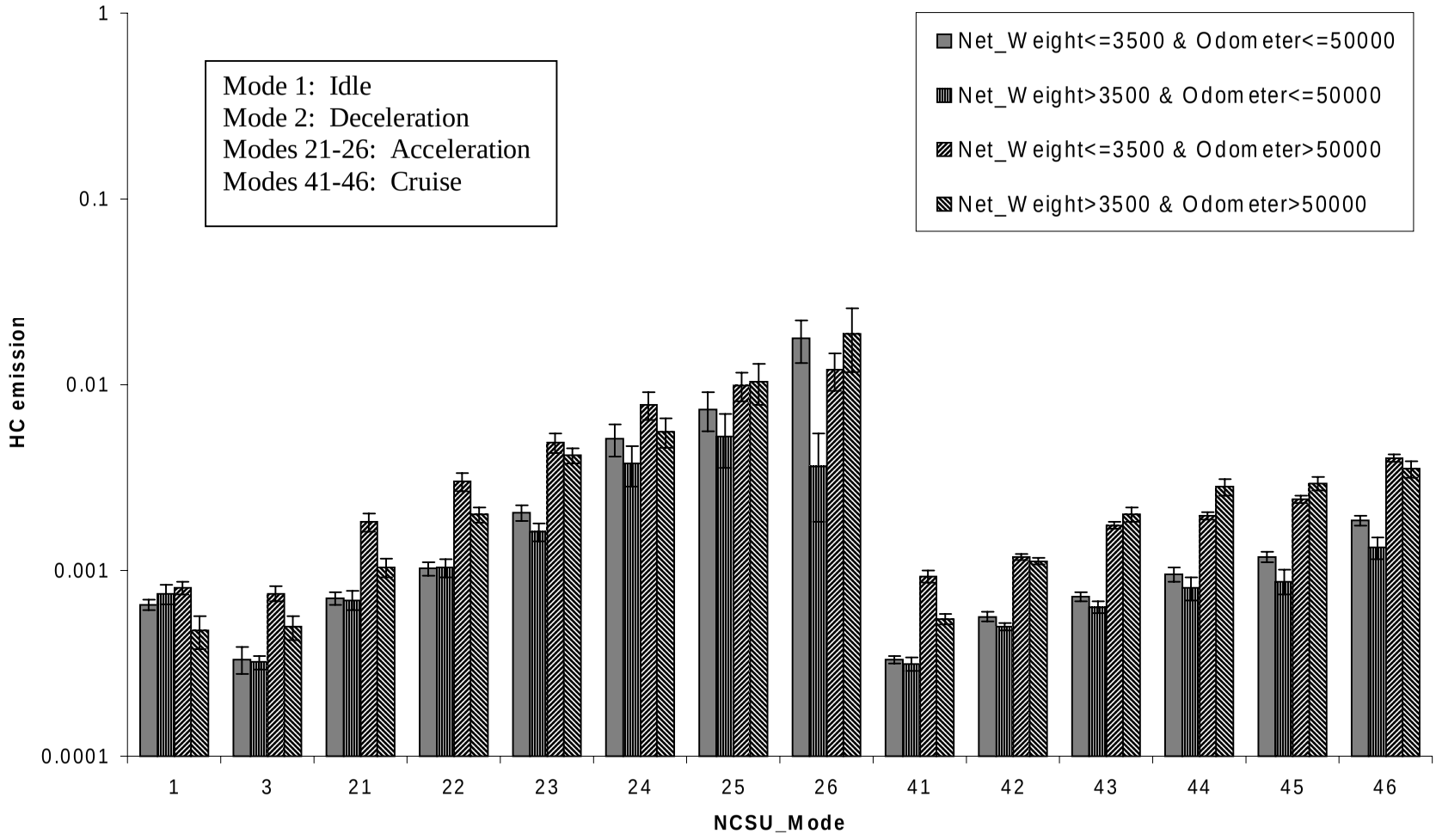


Figure 3-24. Average HC Emissions (g/sec) For the NCSU Idle, Deceleration, Acceleration, and Cruise Modes By Vehicle Weight and Odometer Reading Based Upon the Modeling Database.

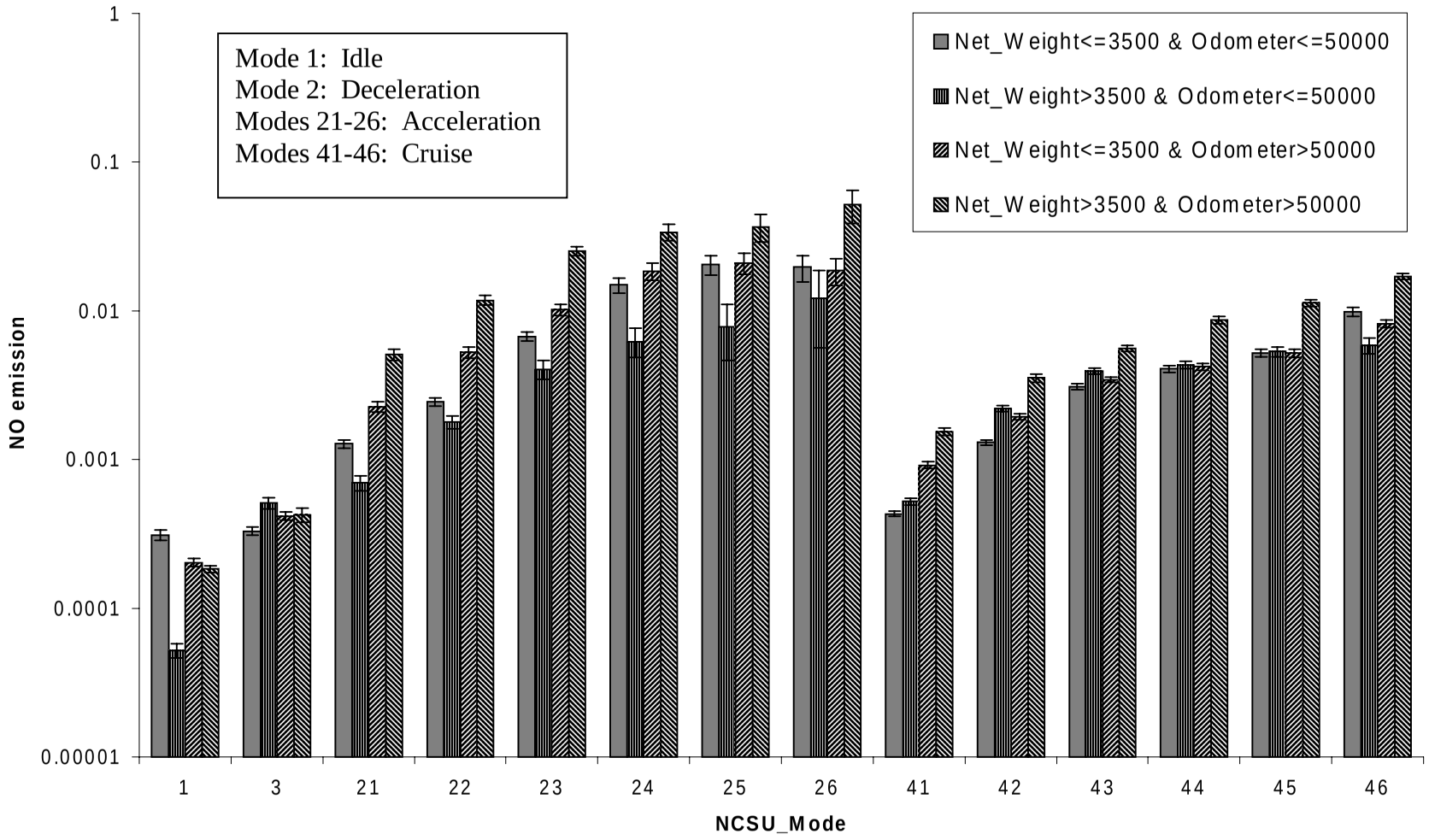


Figure 3-25. Average NO_x Emissions (g/sec) For the NCSU Idle, Deceleration, Acceleration, and Cruise Modes By Vehicle Weight and Odometer Reading Based Upon the Modeling Database.

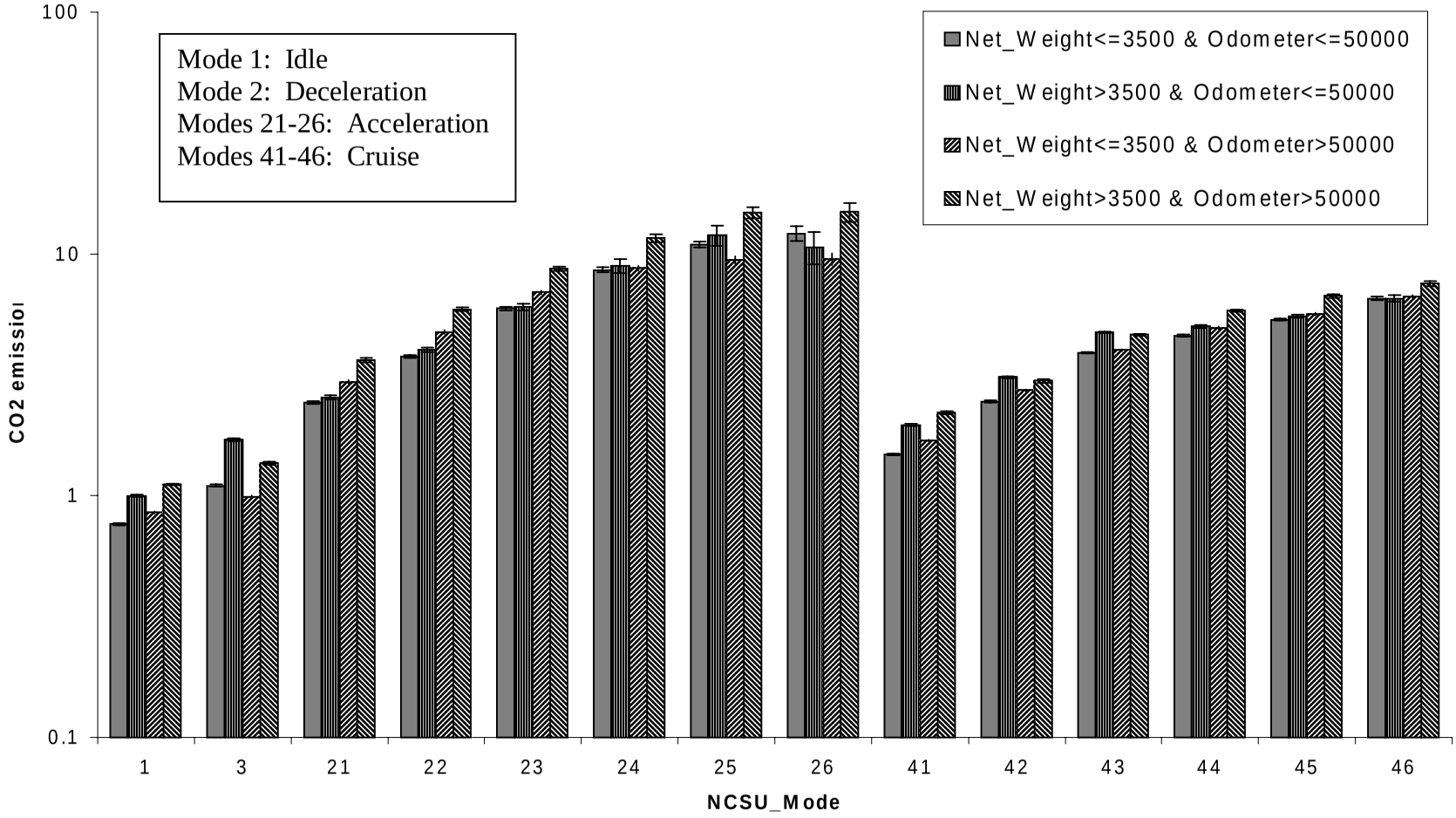


Figure 3-26. Average CO_2 Emissions (g/sec) For the NCSU Idle, Deceleration, Acceleration, and Cruise Modes By Vehicle Weight and Odometer Reading Based Upon the Modeling Database.

reading than vehicle weight. For example, for HC cruise modes, vehicles with higher odometer readings have higher emissions than those with lower odometer readings, and average emissions for a given odometer reading are similar for the two net weight categories. In contrast, for NO_x emissions, it appears that older higher mileage vehicles generally have higher modal emission rates than for the other three categories. However, there are also many specific comparisons that are not statistically significantly different from each other. For example, for CO emissions the average acceleration modal emissions rates for higher mileage vehicles are similar regardless of vehicle weight. Thus, although the specific trends are different for different pollutants, and although in some cases there are not significant differences among the two or more of the four categories for a given pollutant/mode, the results suggest that there are observable differences for many pollutant/mode combinations. Therefore, these categories may be useful in explaining variability in emissions.

3.4 Selection of a Binning Method

The VSP and NCSU binning approaches were compared and evaluated. The criteria for evaluating the two approaches included the utility of each method to explain variability in emissions, the ease of development of the bins, the interpretation of the bins, the ability to explain the approach to model developers and users, and design issues for future model development. The choice of a preferred binning approach was made based upon the application of both approaches to the same data sets.

A comparison of predictions made with both the NCSU-based and VSP-based approaches was developed by using both approaches to predict the average emissions for driving cycles in the modeling database for which there were ten or more vehicles. The comparison is shown in Figure 3-27. The average prediction and the 95 percent confidence interval for the average prediction is shown for each method and for each driving cycle. The 95 percent confidence intervals of the mean predictions overlap for all of the cycles and for all pollutants, indicating that there is no statistically significant difference in predictions for the two methods.

The development of the bins is similar for both methods. The interpretation of bins is different for the two methods, with the NCSU approach being more intuitive to a lay person and the VSP approach being consistent with approaches used in a variety of analyses of vehicle emissions. The NCSU approach produces some bins that have similar average emission rates, even though they represent different activities. For example, the lower emission acceleration and cruise modes have similar emissions. Although neither method clearly stands out when compared to each other, the VSP approach was selected as the basis for further analysis.

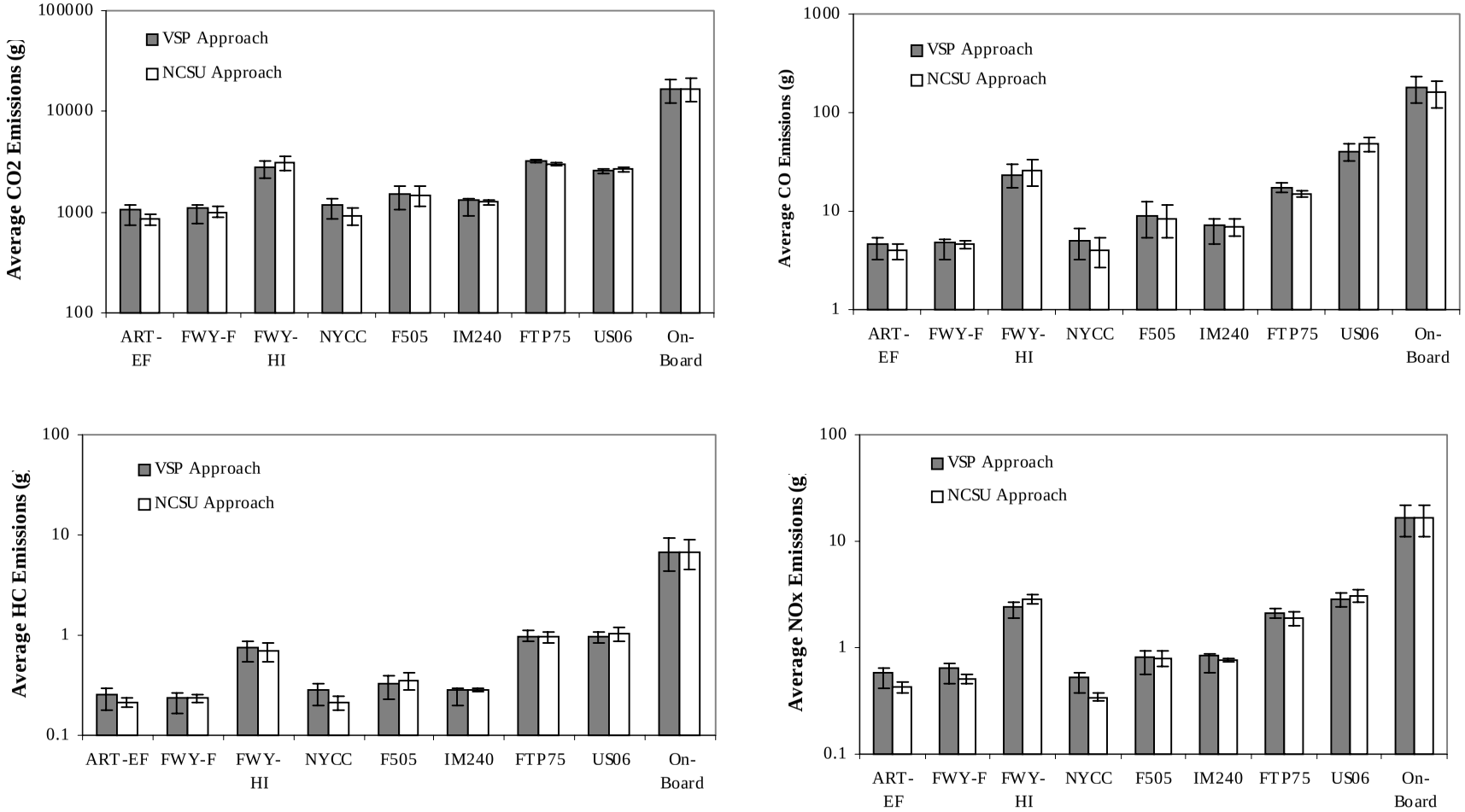


Figure 3-27. Comparison of VSP and NCSU Approach-Based Predictions of Average Emissions of CO_2, CO, HC, and NO_x for Selected Driving Cycles for Vehicles in the Modeling Database.

4 SELECTION OF AN AVERAGING TIME FOR MODEL DEVELOPMENT

The objective of this chapter is to evaluate the potential benefits of working with data that have been averaged over time when developing bins/modes. The effect of data smoothing on binning was determined by comparing the bins developed with data averaged over one second to those of longer periods. For this purpose consecutive averaging of 5 and 10 seconds was utilized and compared with each other and with the use of 1 second data.

4.1 Methodological Approach

As part of the shootout, NCSU found that there is autocorrelation in the second-by-second on-board tailpipe emissions data (Frey *et al*., 2002). In most cases, the autocorrelation was found to be represented by a lag of up to four or five seconds. Therefore, an averaging time of five seconds should be sufficient to decrease the autocorrelation in the data by smoothing with consecutive averaging. However, to provide some margin for variability in the autocorrelation, an averaging time of 10 seconds was also evaluated. It was hypothesized that this longer averaging time should further smooth the data and remove some of the high frequency variability in the data.

In order to determine 5 and 10 second averages based upon the second-by-second data, a program was written in Visual Basic. This program estimated 5 and 10 second consecutive averages for emissions, as well as vehicle activity data, such as vehicle speed and acceleration. In addition to estimating average vehicle activity during each activity period, peak values of vehicle activity were estimated. For example, it was hypothesized that emissions are more sensitive to peak accelerations or peak VSP within an averaging period than they would be to average acceleration or average VSP.

The use of averaging times requires reconsideration of the approach for developing bins. For example, data can be binned by average VSP or by peak VSP during the 5 or 10 second averaging time. It is possible, for example, for a 10 second period to have an average acceleration of, say, only 1 mph/sec but to have a peak acceleration of, say, 5 mph/sec that took place for a short duration. The short duration, high acceleration that took place within the 10 second averaging period may in fact be associated with the largest share of emissions that took place during the averaging time. Therefore, it may be more effective to use the peak values of key variables, such as VSP or power demand, as a basis for binning the data, rather than using average values of these.

The basis for selection of a preferred averaging time was based upon the presence of statistically significant differences in average emissions among modal bins and explanatory power of the overall modal model. In addition, approaches that resulted in less variability in emissions within a bin would typically be preferred over approaches that have more variability in emissions within a bin.

4.2 Results for Five and Ten Second Averaging Times

The assessment of different averaging times was performed for the VSP-based approach identified as the preferred modeling approach in Chapter 3. For the five and ten second-averaged data, unsupervised HBTR was applied to the data sets for each pollutant. The variables used in

the regression tree include mean speed, maximum speed, standard deviation of the speed, mean acceleration, maximum acceleration, standard deviation of the acceleration, mean VSP, maximum VSP, standard deviation of VSP, mean power, maximum power and standard deviation of power. It should be noted that there is positive dependence between VSP and power.

Table 4-1 summarizes the variables that were picked during the unsupervised application of HBTR for the first three cut points. Maximum VSP and maximum power were frequently selected as the most important variables. Since VSP includes power as part of the estimate, these two variables are closely related to each other. Therefore, for simplicity and consistency with the one second averaging time analysis, VSP was chosen as the representative variable for developing modes, and maximum VSP was selected as the specific criteria to use in defining modes. The approach for defining modes using a supervised technique is the same as previously described, based upon seeking modes with average emission rates that differ from each other and that do not contribute more than about 10 percent to total emissions for any individual pollutant. A total of 14 modes were defined for both 5 and 10 second-averaged data, as given in Tables 4-2 and 4-3, respectively. The time spent in each mode and the percentage of total database emissions contributed by each mode for 5 and 10 second-averaged data are given in Figures 4-1 and 4-3, respectively. Similarly, the average modal emission rates for each mode for all four pollutants are given in Figure 4-2 for the 5-second average data and in Figure 4-4 for the 10-second average data.

The sample sizes for the 1-second, 5-second, and 10-second averaging times for each of the 14 modes are compared in Figure 4-5. Because the modal definitions are different for each of the three approaches, it is not expected that there is a proportional distribution of data among the modes when comparing the approaches. However, it is the case that the total sample size summed over all 14 modes for the 5-second averaging time is approximately one-fifth that of the 1-second averaging time, and similarly for the 10-second averaging time the overall sample size is approximately one-tenth that of the 1-second averaging time.

Table 4-1. Key Explanatory Variables for CO, NO_x, HC, and CO_2 Emissions (g/sec) Identified Using Unsupervised HBTR for Five and Ten Second-Averaged Data

	1st Cut Point	2nd Cut Point	3rd Cut Point
5 Seconds Average for CO	Maximum Power	Maximum VSP	Mean VSP
10 Seconds Average for CO	Maximum Power	Maximum VSP	Maximum Speed
5 Seconds Average for NO_x	Maximum VSP	Maximum VSP	Mean Power
10 Seconds Average for NO_x	Mean VSP	Maximum VSP	Maximum Power
5 Seconds Average for HC	Maximum Power	Maximum VSP	Maximum Power
10 Seconds Average for HC	Maximum Power	Maximum VSP	Mean Power
5 Seconds Average for CO_2	Mean VSP	Maximum VSP	Mean VSP
10 Seconds Average for CO_2	Mean VSP	Maximum VSP	Mean VSP

Table 4-2. Maximum VSP-Based Mode Definitions For Five Second-Averaged Data

ID	Definition
1	MaxVSP <0
2	0 ≤ MaxVSP < 2
3	2 ≤ MaxVSP < 6
4	6 ≤ MaxVSP < 9
5	9 ≤ MaxVSP < 12
6	12 ≤ MaxVSP < 15
7	15 ≤ MaxVSP < 18
8	18 ≤ MaxVSP < 21
9	21 ≤ MaxVSP < 25
10	25 ≤ MaxVSP < 29
11	29 ≤ MaxVSP < 34
12	34 ≤ MaxVSP < 38
13	38 ≤ MaxVSP < 42
14	MaxVSP ≥ 42

Table 4-3. Maximum VSP-Based Mode Definitions For Ten Second-Averaged Data

ID	Definition
1	MaxVSP < 1
2	1 ≤ MaxVSP < 6
3	6 ≤ MaxVSP < 9
4	9 ≤ MaxVSP < 12
5	12 ≤ MaxVSP < 15
6	15 ≤ MaxVSP < 18
7	18 ≤ MaxVSP < 21
8	21 ≤ MaxVSP < 24
9	24 ≤ MaxVSP < 27
10	27 ≤ MaxVSP < 31
11	31 ≤ MaxVSP < 35
12	35 ≤ MaxVSP < 39
13	39 ≤ MaxVSP < 43
14	MaxVSP ≥ 43

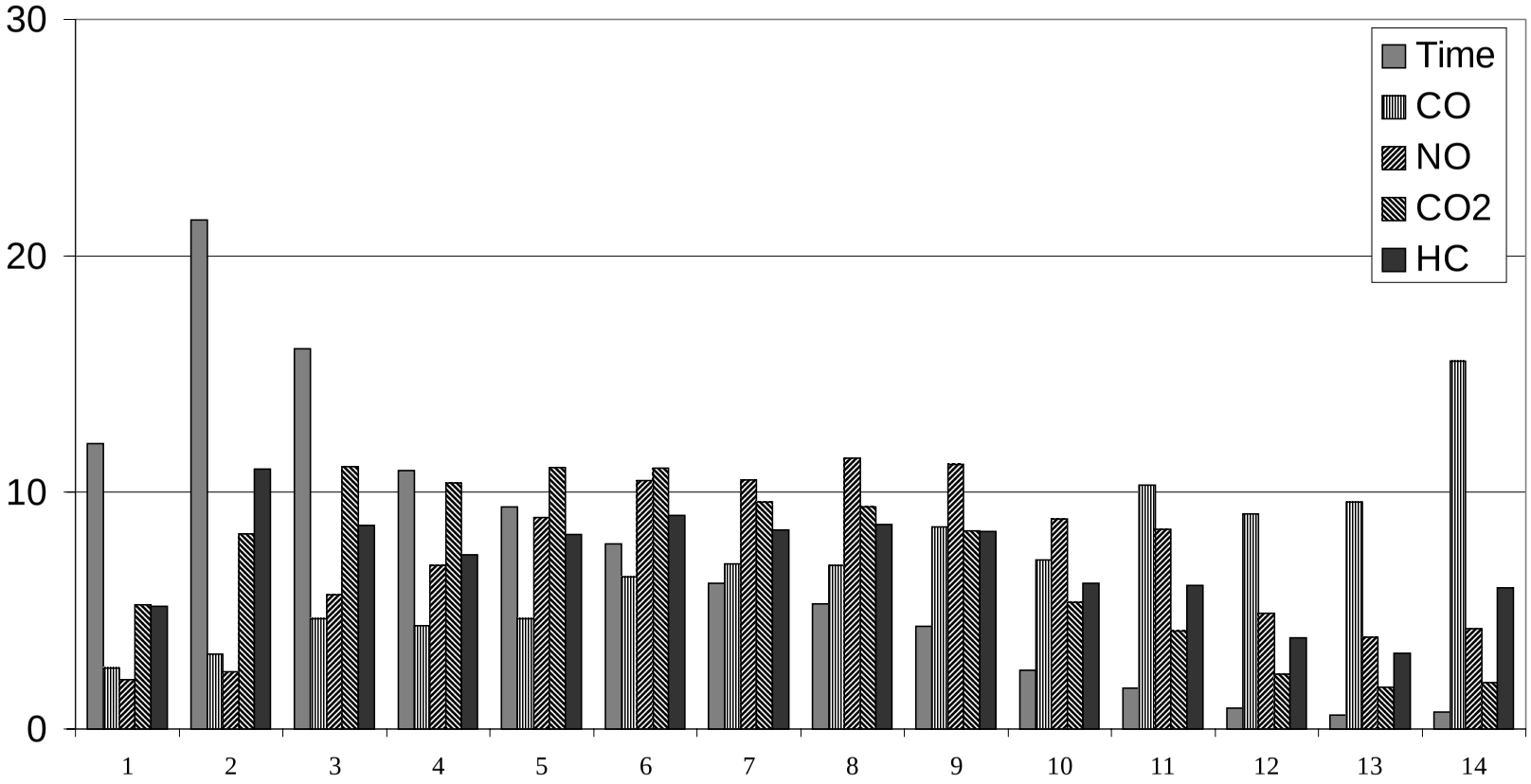


Figure 4-1. Percent of Time Spent in Five Second Averaging Time Maximum VSP-Based Modes and Percentage of Total CO, NO_x, CO_2, and HC Emissions Attributable to Each Mode, Based Upon the Modeling Data Set.

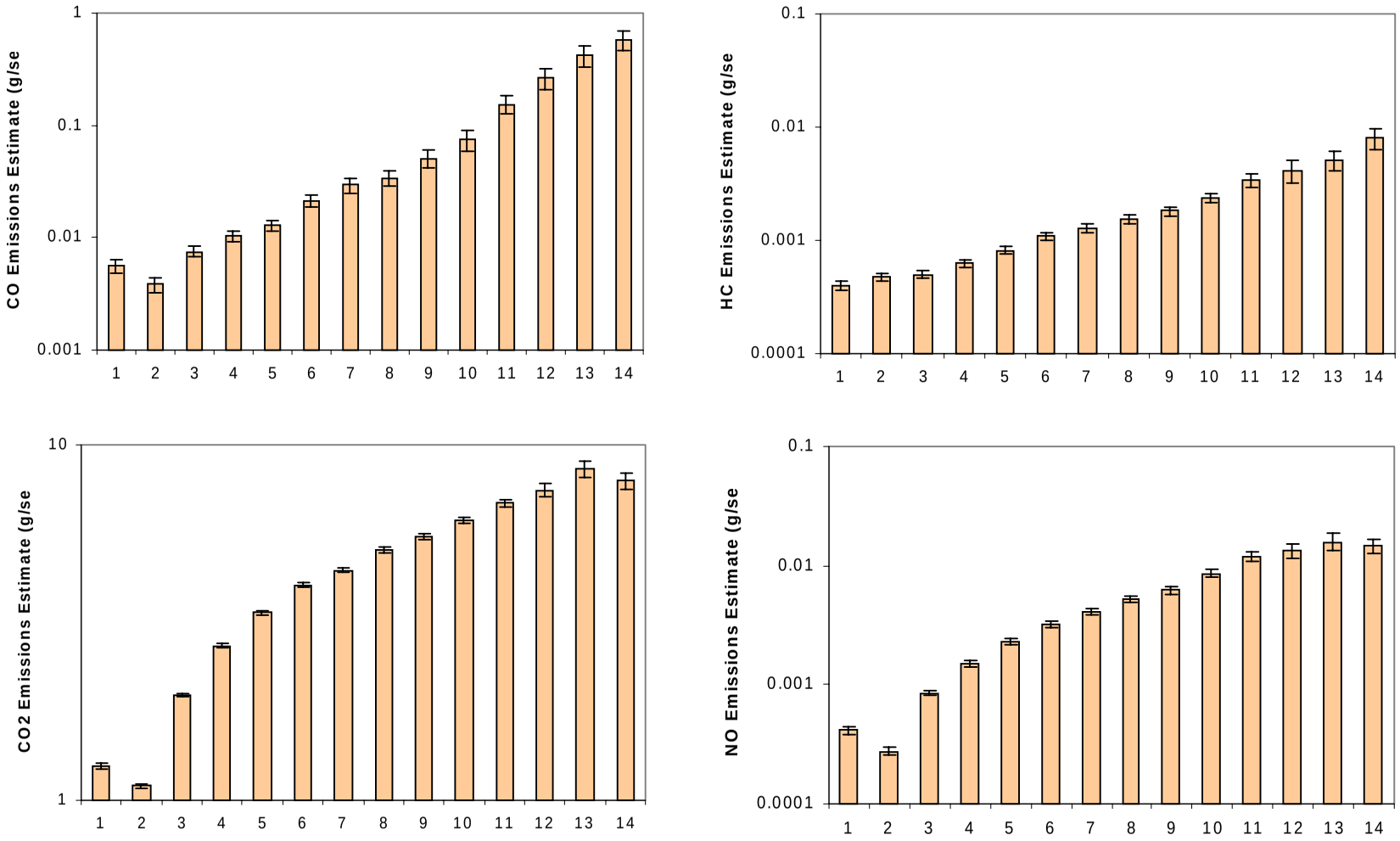


Figure 4-2. Five Second Averaging Time Modal Emission Rates (g/sec) for Maximum VSP Bins for CO, HC, CO_2, and NO_x Based Upon the Modeling Dataset.

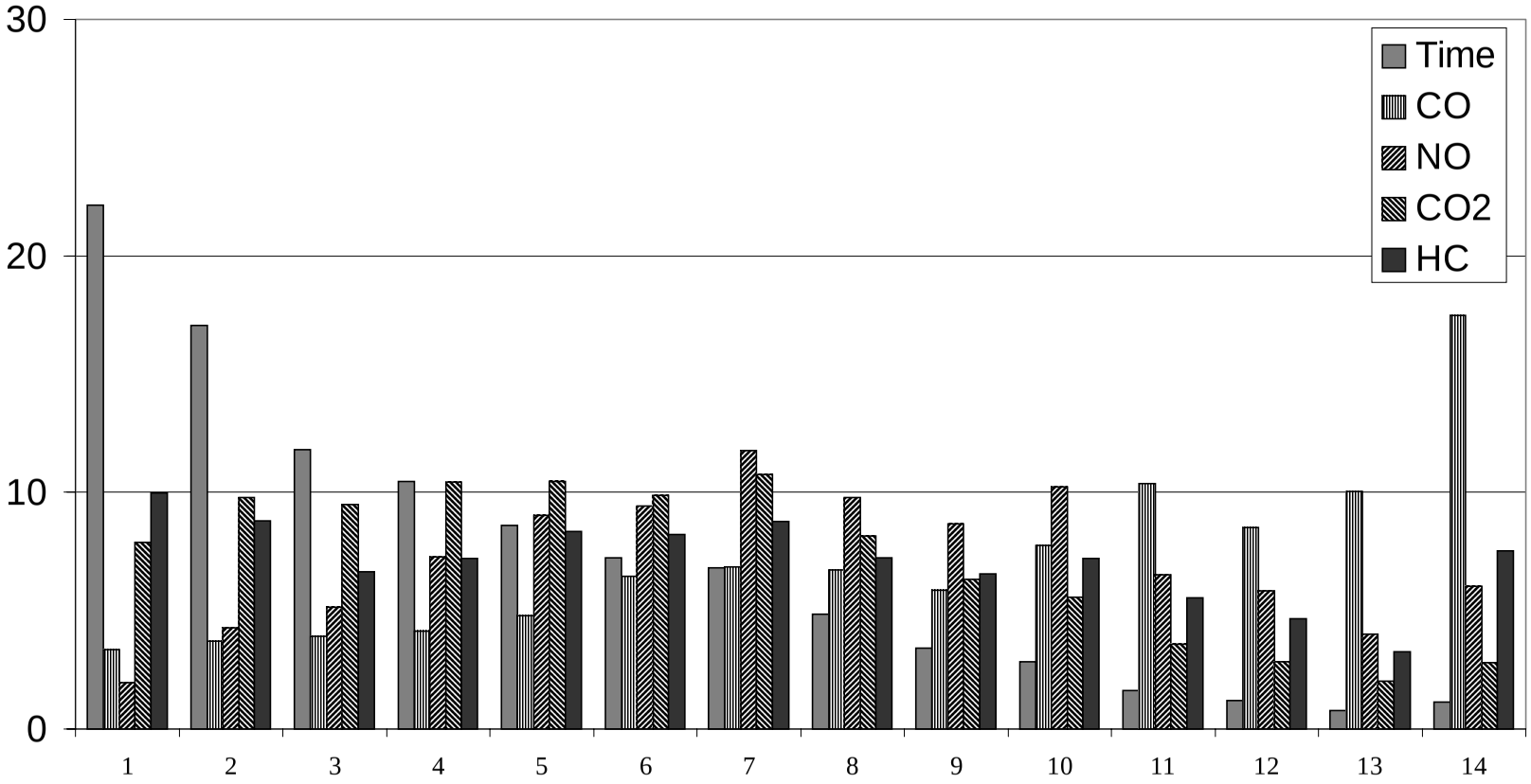


Figure 4-3. Percent of Time Spent in Ten Second Averaging Time Maximum VSP-Based Modes and Percentage of Total CO, NO_x, CO_2, and HC Emissions Attributable to Each Mode, Based Upon the Modeling Data Set.

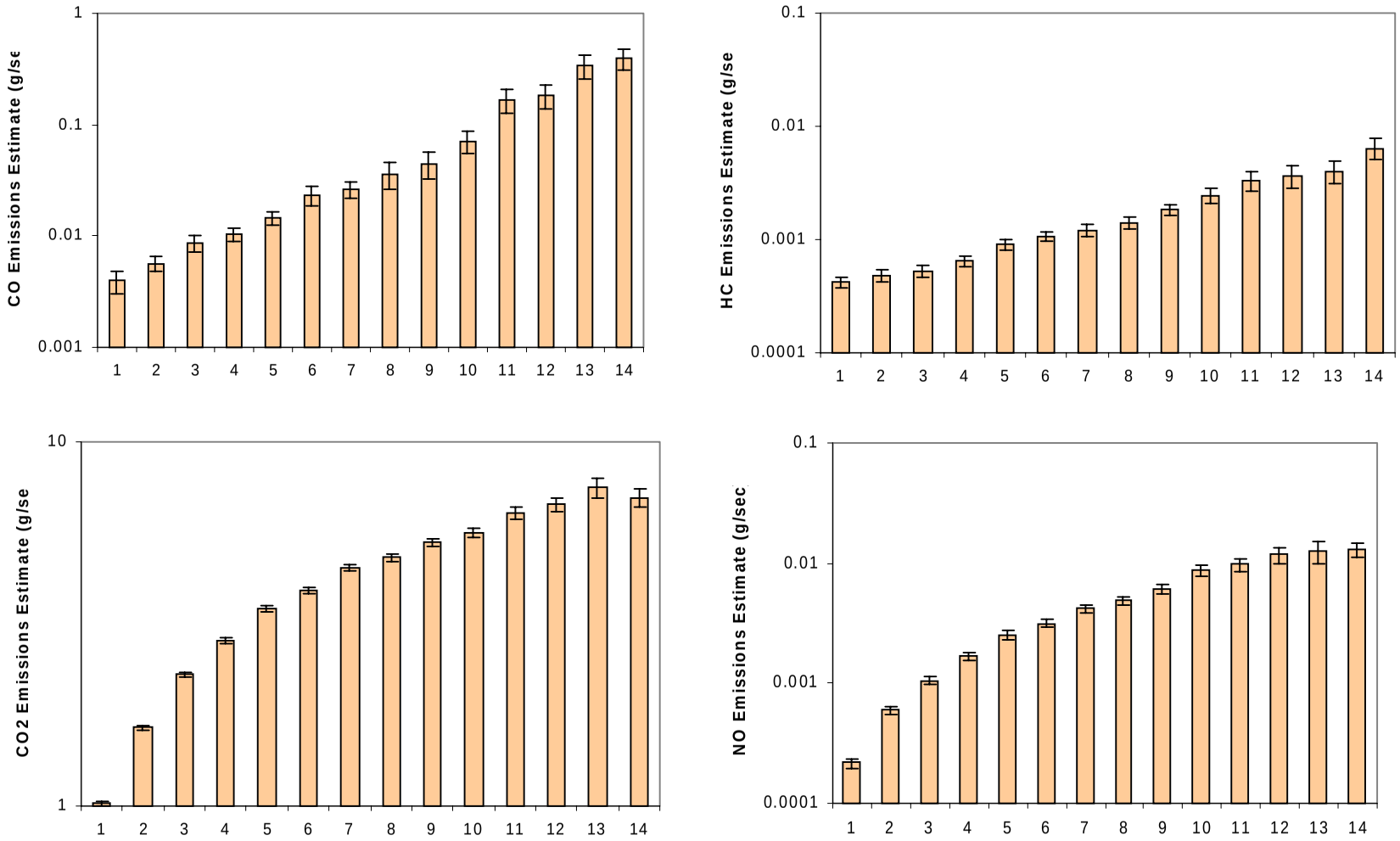


Figure 4-4. Ten Second Averaging Time Modal Emission Rates (g/sec) for Maximum VSP Bins for CO, HC, CO_2, and NO_x Based Upon the Modeling Dataset.

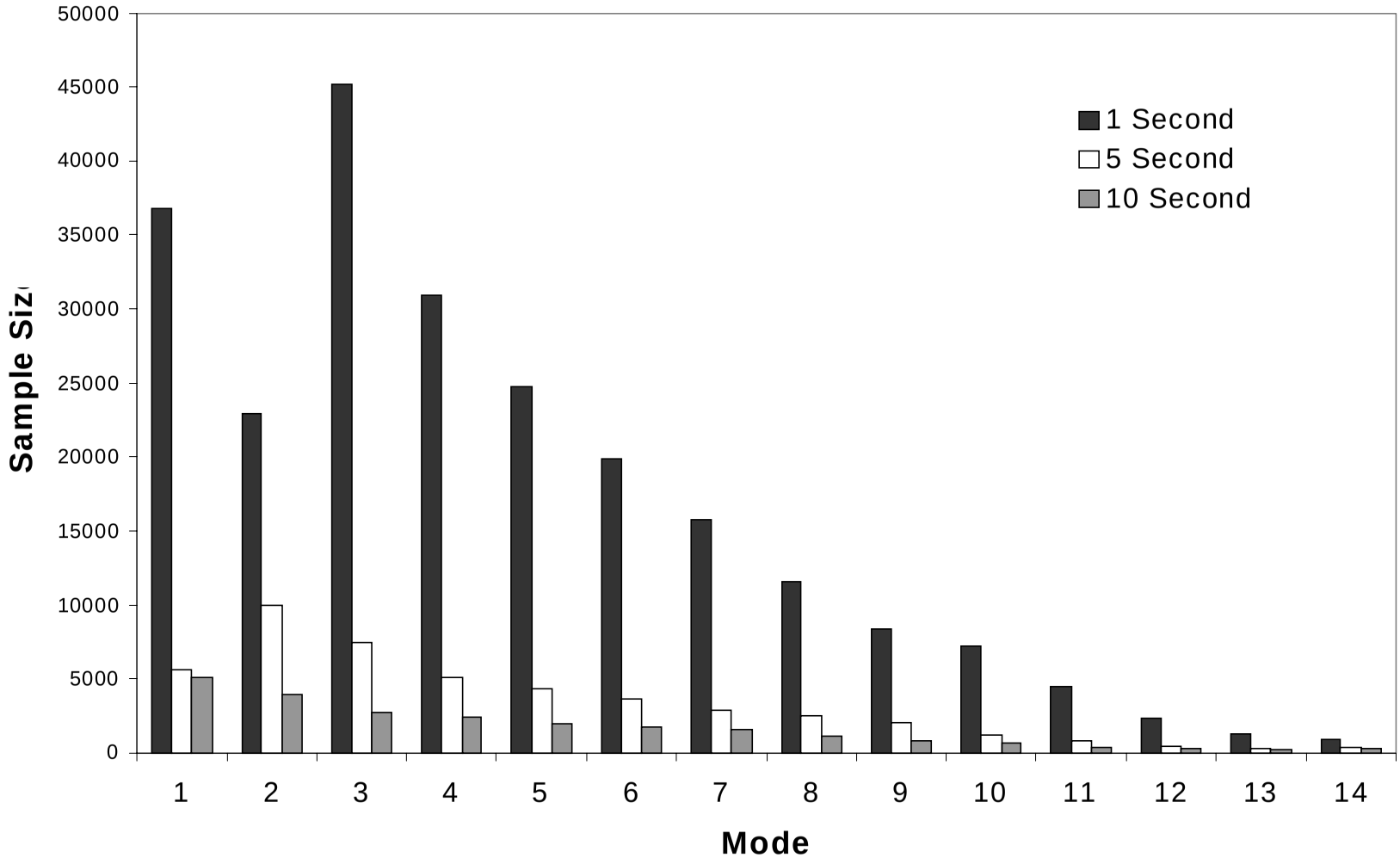


Figure 4-5. Comparison of Sample Sizes for 1 Second, 5 Second, and 10 Second Averaging Time-Based Modes Estimated From the Modeling Data Set.

The results share many qualitative similarities compared to the analysis of 1-second data shown previously. For example, the contribution to total CO emissions is larger for the high maximum VSP modes (e.g., Modes 10, 11, 12, 13, and 14) than the contribution to total emissions of other pollutants. For modes that are based only upon positive maximum VSP, the average emission rates increase from one mode to the next as average VSP increases, for all pollutants and for both averaging times. The range of variability when comparing the mode with the largest average emission rate to that with the lowest average emission rate is similar for all of the averaging times for a given pollutant. Some of the differences that are apparent as the averaging time is increased is that there is less specific treatment of negative VSP cases and that the average emissions for Mode 14 for either the 5-second or 10-second averaging times are typically the same as or perhaps even a little less than that for Mode 13. The lack of a monotonic increase when comparing Modes 13 and 14 could be attributable in part to small sample sizes for these two modes, but also could be attributable to the effects of averaging – for example, perhaps there is less homogeneity in the data of Mode 14 than for other modes.

4.3 Evaluation of Different Averaging Times and Recommendations

Predicted versus actual emissions for individual trips/cycles in the modeling database were evaluated for each of the three averaging times as a consideration to help in selecting a preferred averaging time. For that purpose predictions for Modeling dataset are compared for the three averaging time methods. As seen in Figure 4-6, predictions with all three averaging methods are similar. The 95 percent confidence intervals overlap for almost all of the cycles, for all pollutants. Overall, all three averaging times yield qualitatively similar results. Thus, it is not readily evident that one is clearly superior to another.

The five and ten second averaging times were found to offer no advantage over the one second averaging time in terms of predictive ability with respect to total emissions for a trip. Because it is easier to work directly with the one second average data, the one second averaging time approach was selected.

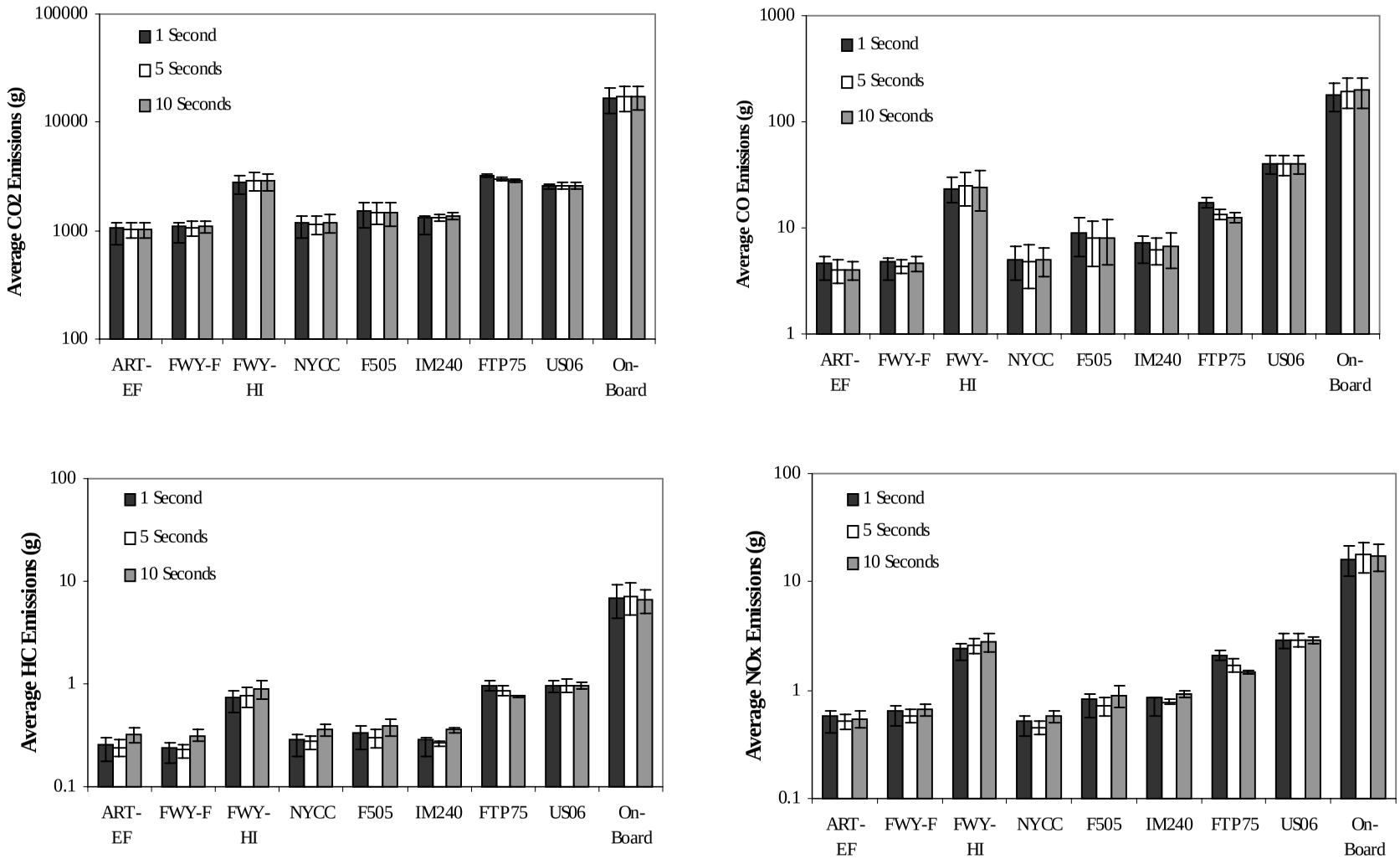


Figure 4-6. Comparison of Predicted Average Emissions of CO_2, CO, HC, and NO_x for Selected Driving Cycles Based Upon 1 Second, 5 Second, and 10 Second Averaging Time VSP Binning Approaches for the Modeling Database.

5 COMPARISON OF EMISSION FACTOR APPROACHES AND EVALUATION OF THE ROLE OF REMOTE SENSING DATA

In this chapter, two different approaches to developing emission factors are compared and evaluated. The objective of this chapter is to develop a recommendation for a preferred emission factor approach, in response to the fifth key question of: what emission factor units should be used?. The two approaches evaluated include mass per time emission factors (e.g., gram/second) and the ratio of emissions of CO, HC, and NO_x with respect to CO_2. The latter was based upon evaluation of the molar ratio of CO/CO_2, HC/CO_2, and NO_x/CO_2. Since most of the carbon in the fuel is emitted in the form of CO_2, the ratio approach is approximately equivalent to a gram per gallon emission factor approach. Previous studies by others (e.g,. Singer and Harley, 1996) have touted the potential benefits of a fuel-based approach to development of area-wide emission inventories. However, such inventories are macro-scale in nature and would require a representative average gram per gallon emission factor combined with good estimates of total area wide fuel consumption. For meso-scale or micro-scale predictions, it will be necessary to estimate emissions at a more local scale. In such instances, an understanding of the influence of different driving modes on emission ratios is critically important. Furthermore, in order to predict mass emissions using emission ratios, it is necessary to be able to predict mass per time CO_2 emission rates or mass per time fuel consumption.

Since one motivation for considering emission factors is potentially to facilitate accommodation of remote sensing data, this chapter also deals with an evaluation of the relevance of remote sensing data for model development. The evaluation is based upon comparison of modal emission rates calculated based upon remote sensing data and compared with those calculated from on-board measurements and dynamometer tests. Therefore, this chapter also addresses the motivating question: What is the potential role and feasibility of incorporating RSD into the conceptual modeling approach?

5.1 Background Regarding Emission Factor Units

Some investigators hypothesize that gram/gallon emission factors have less inherent variability than do mass per time or mass per distance emission factors. NCSU is currently conducting an independent study of this hypothesis, based upon analysis of on-board second-by-second data collected as part of a previous study (Frey *et al*., 2001). Our preliminary findings do not fully support the hypothesis. As an example, we illustrate results for modal analysis of gram per second and gram per gallon emission factors for NO for a 1999 Ford Taurus in Figure 5-1. The gram per gallon emission factors are approximately equivalent to the ratio of NO to CO_2 emissions, since CO_2 emissions are linearly proportional to fuel consumption to a very good approximation. In this case, there is significant variability in emissions among the four driving modes considered regardless of the emission factor units employed. For example, as shown in Figure 5-1, the average acceleration emission rates are approximately a factor of 10 or more greater than average idle emission rates for both emission factor units. Thus, it is clearly not the case in this instance that emission ratios or g/gallon

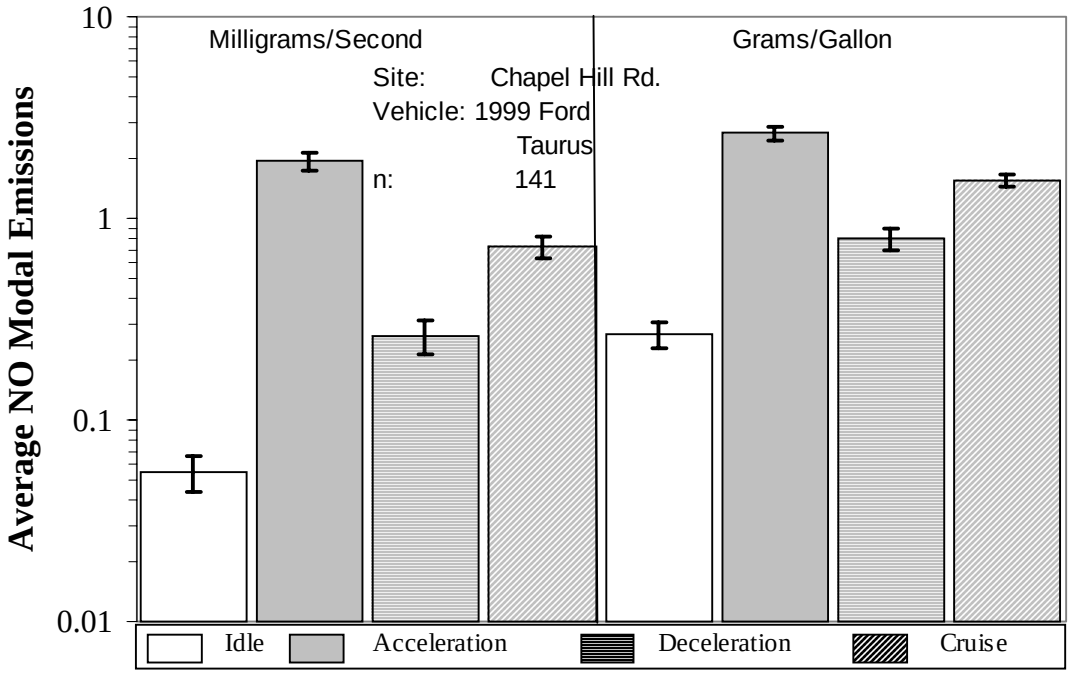


Figure 5-1. Average Modal Rates for Absolute and Normalized NO Emissions for a 1999 Ford Taurus Driven on Chapel Hill Road in Cary, NC (Source: NCSU)

emission factors have substantially less variability from one mode to another than do mass per time emission factors. The results tend to vary for different vehicles and for different pollutants based upon our preliminary study. For example, the g/gallon emission factors for HC may be more nearly similar for different driving modes than the g/gallon emission factors for CO or NO. CO_2 emissions are almost constant regardless of the driving mode; however, this is because the vast majority of carbon in the fuel is emitted as CO_2. Thus, a g CO_2/gallon emission factor is essentially a surrogate for the carbon content of the fuel.

Even if g/gallon emission factors are the same for different driving modes, the fuel consumption rate is not. Figure 5-2 illustrates the variability in fuel consumption rate on a mass per time basis as a function of different driving modes. For example, the average fuel consumption rate during acceleration mode is approximately a factor of five times greater than that during the idle mode, and the average differences in fuel consumption rate among the modes are statistically significant.

5.2 Background Regarding Remote Sensing Data

There are two critically important limitations of RSD data that must be acknowledged: (1) RSD data are for a very short averaging time of approximately 1 second, with no information regarding vehicle activity and emissions either before or after the "snapshot" of the measurement; and (2) RSD data support estimation of relative emission rates (e.g., ratios of HC/CO_2 and NO/CO_2 or similar), or fuel-based emission rates (e.g., g/gallon), but cannot directly provide g/mile or g/sec emission rates. Secondly, one would need to estimate fuel consumption or CO_2 emissions on a mass per time basis in order to convert all other g/gallon or

ratio emission estimates to a mass per time basis. RSD data will not provide a basis for estimating CO_2 emissions on a mass per time basis or for estimating fuel economy in order to estimate gallon/sec fuel consumption.

Before combining RSD data with second-by-second data, it is first important to determine whether RSD data and the second-by-second data are sufficiently consistent that a combination of the two would be meaningful. This comparison is possible if the second-by-second data are converted to the same basis as the RSD data. Therefore, as part of the evaluation of RSD data, modal emission rates were calculated based upon RSD data using the modal definitions that were applied to the modeling dataset, but taking into account the inability to stratify RSD data with respect to odometer reading. We hypothesize that relative differences in average emission rates among the RSD-derived estimates should be similar to those observed based upon the second-by-second data sources. If not, then there may be some significant discrepancy in the data sources that would caution against combining the RSD data into the model development process.

A key limitation of RSD data is that it is essentially a one second (or shorter) snapshot of emissions at a specific location. Therefore, there is no vehicle history available from which to estimate modal emission rates for an averaging time greater than one second. The range of inter-vehicle variability and the range of uncertainty in average modal emissions estimated based upon RSD data were also evaluated. For example, if the RSD data were excessively noisy (high variability) then it may not be useful as a supplement to other data sources in developing the modal.

The appropriateness of using RSD data for developing the model depends on what type of weighting scheme is preferable. If a time-based weighting scheme is selected, then RSD data will likely contribute only modestly to the estimation of average emissions within a bin, because of the short duration of the RSD measurements. If a vehicle weighted approach is selected, then RSD data will contribute disproportionately to the estimation of average emissions, because it is possible to obtain measurements on thousands of vehicles per day using RSDs, but each measurement is for less than one second (typically).

The two emission factor approaches were compared and evaluated based upon the following criteria: (1) which approach results in a “simpler” model; (2) which approach is best able to explain variability in emissions; (3) which approach has the least amount of residual error; (4) which approach can best support model verification or validation; and (5) which approach offers the most flexibility. The comparison of mass per time factors versus ratios was performed for both the NCSU and VSP based approaches, and results for both approaches are presented. In addition, the modal emission rates of both approaches were compared with those estimated from RSD data. Because RSD data are based upon measurements made during less than one second, the comparison of mass per time emission factors and emission ratios was done based only upon the one second averaging time for the modeling database.

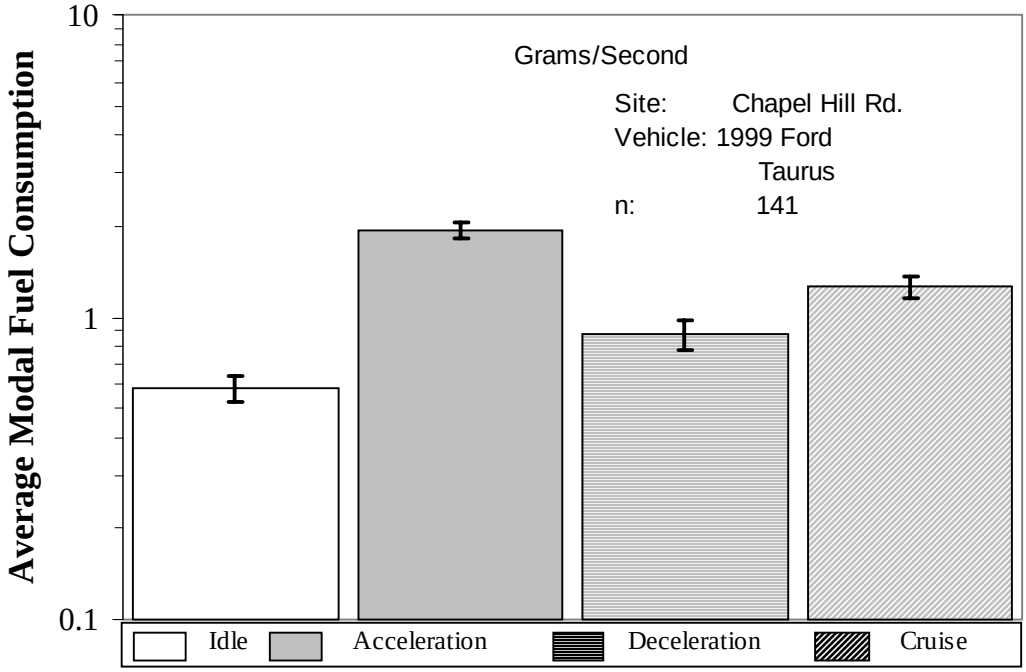


Figure 5-2. Average Modal Rates for Absolute Fuel Consumption for 1999 Ford Taurus Driven on Chapel Hill Road (Source: NCSU)

5.3 Comparison of Emission Factors and Emission Ratios Based Upon the NCSU Modal Approach

The NCSU modal definitions were applied to emission ratios calculated from the modeling dataset. The results when applied to mass per time emission factors were previously described. To compare with remote sensing data, the emission rates in the modeling dataset were converted to molar ratios with respect to CO_2. Specifically, the emission rate in g/sec was divided by the molecule weight of the pollutant to get the emission rate in mole/sec, and was further divided by the CO_2 emission rate in mole/sec. The molecular weight used for the HC emission rate is assumed to be as hexane (C_6H_{14}). Figure 5-3 gives the comparison between the modeling dataset and remote sensing data for each NCSU mode for each pollutant.

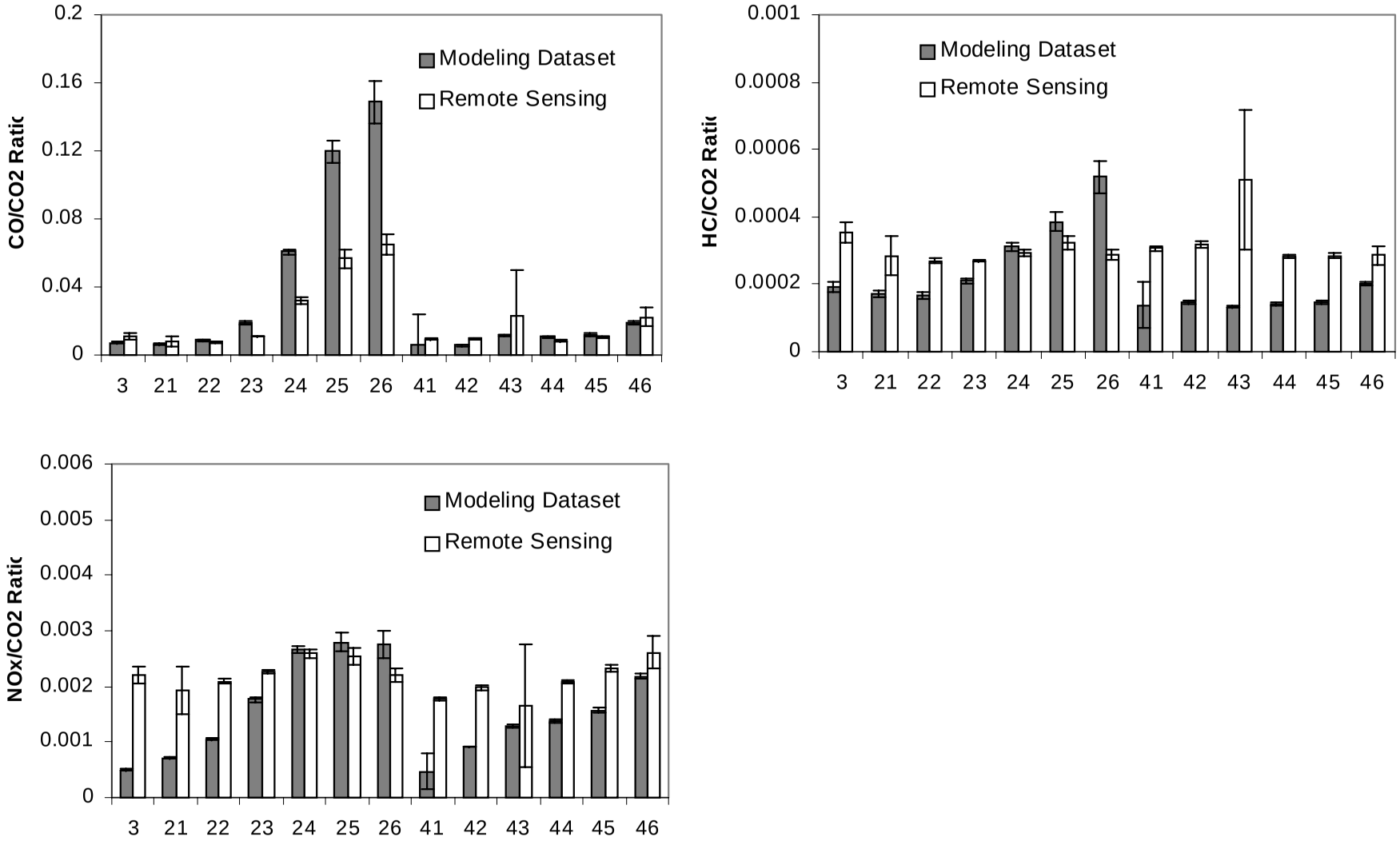


Figure 5-3. Average Modal Emission Ratios for CO/CO_2, HC/CO_2, and NO_x/CO_2 Based Upon NCSU Modes for the Modeling Data and Remote Sensing Data

The average emission rates for the NCSU modal bins have a different sensitivity when evaluated in terms of emission ratios compared to the previously described analysis in terms of grams per second. For example, for the CO/CO_2 ratio, there is relatively little sensitivity to the mode definitions applied to the calibration data set when comparing the deceleration and cruise modes. Idle is not shown because idle cannot be observed with the RSD database. However, for the acceleration modes, and particularly Modes 23, 24, 25, and 26, there is a substantial increase in the CO/CO_2 ratio as VSP increases. Similar results are observed for the HC/CO_2 ratios based upon the calibration data set. However, for the NO/CO_2 ratio, the results for the calibration data set are qualitatively similar to those obtained for the gram/second emission factor units. Specifically, emissions for deceleration (Mode 3) are comparatively low. Within the acceleration mode, the emissions ratio increases as VSP increases, when comparing Modes 21 through 26. For the cruise mode, the emissions ratio increases with average speed among the three low VSP modes (Modes 41, 42, and 43) and with VSP for the three high VSP modes (Modes 44, 45, and 46). The results obtained with the second-by-second data help set expectations for trends that would be expected in the RSD data set.

The results from analysis of the RSD data are qualitatively different from those obtained with the calibration database, in at least two key respects. First, the trend for inter-modal variability in emissions is very different for the RSD data than for the calibration database for both NO_x and HC. Specifically, there is much less variability when comparing the lowest and highest average modal rates and the trends when comparing modes are either not as strong or are not apparent at all. For example, for the RSD HC/CO_2 ratios, there is little apparent sensitivity to VSP among the acceleration modes, in contrast to the observation based upon the calibration database. The average NO_x/CO_2 ratios estimated based upon RSD data are less sensitive to changes in VSP for the acceleration modes, and to changes in speed and VSP for the cruise modes, than the calibration data. Because RSDs measure HC using NDIR, it may be the case that the RSD measurements are not responding to total HC and that the ratio of measurable HC to total HC might vary depending on the mode. For the NO_x/CO_2 ratio, there has been discussion in the literature and elsewhere to the effect that RSDs have less sensitivity to NO_x than to measurements for other pollutants; however, it is not known if this is an important factor in this particular case.

The trends for the CO/CO_2 ratio from the RSD data are more comparable to those from the calibration data compared to the other two pollutants; however, the magnitude of the average CO/CO_2 emission estimates for the three highest VSP acceleration modes is substantially less than that for calibration data set. This might be because of differences in the vehicle mix; however, the RSD data used for this analysis is based upon Tier 1 vehicles, as is the calibration data set. It is possible, perhaps, that there is a different mix of mileage accumulation or other factors; however, since the average emission rates differ by a factor of two, and each average is based upon a fairly large sample size, it could be the case that there are differences in the estimates because of differences in the measurement techniques. It is possible that the RSD data may contain a better representation of high emitting vehicles, or of high emissions episodes for normal emitting vehicles, than does the modeling data set. These questions are revisited in the next sections based upon comparison of emission ratios for the VSP-based approach using both the modeling data set and the RSD data.

5.4 Comparison of Emission Factors and Emission Ratios Based Upon the VSP Modal Approach

Emission ratios were estimated for the 14 VSP modes based upon the modeling data set and were compared with modal emission ratios estimated from the RSD data, as shown in Figure 5-4.

The results for the emission ratios estimated based upon the modeling data set indicate that for the CO/CO_2 ratio there is relatively little sensitivity of the ratios for the low VSP modes, including Modes 1 through 10. However, for the high VSP modes, the emission ratios increase substantially with VSP. An almost similar trend is observed for the HC/CO_2 ratio, with the exception that Mode 3 has a higher average emission rate than the other low VSP modes. For the NO_x/CO_2 ratio, the relative trend among the average emission ratios for each mode is very similar to that observed for the mass per time emission rates. For example, there is a monotonic increase in the average NO_x/CO_2 emissions ratio from Mode 3 through Mode 14. These results illustrate that in order to capture variability in NO_x emissions with a model, it would be necessary to retain approximately the same number of modes as for the mass per time emission factor approach. Because the implementation of a modal modeling approach is simpler from a software design and data management perspective if the same modal definitions are used for all pollutants, the ability to capture variability in NO_x emissions would be binding constraint regarding a lower bound for the number of modes needed. Thus, even though it might be possible to have far fewer than 14 modes to adequately capture variability in CO and HC emissions, a reduction in the number of modes applied to all pollutants would result in loss of explanatory power for NO_x.

The comparison of RSD data with the results from the modeling data set illustrates important similarities and important differences. The key similarities are the following: (1) the average CO/CO_2 ratios are relatively small for the 10 lowest VSP modes; (2) the average CO/CO_2 ratios increase monotonically for the four highest VSP modes; and (3) the average emission ratios agree well between the two data sources for both NO_x/CO_2 and HC/CO_2 for Modes 12 and 13. The key differences are: (1) there is generally less variability among the average modal emission ratios for the RSD data than for the modeling data set; (2) the RSD data produces lower average ratios for CO/CO_2 for Modes 13 and 14; and (3) the RSD data produces much higher average ratio estimates for both HC/CO_2 and NO_x/CO_2 for the low VSP modes. These differences could be because of a different combination of fuel, vehicle characteristics, and odometer reading (which is unobservable with RSD technology) between the two data sets. Presumably, the RSD would contain better representation of on-road high emitters, and possibly such vehicles lead to higher emissions for the lower VSP modes more so than for the higher VSP modes. Thus, at best, the comparison is inclusive. However, it is not possible to stratify the RSD by odometer reading, which complicates the ability to refine the comparison.

In the next sections, the activity underlying the RSD data is compared to that of the modeling data set and of the IM240 data set to obtain additional insights regarding key differences between the RSD data and the modeling data set.

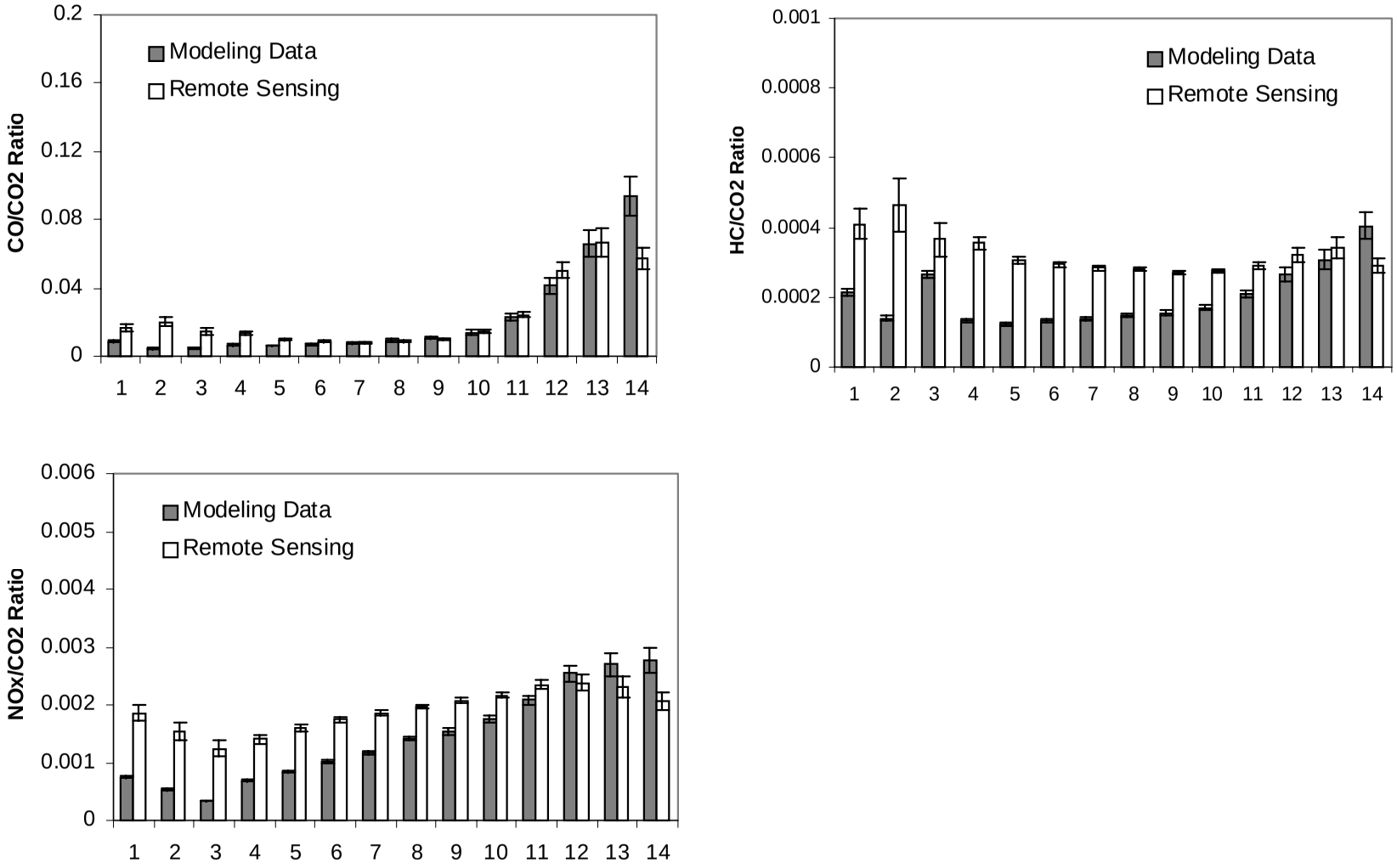


Figure 5-4. Average Modal Emission Ratios for CO/CO_2, HC/CO_2, and NO_x/CO_2 Based Upon VSP Modes for the Modeling Data and Remote Sensing Data for Vehicles with Engine Displacement of Less than 3.5 Liters

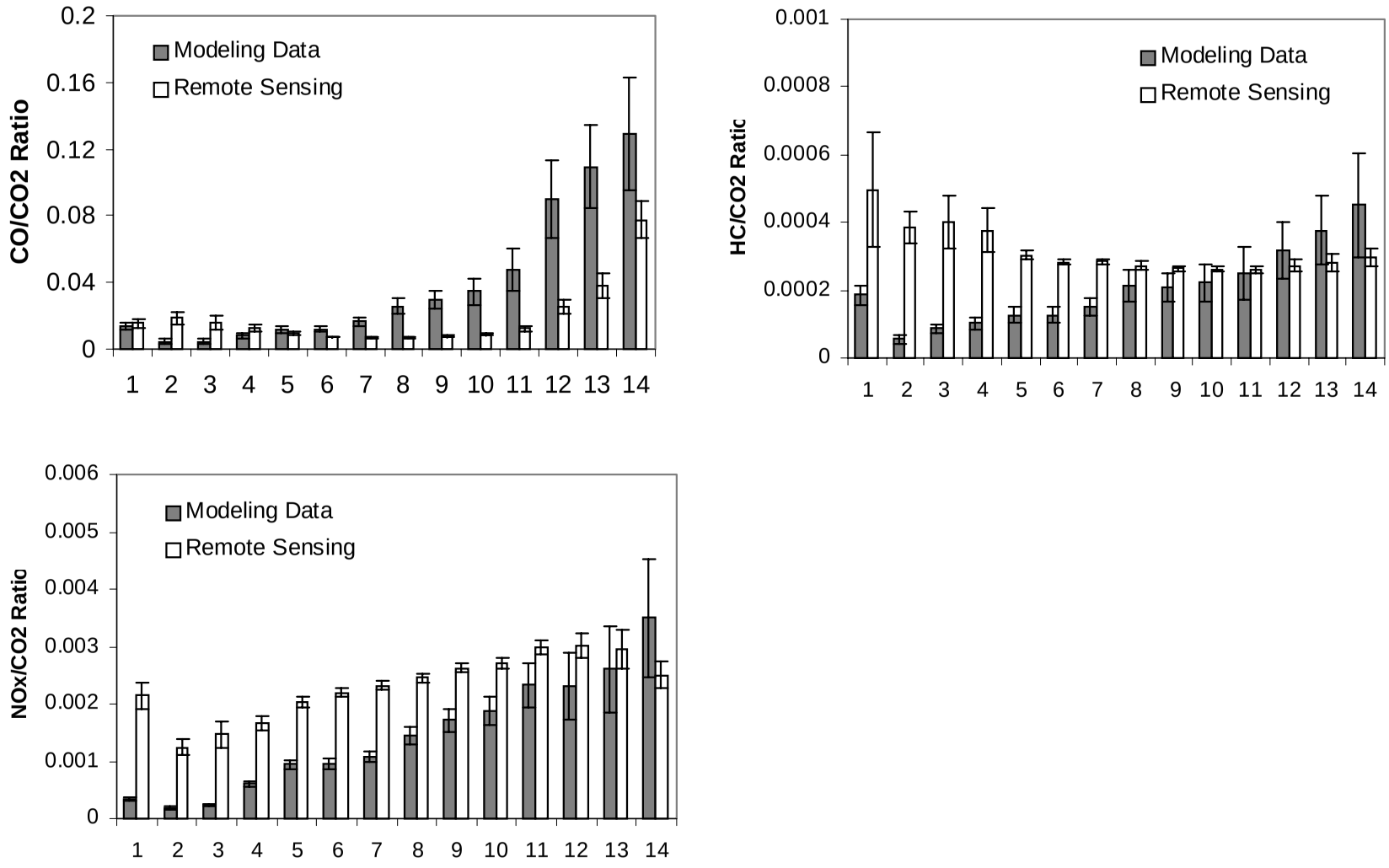


Figure 5-5. Average Modal Emission Ratios for CO/CO_2, HC/CO_2, and NO_x/CO_2 Based Upon VSP Bins for the Modeling Data and Remote Sensing Data for Vehicles with Engine Displacement of Greater than 3.5 Liters

5.5 Comparison of Variability in Emission Ratios for Selected VSP Bins for the Modeling and RSD Data Sets

In this section, the variability in emission ratios for selected modes is compared for both the modeling and RSD data sets in order to evaluate the characteristics of the RSD data. Since odometer reading is not given in the remote sensing data, it is not possible to stratify the data by odometer reading. However, engine displacement is available in the RSD data. Therefore, the comparison is based upon the 14 VSP modes stratified by two engine displacement categories with a cutpoint of 3.5 liters. Examples are shown here for three selected modes based upon engine displacements of less than or equal to 3.5 liters.

For VSP Mode 1, a comparison is shown in Figure 5-6 of the distribution of variability for second-by-second data of the modeling dataset and of the data in the RSD data set. Mode 1 is based upon negative values of VSP. For both the CO/CO_2 and NO_x/CO_2 ratios, the RSD data generally produces higher values than does the modeling data set. Although not shown as data values in the graphs because a log scale was used for the x-axis, the modeling data set contained data values of less than zero, which are considered to reflect measurement error and not to be significantly different than a true value of zero or just slightly greater than zero. For the HC/CO_2 ratio, the RSD data produced a distribution with less variability than the modeling data set. Most of the data in the modeling data set are based upon FID measurements, in comparison to the NDIR method used in remote sensing. Therefore, the difference in the shape of the distributions from the two datasets may reflect differences attributable to the measurement methods.

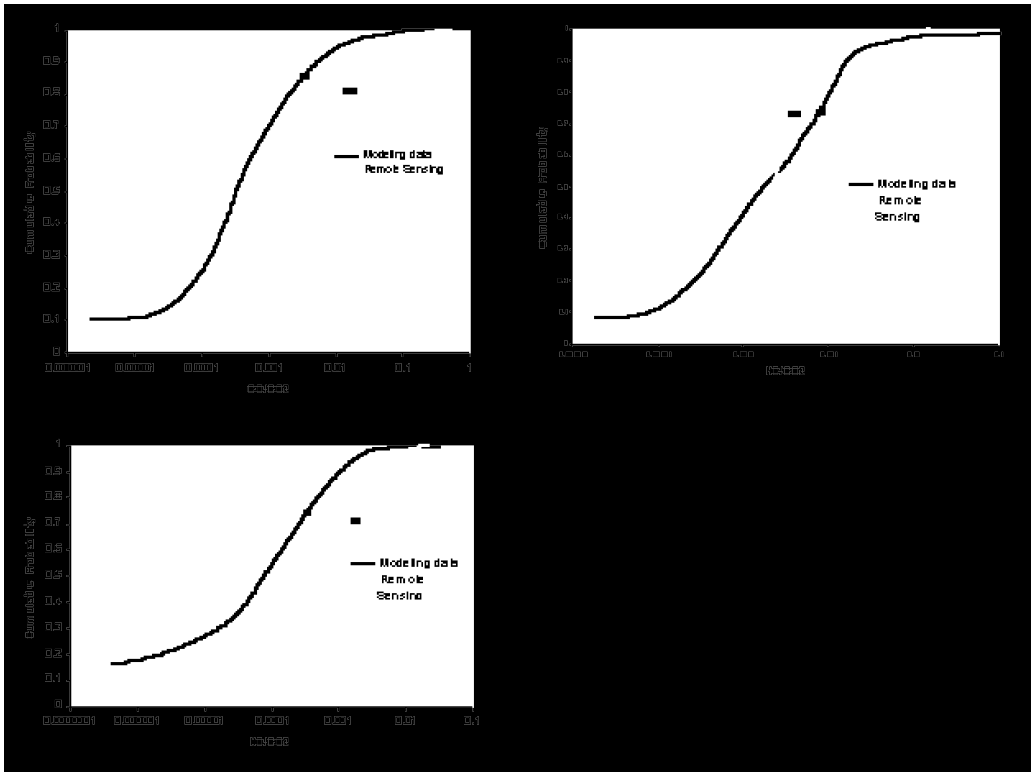


Figure 5-6. Comparison of Variability for CO/CO_2, HC/CO_2, and NO_x/CO_2 Ratios for Modeling Data and Remote Sensing Data for VSP Mode 1 with Engine Size Less Than 3.5 Liters

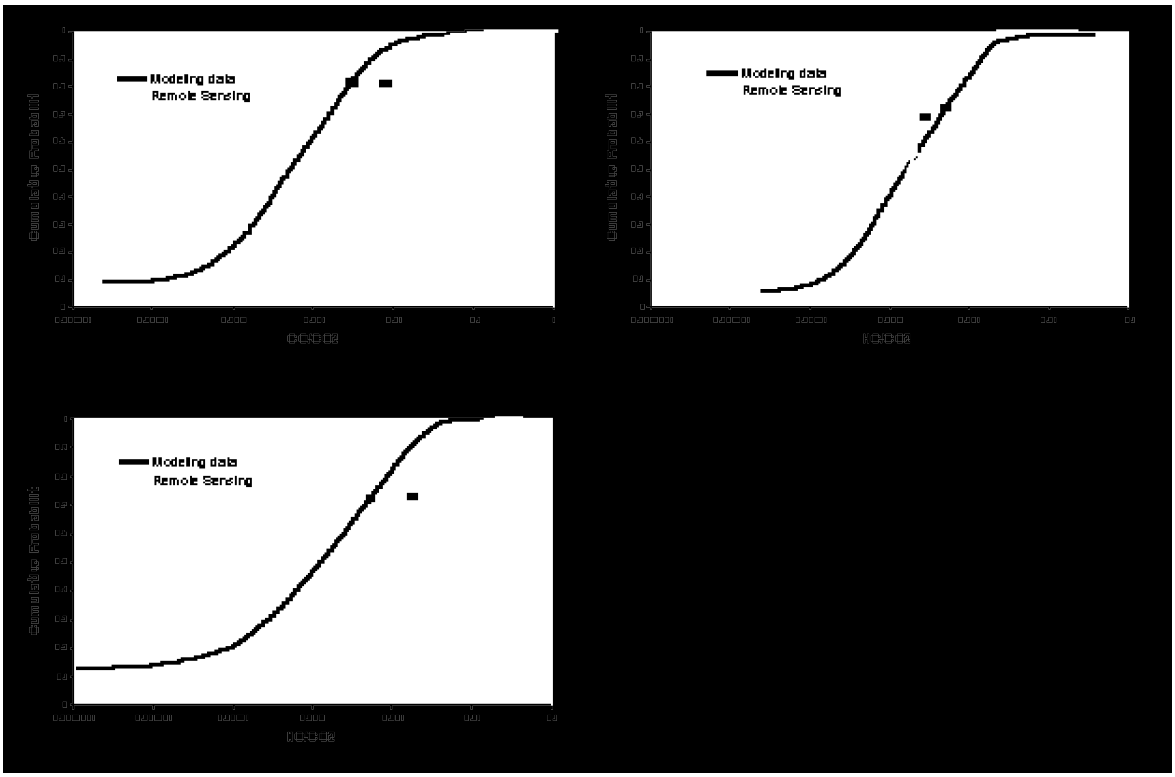


Figure 5-7. Comparison of Variability for CO/CO_2, HC/CO_2, and NO_x/CO_2 Ratios for Modeling Data and Remote Sensing Data for VSP Mode 7 with Engine Size Less Than 3.5 Liters

Figures 5-7 and 5-8 show comparisons of the variability in emission ratios for Modes 7 and 12, respectively. For the CO/CO_2 and NO_x/CO_2 ratios, the general trends are similar to that for Mode 1 in that the average value of the RSD data is generally larger than that of the modeling data set. Furthermore, the entire distribution of ratios for the RSD data is toward larger values for most of the percentiles of the distribution, when compared to the modeling data set. However, the modeling data set typically captures a wider range of variability than the RSD data, as indicated by comparing the range from the lowest to the highest values of the distributions. For example, the modeling data typically span three to five orders of magnitude, whereas the RSD data typically span approximately two to three orders of magnitude in most cases. The upper tails of the emission ratio distributions are comparable for Modes 1 and 7 for both the CO/CO_2 and NO_x/CO_2 ratios. For Mode 12, the upper tail of the RSD data distributions typically have larger values than for the modeling data set.

For the HC/CO_2 ratio, the results for Mode 7 are qualitatively similar to that for Mode 1. For Mode 12, the modeling data set produced a higher average value of the HC/CO_2 ratio compared to the RSD data set. Typically, the RSD data produced a narrower range of values and smaller values at the upper tail of the distribution when compared to the modeling data in the case of the HC/CO_2 ratio.

When comparing the three modes illustrated in Figures 5-6 through 5-8, it should be borne in mind that the relative difference between the RSD data and the modeling data set decrease as the

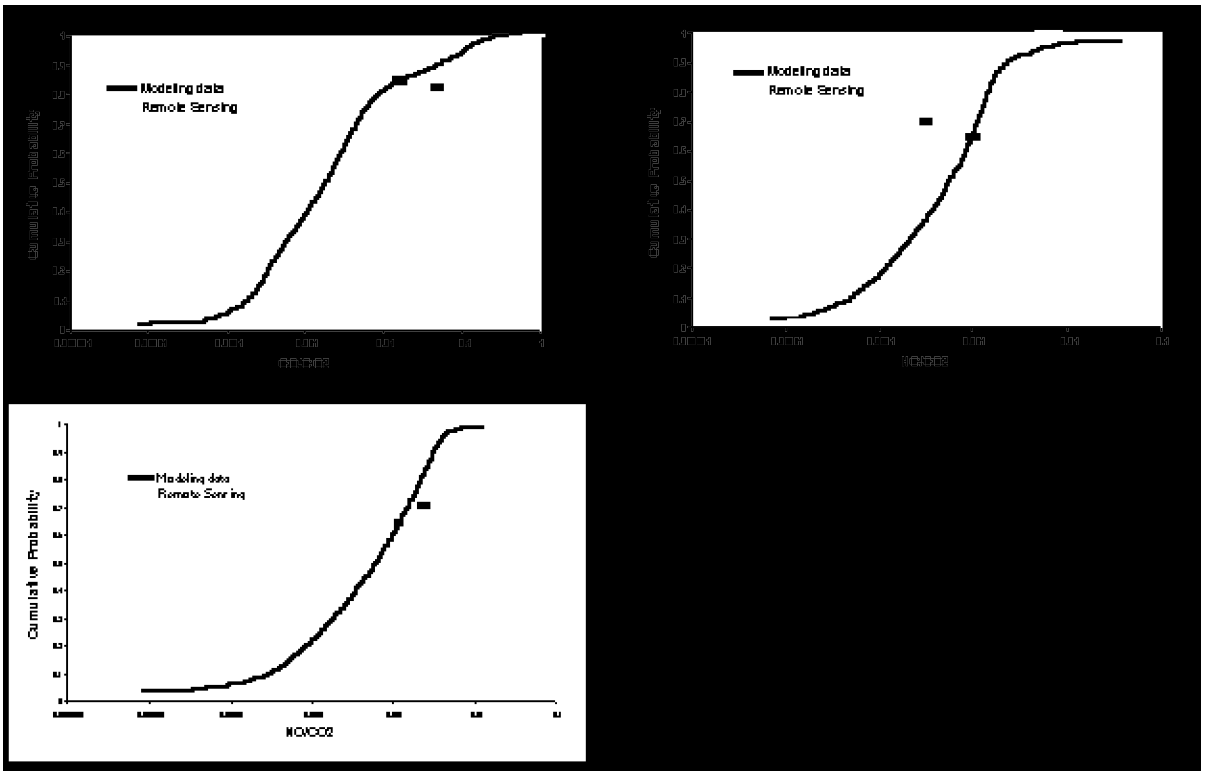


Figure 5-8. Comparison of Variability for CO/CO_2, HC/CO_2, and NO_x/CO_2 Ratios for Modeling Data and Remote Sensing Data for VSP Mode 12 with Engine Size Less Than 3.5 Liters

VSP increases. For example, the distributions for the NO_x/CO_2 ratios for Mode 1 are more separated from each other than is the case for Mode 12.

5.6 Comparison of Vehicle Activity in the RSD and Modeling Databases

For the CO/CO_2 and NO_x/CO_2 ratios when compared for VSP modes, it is typically the case that the RSD data produces larger average emission estimates and generally has higher emission ratios than does the modeling data set. In order to gain insight into possible reasons for these differences, the vehicle activity in the RSD data base was compared with that of the modeling database. The comparison was done on the basis of the distribution of speed and acceleration within specific modes. The comparison was done for selected modes for vehicles with engine displacement less than 3.5 liters. Because odometer reading is unobservable for RSD measurements, it was not possible to stratify the comparison with respect to odometer reading. Three modes were selected for the comparison: (1) Mode 1 to represent low VSP values; (2) Mode 7 to represent moderate VSP values; and (3) Mode 12 to represent large VSP values. The cumulative distributions of both speed and acceleration, and the joint distributions of speed and acceleration, are shown for both the modeling data and the RSD data in Figures 5-9, 5-10, and 5-11 for VSP Modes 1, 7, and 12, respectively, for vehicles with engine displacement less than 3.5 liters.

For Mode 1, it is clear that the RSD data have less variability in speed than the modeling data. Furthermore, the RSD data have a larger proportion of larger acceleration rates than the

modeling data. Mode 1 is based upon VSP values of less than -2 kW/ton. Although the range of VSP values in any individual bin is constrained by the definition of the mode, there are many different combinations of speed and acceleration that can produce a narrow range of values of VSP. For example, large magnitudes of deceleration at low speed can produce the same VSP estimate as a small magnitude of deceleration at higher speed. When comparing the scatter plots of acceleration versus speed for the modeling data set and the RSD data set, it is clear that the modeling data set addresses a much wider range of combinations of acceleration and speed than does the RSD data. Most of the RSD data are for decelerations of greater than -3 mph/sec and for speeds between 20 mph and 40 mph, versus decelerations of typically -5 mph/sec or greater and speeds ranging from approximately zero to greater than 70 mph. For this mode and strata, the RSD data produced higher average emission ratios for all three pollutants. It is clear that the range of activity for Mode 1 is very different for the RSD data compared to the remote sensing data.

For Mode 7, the remote sensing data have a much narrower range of speeds, from approximately 20 mph to 40 mph, compared to the modeling data, for which speed varies from approximately 10 mph to over 80 mph. However, the RSD data typically have much larger values of acceleration, with a range from approximately 1 mph/sec to as much as approximately 4 mph/sec. The modeling data set has a large proportion of acceleration data of less than 1 mph/sec, although the upper tail of the cumulative distribution of acceleration includes a small percentage of values greater than 4 mph/sec. When comparing the scatter plots of acceleration versus speed, it is clear that the modeling data set has a wider range of activity. The larger average acceleration for the RSD data set is a notable difference compared to the modeling data set, and may be a key reason as to why the emission ratios for the RSD data tend to be larger than for the modeling data set.

For Mode 12, the modeling data set has a remarkably wider range of variability in speed than the RSD data, but also has a noticeably lower average value of acceleration. The RSD data have speeds ranging typically from approximately 25 mph to 50 mph, versus a range of approximately 20 mph to 80 mph for the modeling data set. The RSD data have accelerations ranging from 2 mph/sec to 4 mph/sec, compared to a range of approximately 0 mph/sec to 4 mph/sec for the modeling data. A comparison of the scatter plots in Figure 5-11 suggests that the modeling data capture a wider range of variability in activity, but have a much smaller proportion of activity associated with larger accelerations when compared to the RSD data. Thus, it is likely that these differences in activity account for at least some of the differences in emissions.

It should be pointed out that although the statistical analysis presented in Chapter 3 identified VSP, engine displacement, and odometer reading as the three most important explanatory variables, there may be opportunities to further disaggregate the data in the future when working with larger data sets than the one used in this study. For example, as shown in Chapter 9, there are some differences in average emissions for a VSP mode when taking into account differences in speed and/or acceleration that might help explain additional variability not captured by the model developed in Chapter 3.

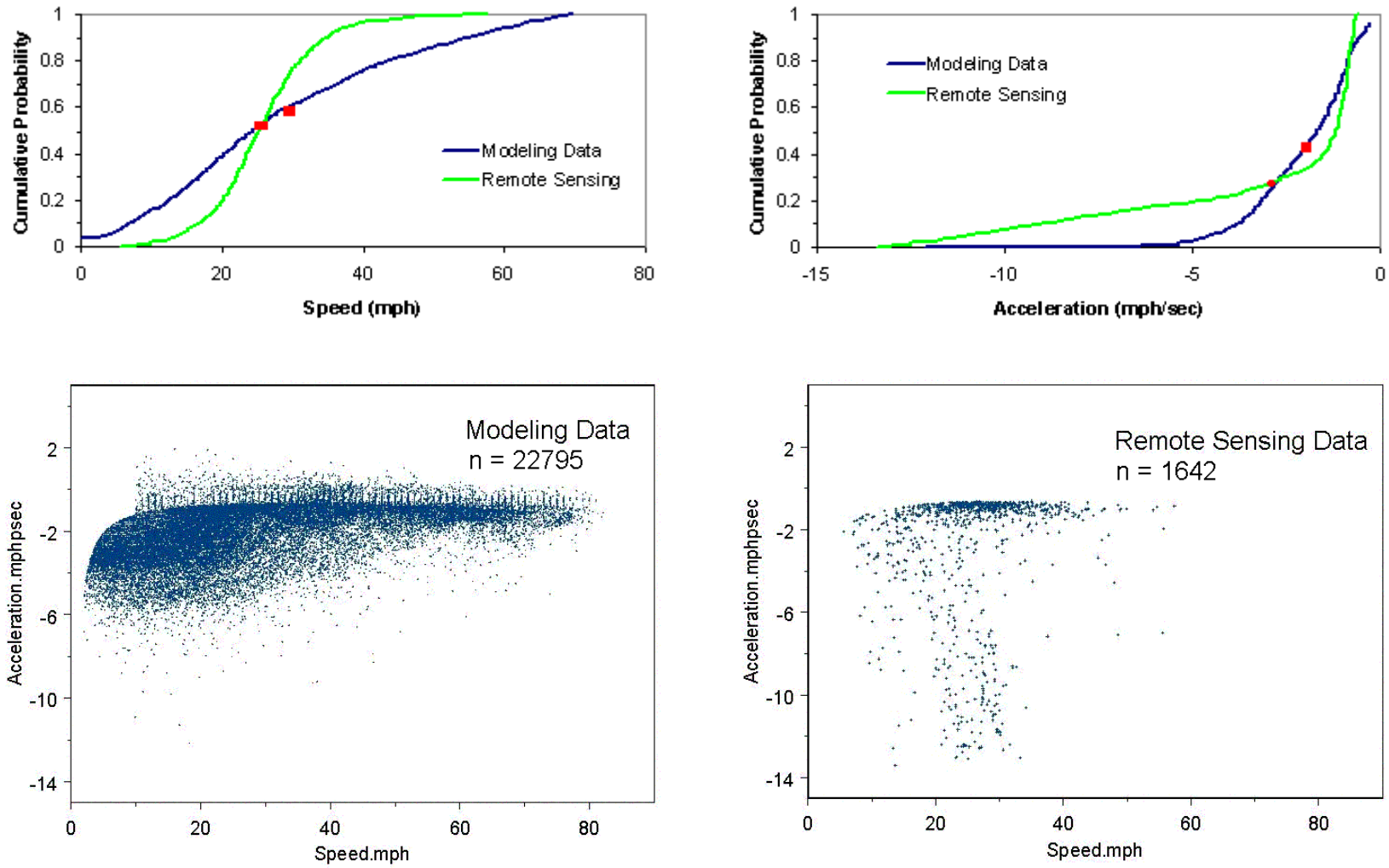


Figure 5-9. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and Modeling Data Sets, for VSP Mode 1 for Vehicles with Engine Displacement Less Than 3.5 Liters.

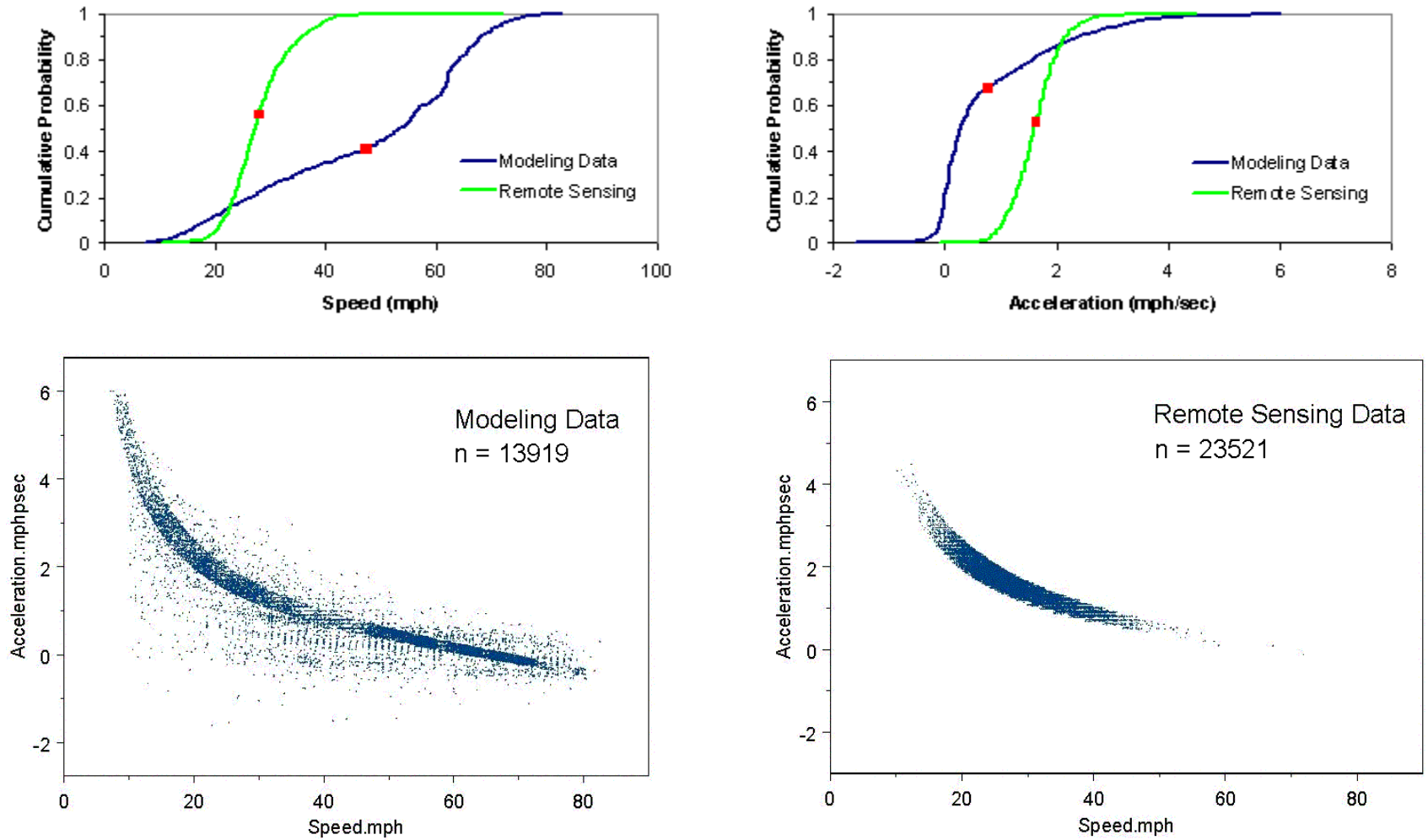


Figure 5-10. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and Modeling Data Sets, for VSP Mode 7 for Vehicles with Engine Displacement Less Than 3.5 Liters.

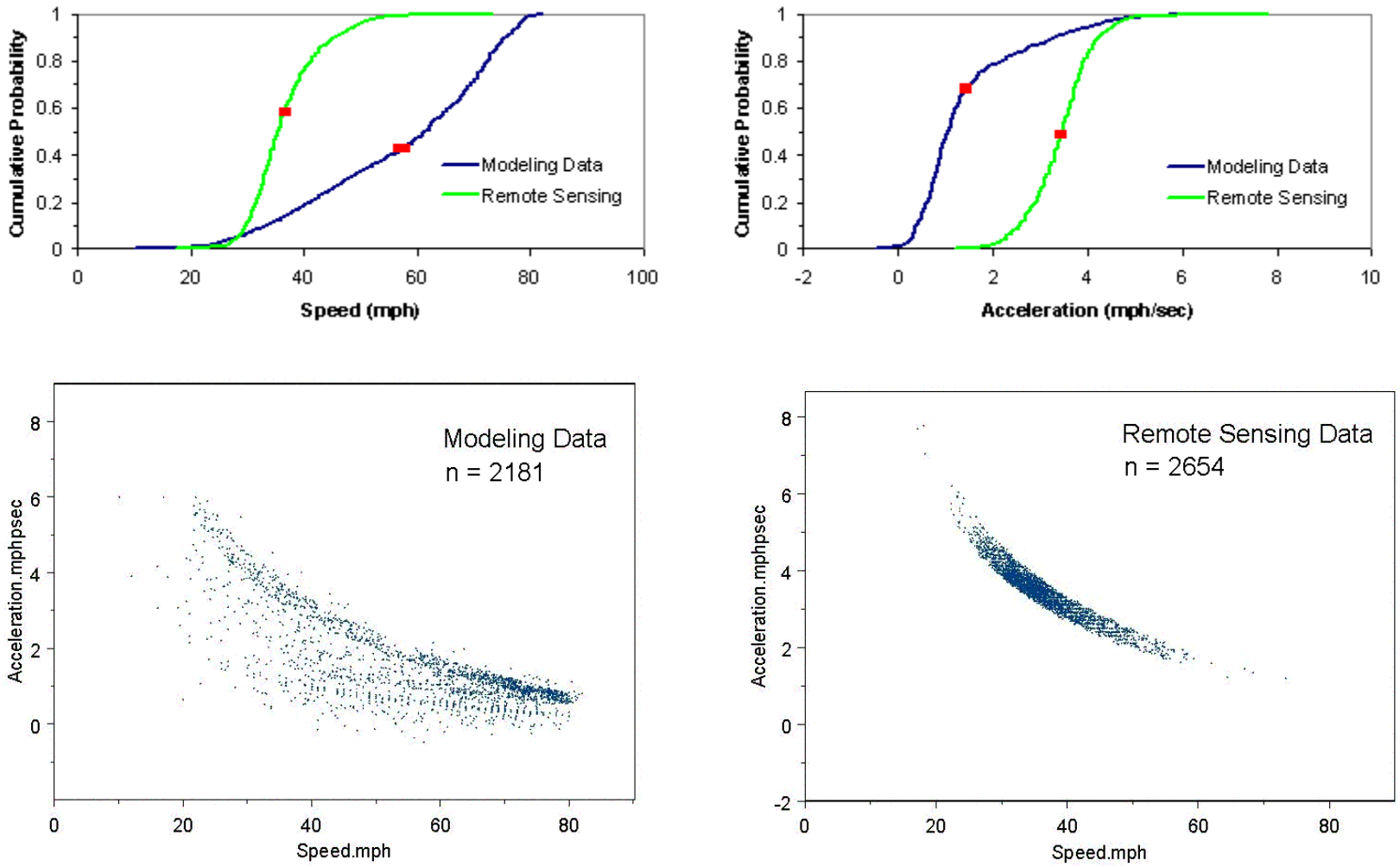


Figure 5-11. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and Modeling Data Sets, for VSP Mode 12 for Vehicles with Engine Displacement Less Than 3.5 Liters.

5.7 Comparison of Emissions Ratios and Vehicle Activity Between the RSD and IM240 Databases

Because the RSD data are based upon observations of a large number of on-road vehicles, and because the IM240 are based upon a sample of on-road vehicles that is believed to better represent high emitters than other data sets used in this study, it was hypothesized that there may be similarities between the IM240 dynamometer data and the RSD data. To explore this hypothesis, the average modal emission ratios estimated from the two data sets were compared. The comparison was stratified based upon engine displacement since information was available in both data sets regarding this explanatory variable. The average emission ratios based upon both data sets are shown in Figure 5-12 for vehicles with engine displacement of less than 3.5 liters and in Figure 5-13 for vehicles with engine displacement of greater than 3.5 liters.

Figure 5-12 illustrates a general similarity between the emission ratios estimated from the two different datasets. Particularly in the case of the HC/CO_2 ratios, for 9 of the 14 modes there is not a significant difference in the average ratios when comparing the two datasets. Both datasets imply high emission ratios for the low VSP modes, slightly lower emission ratios for the moderate VSP modes, and relatively high values for Mode 13. In the case of the CO/CO_2 ratios, although only 5 of the 14 modes are statistically similar to each other, the qualitative trends for both data sets are similar. In particular, the emission ratios for Modes 1 through 10 are relatively constant for a given data set, but the average ratios increase substantially for Modes 11 through 13. Mode 14 tends to have somewhat lower values than does Mode 13. For the NO_x/CO_2 ratios, the RSD data tends to have higher average values for the lowest VSP modes, and the IM240 data tends to have higher average values for Modes 5 to 14.

The comparisons in Figure 5-13 are less clear than those of Figure 5-12 mainly because there are fewer data, particularly for the IM240 database, that fall into this particular strata, and especially for the high VSP modes (e.g., Modes 12, 13, and 14). The results suggest that there are similarities in the two datasets for CO and NO_x, except for the highest VSP modes, and that for HC the RSD data typically have higher ratios than the IM240 data except for Mode 1.

Overall, based upon the results shown in Figures 5-12 and 5-13, there are important qualitative similarities in the average emission ratios for both data sets. However, a key question is whether the similarities in emissions are because of similarities in vehicle activity. In order to answer this question, the distributions of each of speed and acceleration were compared, as were the joint distributions of both speed and acceleration. These comparisons are shown in Figures 5-14, 5-15, and 5-16 for Modes 1, 7, and 12 for vehicles with engine displacement of less than 3.5 liters.

For the Mode 1 comparison shown in Figure 5-14, the IM240 data have a wider range of speed, but it is apparent that the distribution of speeds for the IM240 data are bimodal. Thus, there is a large proportion of speeds in the range of approximately 10 to 30 mph, as well as a smaller proportion of speeds in the range of approximately 50 to 60 mph. In contrast, as noted in the previous section, the distribution of speeds for the RSD data is primarily between 20 mph and 40 mph. The RSD data tend to have a larger proportion of larger acceleration rates than does the IM240 data. A comparison of the scatter plots for acceleration versus speed indicates that the IM240 data captures a much wider range of variability in terms of different combinations of

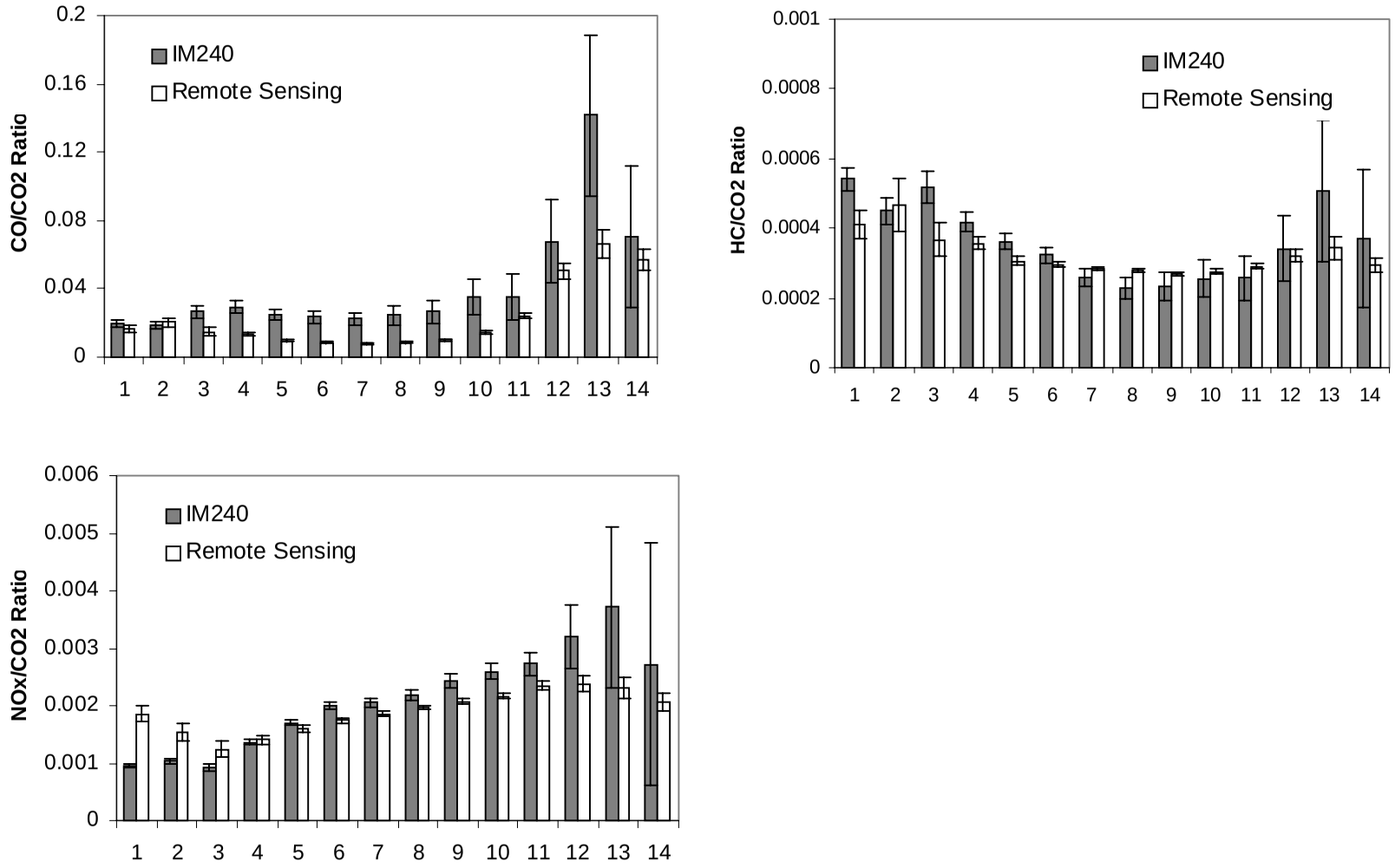


Figure 5-12. Average Modal CO/CO_2, HC/CO_2, and NO_x/CO_2 Emission Ratios Based Upon VSP Bins for the Modeling Data and IM240 Driving Cycle Data for Vehicles with Engine Displacement of Less Than 3.5 Liters.

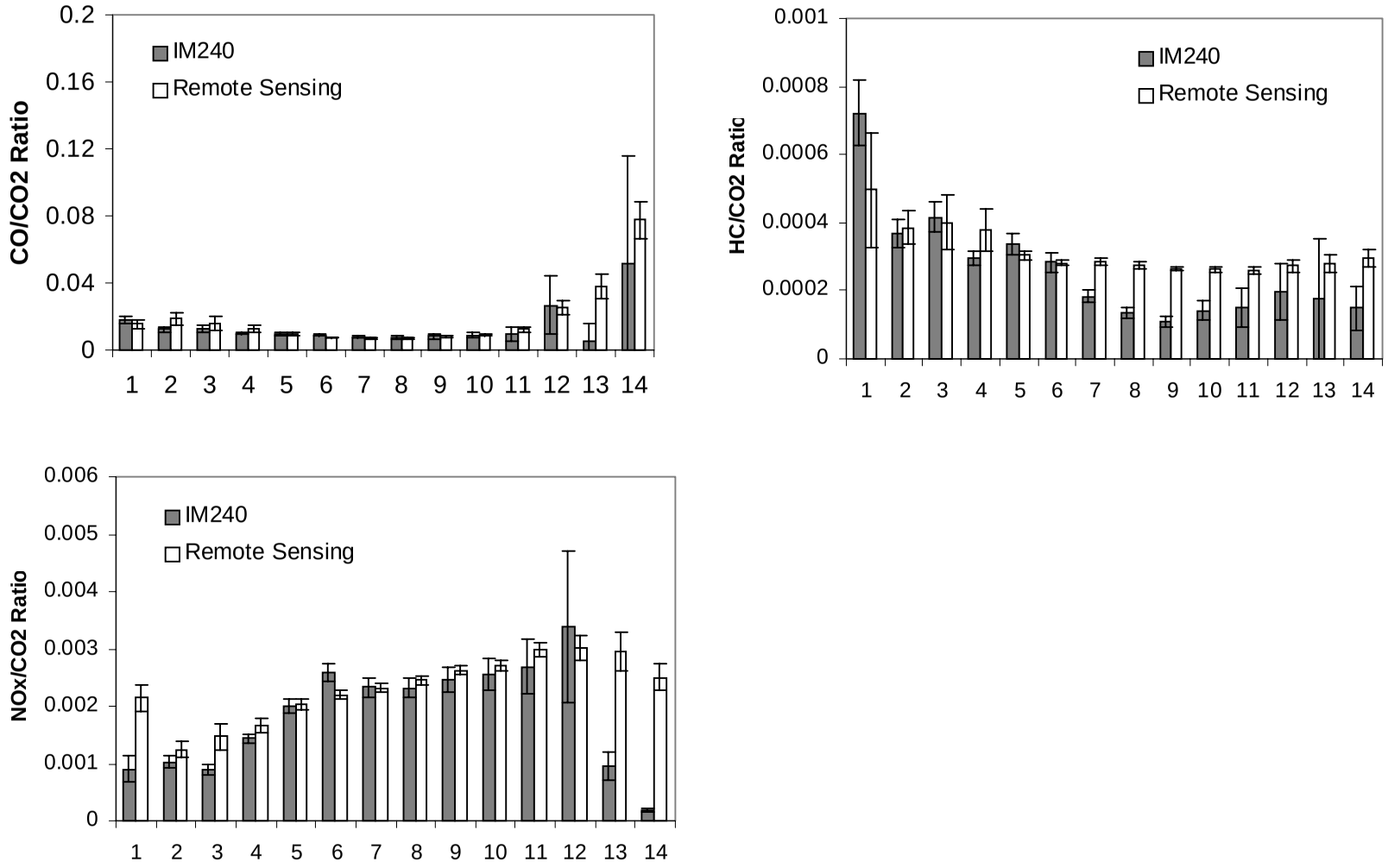


Figure 5-13. Average Modal CO/CO_2, HC/CO_2, and NO_x/CO_2 Emission Ratios Based Upon VSP Bins for the Modeling Data and IM240 Driving Cycle Data for Vehicles with Engine Displacement of Greater Than 3.5 Liters.

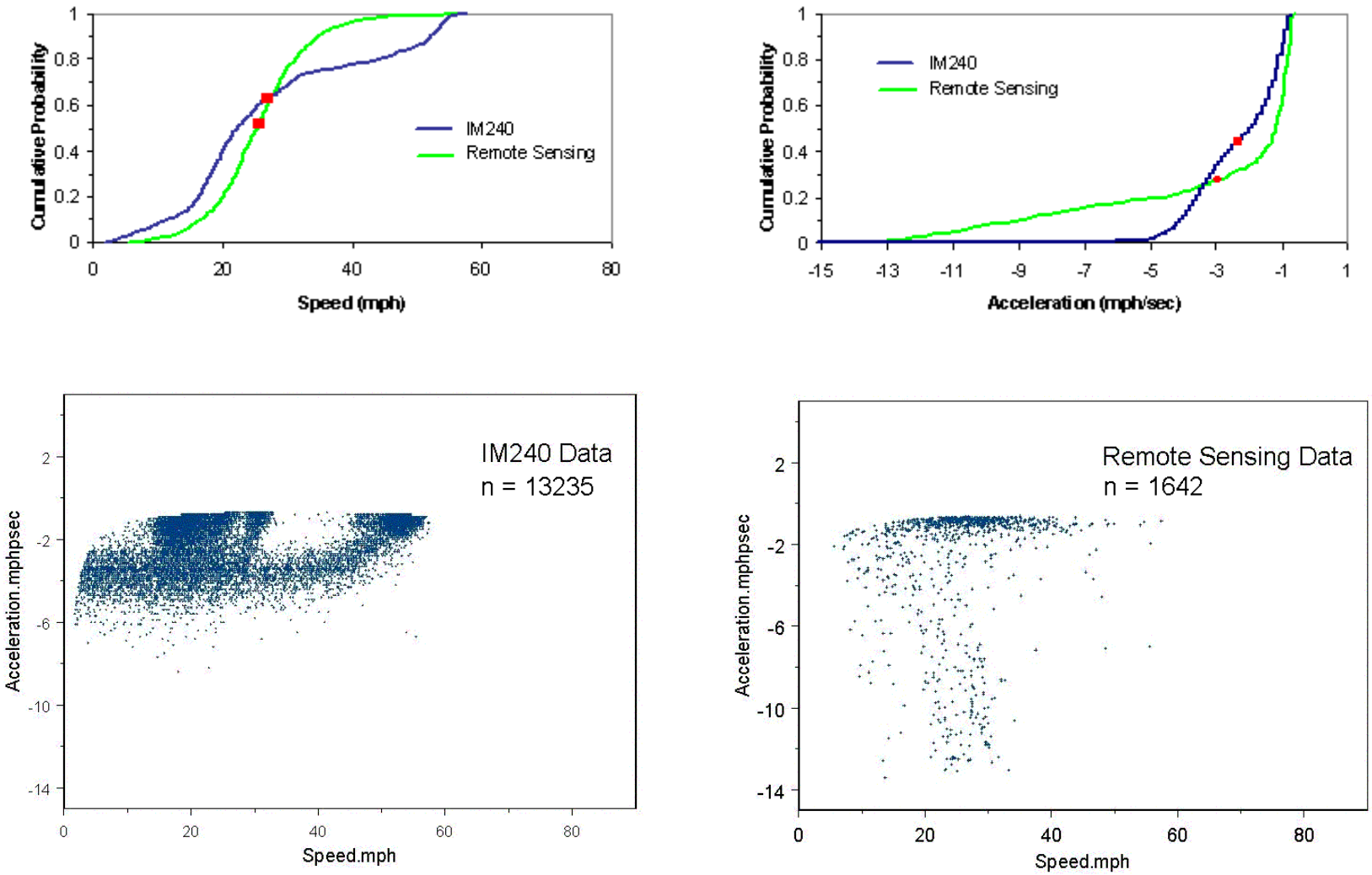


Figure 5-14. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and IM240 Driving Cycle Data Sets, for VSP Mode 1 for Vehicles with Engine Displacement Less Than 3.5 Liters.

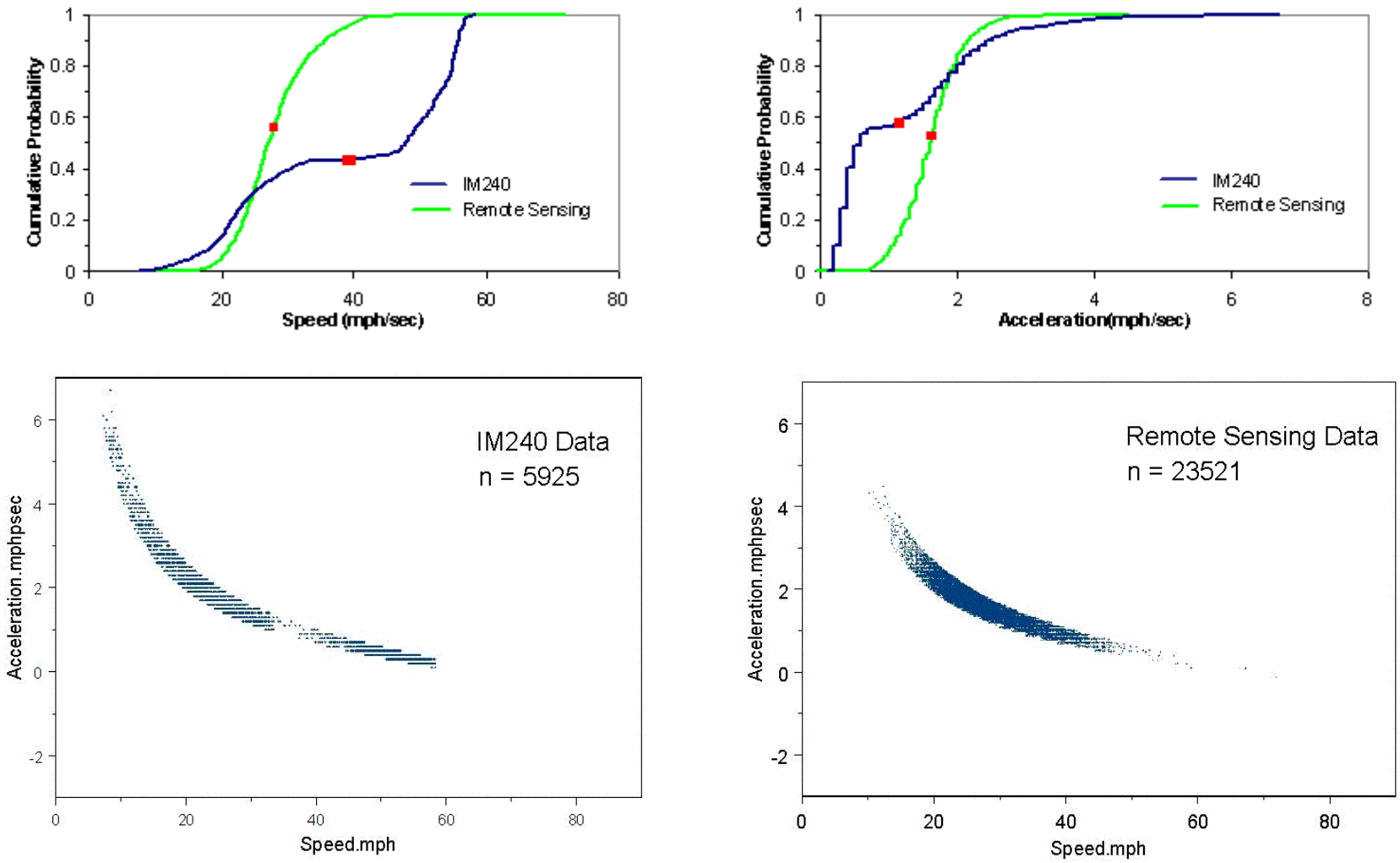


Figure 5-15. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and IM240 Driving Cycle Data Sets, for VSP Mode 7 for Vehicles with Engine Displacement Less Than 3.5 Liters.

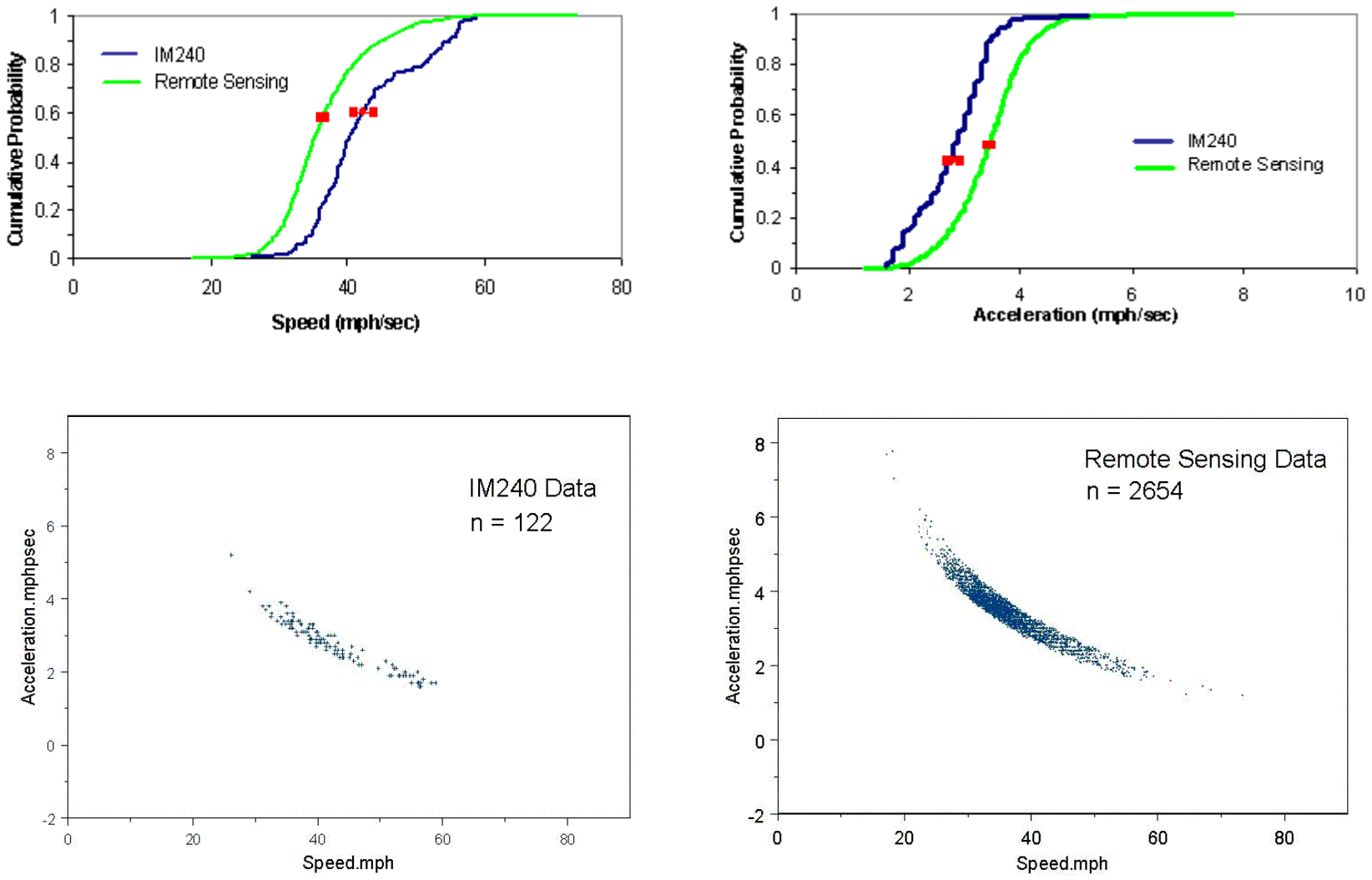


Figure 5-16. Comparison of Vehicle Activity, In Terms of Speed and Acceleration, for the Remote Sensing and IM240 Driving Cycle Data Sets, for VSP Mode 12 for Vehicles with Engine Displacement Less Than 3.5 Liters.

speed and acceleration than does the RSD data. The RSD data had a higher average emission ratio for NO_x but lower ratios for CO and HC for Mode 1 for vehicles with engine displacements less than 3.5 liters.

For the Mode 7 comparison, the IM240 data are strongly bimodal with respect to both speed and acceleration. The IM240 data have a wider range of values for speed and acceleration than do the RSD data. In particular, there is more representation of higher speeds and a similar representation of the upper tail of the distribution of acceleration when comparing the IM240 data to the RSD data.

For Mode 12, the IM240 data typically represent somewhat higher speeds but also somewhat smaller accelerations than does the RSD data. However, for Mode 12, there are relatively few data points for the IM240 data set in comparison to the RSD data.

Overall, although not conclusive, the comparison of vehicle activity in terms of speed and acceleration between the IM240 and RSD data suggests that there are substantial differences in activity patterns between the two data sets. Thus, although in some cases both data sets have similar emission ratios, it is possible that such apparent similarities are actually based upon differences in the vehicle and in the vehicle activity.

5.8 Summary and Recommendations

The key findings from the comparison of emission factor units and from the evaluation of RSD data are briefly summarized here, followed by more detailed discussion:

- When comparing RSD to the modeling data:
  - There is less variability in emission ratios of CO/CO_2 and HC/CO_2 for the low VSP bins
  - There is substantial variability in emissions for the high VSP bins
- for NO_x, there is a need for a similar number of modes for the emission ratios and for mass per time units in order to explain variability in emissions.
- Need CO_2 (or fuel use) on a mass per time basis anyway, which motivates the need for a modal approach such as that developed in Chapter 3 on a mass per time basis
- Because of the variability in NO_x emissions even when emission ratios are used, and because of the need to use a mass per time approach to estimate CO_2 emissions, the use of emission ratios instead of mass per time emission factors for only a subset of pollutants does not offer any significant advantage, especially from a software/model design perspective.
- RSD data are not a strong candidate for use in model development because some key variables are not observable, such as odometer reading.
- The HC/CO_2 emissions data from RSD do not appear to be comparable to that from the modeling dataset because of the measurement techniques employed.

The results of the application of the binning methods to the modeling data set suggest that there is less variability in emission ratios of CO/CO_2 and HC/CO_2 for the low VSP bins. However, there is substantial variability in the NO_x/CO_2 ratio for the low VSP bins, and for all three pollutants there is substantial variability in emissions among the high VSP bins. Therefore, the

use of emission ratios instead of mass per time emission factors does not offer any advantage in terms of reducing the number of modes needed to model emissions, if the same number of modes are to be applied to all pollutants for simplicity of software design and data management.

The potential role of RSD data was evaluated based upon several comparisons: (1) comparison of emission ratios for the RSD data versus the modeling data; (2) comparison of vehicle activity for the RSD data versus the modeling data; (3) comparison of emission ratios for the RSD data versus IM240 data; and (4) comparison of vehicle activity for the RSD data versus the IM240 data. The RSD data typically lead to higher emission ratios than the modeling data, especially for lower VSP modes (e.g., Modes 1 through 10), especially for the NO_x/CO_2 and HC/CO_2 ratios. Although it may be tempting to conclude that such differences are because the RSD data might have a better representation of higher emitting vehicles, or of higher emissions episodes with normal emitting vehicles, it is important to compare the vehicle activity of both data sets. A comparison of the speed and acceleration distributions for both data sets revealed that the RSD data typically had lower average speeds and higher average accelerations than the modeling data set. As shown in Chapter 9, it can be the case within a VSP mode that some of the variability in emissions can be explained in terms of speed and/or acceleration. Therefore, although not conclusive at this time, it is possible that the differences in emissions between the RSD data and the modeling data may be attributable, at least in part, to differences in activity patterns.

A comparison of the IM240 and RSD data suggests that these two data sets have quantitatively similar emission ratios in some cases and qualitatively similar emission ratio trends among the modes in a number of cases. However, a comparison of the speed and acceleration distributions of the two datasets indicates that there is a substantially different activity pattern for the two data sets, with the IM240 data based upon bimodal speed distributions with a wider range in variability in speed, higher average speed, and lower average acceleration, than the RSD data. Thus, it is possible that the apparent similarities between these two data sets in terms of average emission ratios may be because of compensating differences in fleet mix and activity patterns, or it is possible that the emission ratios are robust to the differences in activity patterns.

The key findings regarding the potential role of RSD data are discussed here. RSD data were not considered to be a strong candidate for use in model development because some key variables, particularly odometer reading, are not observable. Odometer reading has been shown in earlier chapters to be an important predictive variable. The HC/CO_2 emissions data from RSD do not appear to be comparable to that from the modeling dataset, which may be because of significant differences in the measurement technique employed. It is also possible that there are differences in fuel composition that may cause some of the observed differences. Finally, the differences in emission ratios for the RSD data versus the modeling data may be attributable in part to differences in activity patterns not yet captured by the conceptual modeling approach. This latter issue deserves some exploration as part of future work.

It has been hypothesized that RSD data may be useful in helping to better characterize the distribution of different emitting vehicles, and particularly high emitting vehicles. It should be noted that because RSD measurements are a snapshot of typically less than one second, and because a normal emitting vehicle can have episodes of high emissions depending on the activity pattern, it is not conclusive that a single high emissions ratio measurement of a vehicle enables

identification of such a vehicle as a high emitter. Thus, it is possible that a high emission ratio may be associated with a high emitting vehicle or it could be associated with a high emissions episode for a normal emitting vehicle. A comparison of the distribution of emission ratios for the modeling data set versus that of the RSD data set suggests that the modeling data set captures a wider relative range of variability than does the RSD data set, while at the same time the RSD data often had higher average values than did the modeling data set. The upper tails of the distributions of variability for a given mode for the modeling data set often overlapped substantially with the upper tails of the distributions for the RSD data, suggesting that the highest emission ratios in either data set were comparable. Thus, it could be the case that the modeling dataset does not have the same proportional representation of high emitting vehicles, or of high emissions episodes for normal emitting vehicles, as does the RSD data. These differences were typically more pronounced for the low and moderate VSP modes. For the higher VSP modes, the shapes of the distributions from the modeling data set and the RSD data set were very similar for both the CO/CO_2 and NO_x/CO_2 ratios.

The siting of the RSD instrument plays an important role in the range of activity that is observed. It is clear from these data that the RSD sites had a much smaller range of variability in activity patterns than did the dynamometer data or the onboard data that comprised the modeling data base and the IM240 database. Since RSD's are often sited at locations that are expected to have positive accelerations or situations in which vehicles are under load, it is possible that there is a bias in the activity pattern of the RSD data that is perhaps in part responsible for the apparent differences in emissions when compared to the modeling data set. In this particular case, although the range of speeds was typically less for the RSD data than for the other data sets, the accelerations tended to be larger on average. Given these differences, it did not seem fruitful to try to proceed with methods for making adjustments to the modeling data set in order to better match the emission ratios estimated from the RSD data.

It is possible that RSD data could be used indirectly as a recruiting tool to try to obtain a representative sample of vehicles for dynamometer and on-board testing, in order to improve the representation of differently emitting vehicles.

In brief summary, for the purposes of this study, there was no substantial advantage found for using emission ratios instead of mass per time emission factors. In either case, it is necessary to estimate CO_2 emission in mass per time units. Therefore, for consistency, mass per time units are recommended for further analysis. Although there were differences in the emission ratios for the RSD data versus the modeling data, there were also substantial differences in activity patterns for the two data sets. Therefore, the RSD data were not used as part of model development, but the comparisons suggest that there may be opportunities to refine the conceptual modeling approach in the future by considering additional binning criteria based upon speed and/or acceleration for the VSP modes.

6 COMPARISON AND EVALUATION OF DATA WEIGHTING APPROACHES

The objective of this chapter is to compare and evaluate three approaches for weighting data: (1) time-weighted; (2) vehicle weighted; or (3) trip-weighted. Based upon comparison and evaluation of these three approaches, a preferred approach is recommended.

6.1 Methodological Considerations

In the time-weighted approach, data in each bin are averaged with respect to time. For second-by-second data, each second of data will have equal weight. For five second average data, each five second time period of data will have equal weight. For ten second average data, each ten second time period of data will have equal weight. The advantage of this approach is that data can be combined from any number of vehicles within a vehicle category and the sample sizes within each bin can become quite large. Furthermore, the time-weighted approach can be used to support estimation of emissions for any arbitrary averaging time larger than that of the original data. For example, 10 second average emission estimates can be developed by averaging over 10 seconds of one second data. Therefore, it is possible to consider, for example, how cruise emissions that take place during a one minute period of freeway cruising might vary from one time period to another. The inter-vehicle variability and fleet average uncertainty in emission will be a function of the desired time periods. Another advantage of the time-weighted approach is that more weight is given to vehicles that have undergone longer periods of testing. For example, if RSD data were to be included in the development of a model based upon one second averaging, each vehicle measured by the RSD would typically be represented by only one second worth of data. In contrast, a vehicle that has undergone substantial on-road emissions measurement might be represented by tens of thousands of seconds of data. Intuitively, it seems appropriate to give more weight to vehicles that have undergone more testing time.

In the vehicle-weighted approach, data in each bin are averaged with respect to each vehicle. Thus, for each vehicle, a single representative estimate of emissions would be developed. For example, the simplest vehicle-weighted approach would be to calculate an average emission rate for each vehicle based upon data for that vehicle within a given bin. The average emission rate for all data in the bin would then be calculated by averaging the emission rates estimated for each vehicle represented in the bin. This approach will tend to give less weight to vehicles for which there are many seconds (or other averaging time periods) of data, and will give disproportionate weight to vehicles for which there are relatively few time periods of data. For example, if there are 10 seconds of data for vehicle 1, 30 seconds of data for vehicle 2, and 50 seconds of data for vehicle 3, the average emission rate for each vehicle would first be calculated Then, the three vehicle average values would be given equal weight to determine the average over all three vehicles. Thus, the average emission rate for Vehicle 1 would have equal weight to that of Vehicle 2 or Vehicle 3 even though there are three and five times, respectively, as much data for these latter two vehicles. Of course, a minimum data requirement criterion could be specified such that a vehicle average would be calculated only for vehicles for which there are a minimum number of seconds of data. However, there would still be variability in the amount of testing time for different vehicles in the database, and there would remain a potential problem that vehicles with less testing time than others would in effect have an influence comparable to those with more testing time.

The vehicle weight approach offers some potential disadvantages. One is that the weight given to different vehicles may be intuitively unappealing. For example, in the extreme case, one second of RSD data for a vehicle could be equally weighted with many hours of on-board data for another vehicle. Secondly, the use of a vehicle-weighted approach may complicate the quantification of variability and uncertainty. The range of inter-vehicle variability and of fleet average uncertainty is a function of averaging time, with the latter point illustrated quantitatively in Chapter 7. For example, one second emissions of a vehicle varies much more from one second to another than 10 second average emissions vary from one 10 second period to another. With the time-weighted approach, it is possible to combine data to represent any averaging time of interest, conditioned on assumptions regarding the structure of the database (e.g., statistical independence). With the vehicle weighted approach, the averaging time of the analysis is unknown and is itself variable, because the average modal emission rate for one vehicle will typically be based upon a different time period than that for another vehicle. For example, if there are five seconds of data in a given bin for one vehicle, and 10 minutes of data in the same bin for another vehicle, the averages of each of the two vehicles are based upon disparate averaging times.

The trip-weighted approach was included as an alternative to be evaluated in this study. The term "trip" essentially refers to an averaging time selected as the basis for aggregate emissions measurements. For example, data for each vehicle could be divided into segments representing trips. Each set of data from the same vehicle and "trip" within a bin would be averaged to arrive at a "trip-average" emission estimate for that vehicle. A vehicle for which there is a large amount of on-board data might be represented by more than one such "trip". Therefore, this approach will tend to give more weight to vehicles for which there are more data, similar to the time-weighted approach. Unlike the vehicle-weighted approach, there is some attempt in the trip-weighted approach to have more comparability with respect to the averaging time of the data. However, there will still be variation in the number of averaging time periods that are the basis for any trip average emission estimate in any given bin, since the speed profile of any given trip will differ from any other given trip. Therefore, this approach has the same qualitative limitations as the vehicle-weighted approach.

In the vehicle weighted and trip-weighted approach, there is no direct way to control for averaging time. Therefore, the binned data will represent a mixture of unknown averaging times, and any uncertainty estimate developed from these data will be of unknown pedigree with respect to averaging time. Thus, we compared the three approaches with respect to the characterization of uncertainty in average emission rates.

In choosing a preferred weighting method, consideration was given to the following criteria: (1) technical rigor to support a defensible estimate of variability and uncertainty; (2) flexibility to estimate variability and uncertainty for different averaging times; (3) practical aspects of the performance of each method (e.g., tractability, ease of developing estimates); (4) compatibility of the method with data availability and overall modeling objectives.

6.2 Comparison of Weighting Approaches

A component of this work that is also closely related to the issue of analysis of variability and uncertainty is comparison of different approaches for weighting data. Specifically, time, trip,

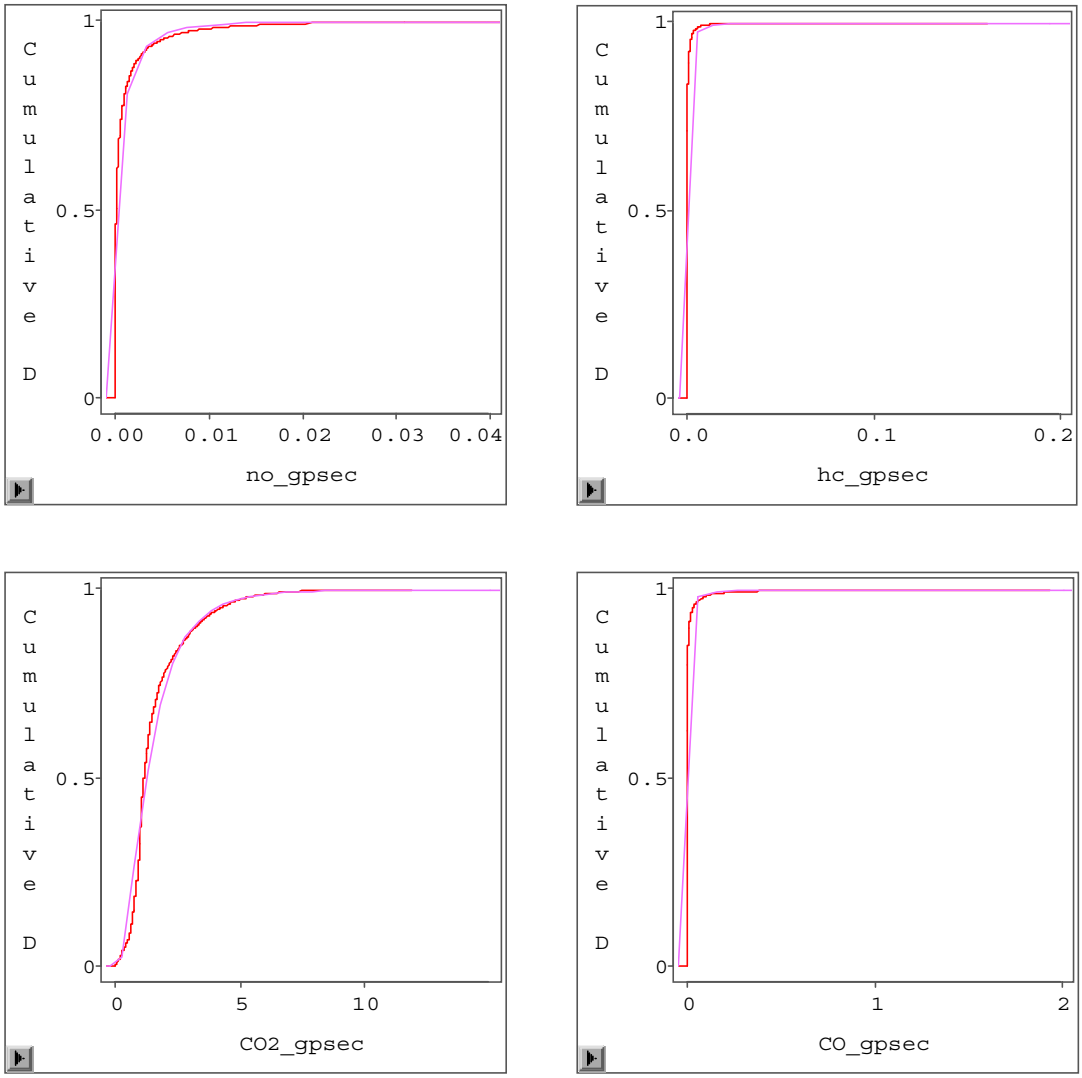
and vehicle-weighted approaches were compared. The analysis results reported in this section are based upon 14 VSP bins without further binning. The quantitative results for comparison of the three approaches with respect to the 56-bin approach are given in the Appendix.

The empirical distributions of variability and fitted parametric distributions are displayed for the examples of VSP Modes 1, 7, and 14 for each of the four pollutants considered and for the time-weighted approach in Figures 6-1, 6-2, and 6-3, respectively. For example, for VSP Mode 1, the Weibull distribution fitted to the NO_x data appears to adequately describe the general characteristics of the data, including the central tendency, the upper tail, and the positive skewness. However, there are some deviances in the fit that are noticeable, such between the 50th and 90th percentiles. Similarly, the lognormal distribution fit to the CO_2 data offers a qualitatively good fit, but deviates from the data in some respects, such as near the 20th percentile and near the 65th percentile. The deviations of the fitted distribution from the data in these two cases are not large in an absolute sense, and are likely to be acceptable. In contrast, the fitted distributions for HC and CO for Mode 1 do not appear to offer good fits. For Mode 7, all the distributions fitted appear to capture the key trends in the data for all four pollutants. For Mode 14, the fits are generally very good for NO_x, HC, and CO_2, but in the case of CO the fitted distribution does not agree with the data, especially above the 70th percentile. Overall, in most cases, the fitted distributions appear to perform well. In the case of CO for Mode 14, the mean and standard deviation of the fitted distribution are substantially different than that of the data.

In addition to the time-weighted approach, the results shown graphically in Figures 6-4 through 6-6 are for the trip-weighted approach for Modes 1, 7, and 14, respectively. Similar results are displayed for the vehicle-weighted approach in Figures 6-7, 6-8, and 6-9 for Modes 1, 7, and 14, respectively. For the trip-weighted approach, the parametric distributions provide a good fit to the data for Modes 1 and 7. For Mode 14, the fits for HC and CO_2 are good. The fits for NO_x and particularly CO are less than ideal, although key qualitative trends are captured by the fits. Generally, the comparison of the parametric distributions with the data is similar for the vehicle-weighted approach: the fits are typically good for Modes 1 and 7; the fits for HC and CO_2 for Mode 14 are good; and the fits for NO_x and CO for Mode 14 are not as good. As discussed in Chaper 7, an alternative to fitting distributions using Maximum Likelihood Estimation (MLE) is to use the Method of Matching Moments (MoMM). In the latter method, the fitted distribution such as a lognormal will have a mean and standard deviation the same as that of the data. This point is further illustrated in Chapter 7.

The selected types of distributions and the parameters of the fitted distributions are summarized for all modes and pollutants in Table 6-1 for the trip-weighted approach. A similar summary is given for the vehicle weighted approach in Table 6-2. Similar information regarding the time weighted approach is given in the chapter on uncertainty analysis.

A direct graphical comparison of the variability associated with the time, trip, and vehicle weighted approaches is given in Figures 6-10 and 6-11 for NO and HC, respectively, for Modes 1, 7, and 14. It is typically the case that the time-based approach has a longer upper tail to the right than the other approaches, which involve averaging of the data. Mode 7 for NO_x offers the clearest example of the effects of averaging the data; in this case, the upper tail of the distribution is substantially smaller than for the time-based approach.



Sec-By-Sec, VSP Bin 1

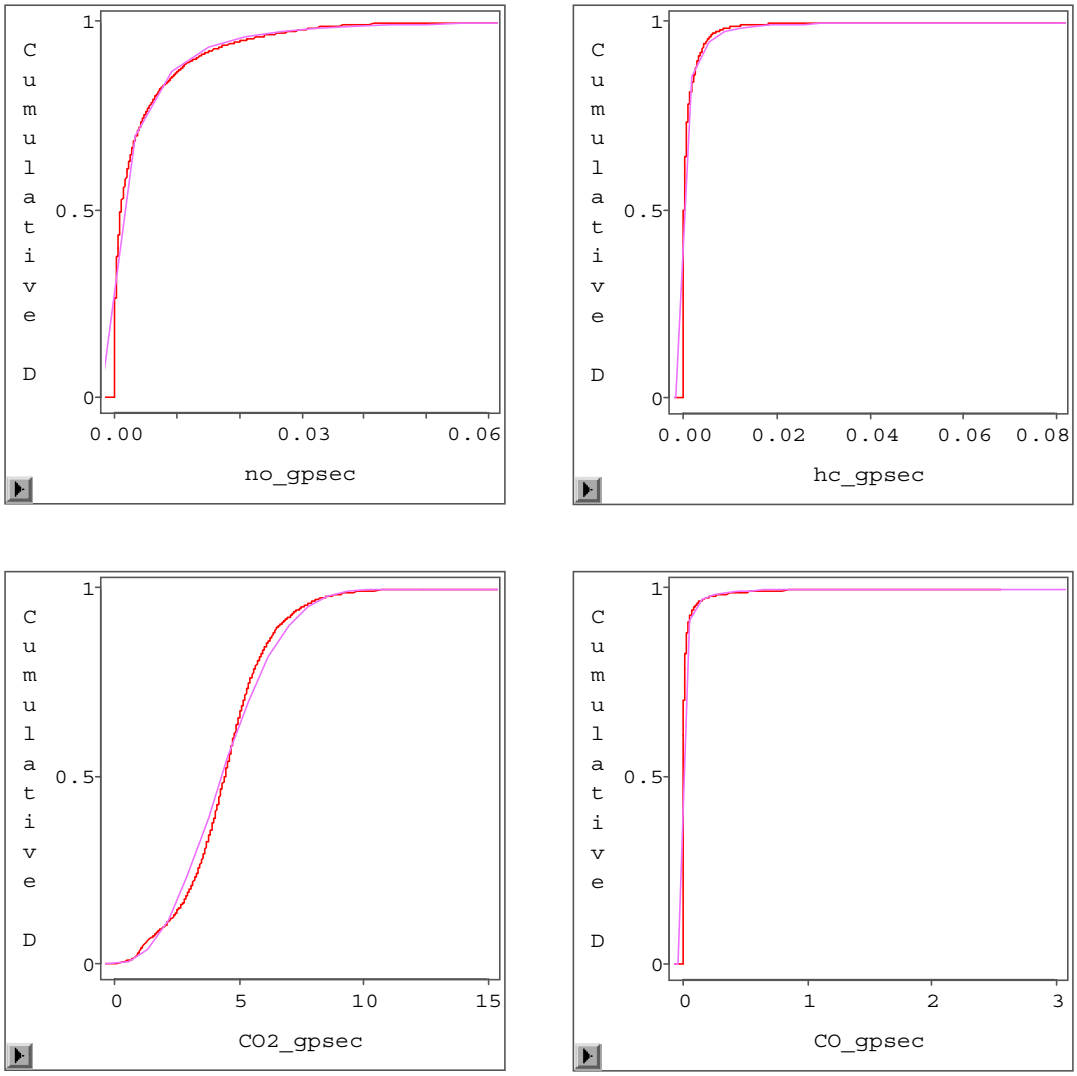
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	L	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-1. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #1 Characterized by Empirical and Fitted Parametric Probability Distribution Models for Second-by-Second Data.



Sec-By-Sec, VSP Bin 7

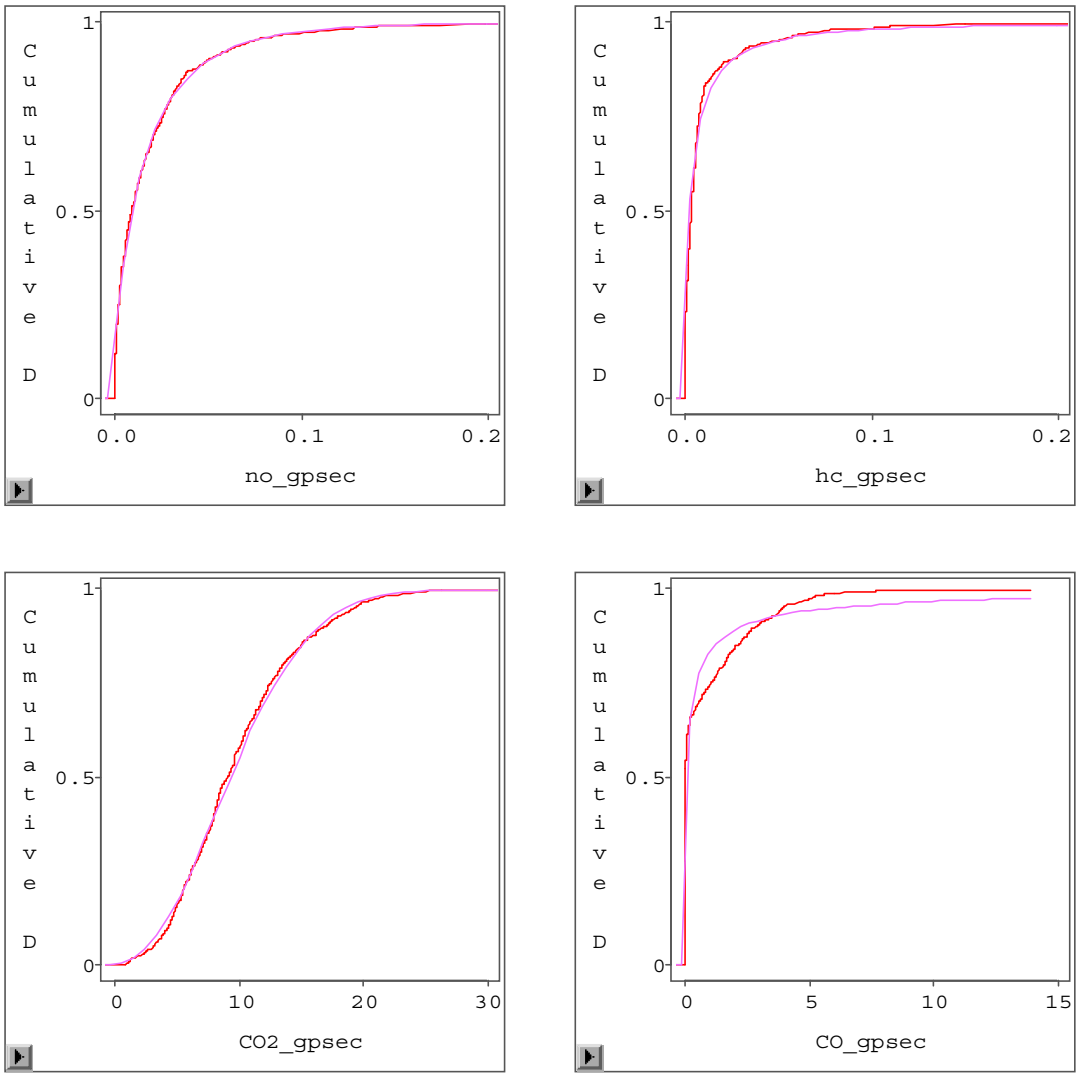
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	W	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-2. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #7 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Second-by-Second Data.



Sec-By-Sec, VSP Bin 14

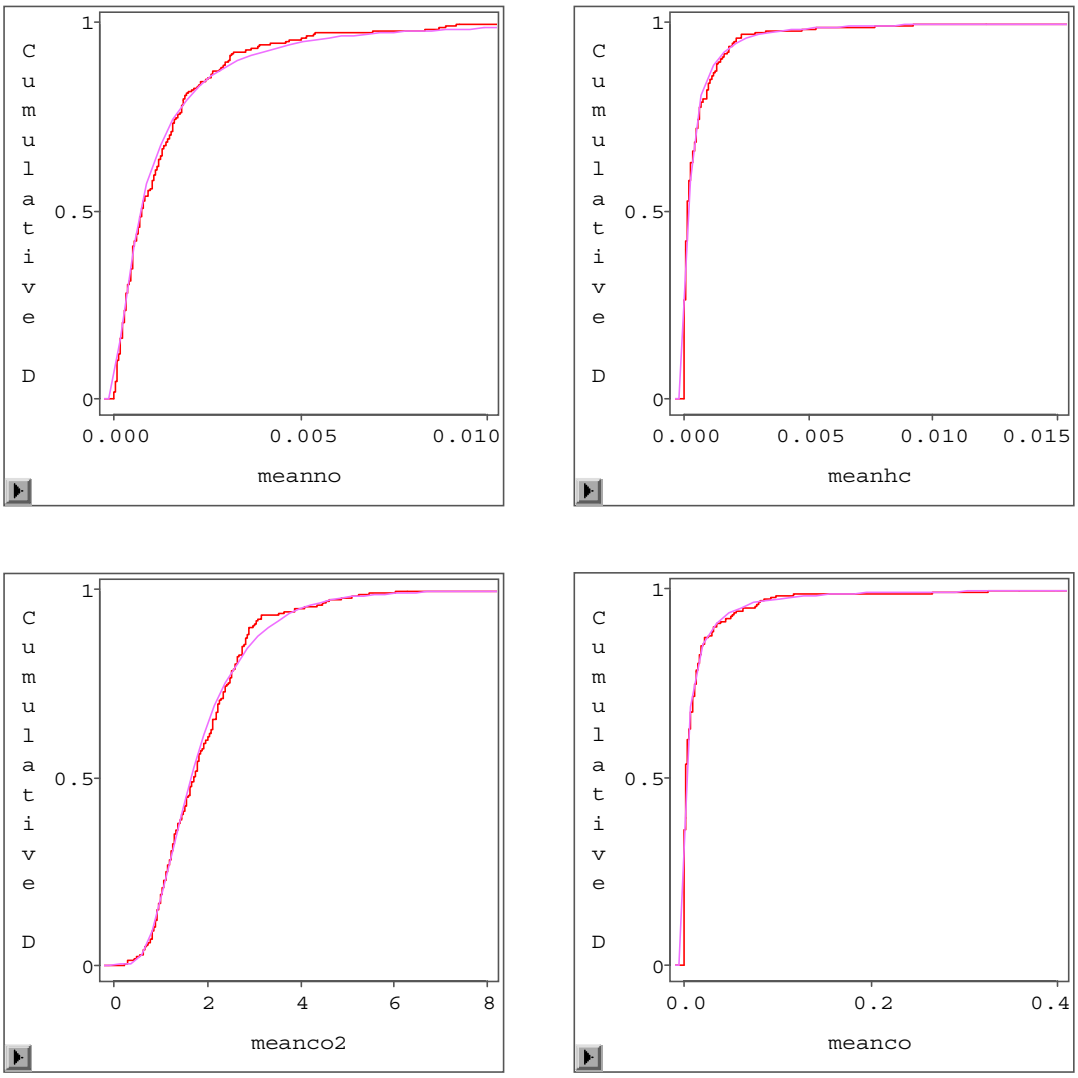
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	W	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-3. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #14 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Second-by-Second Data.



Trip Average, VSP Bin 1

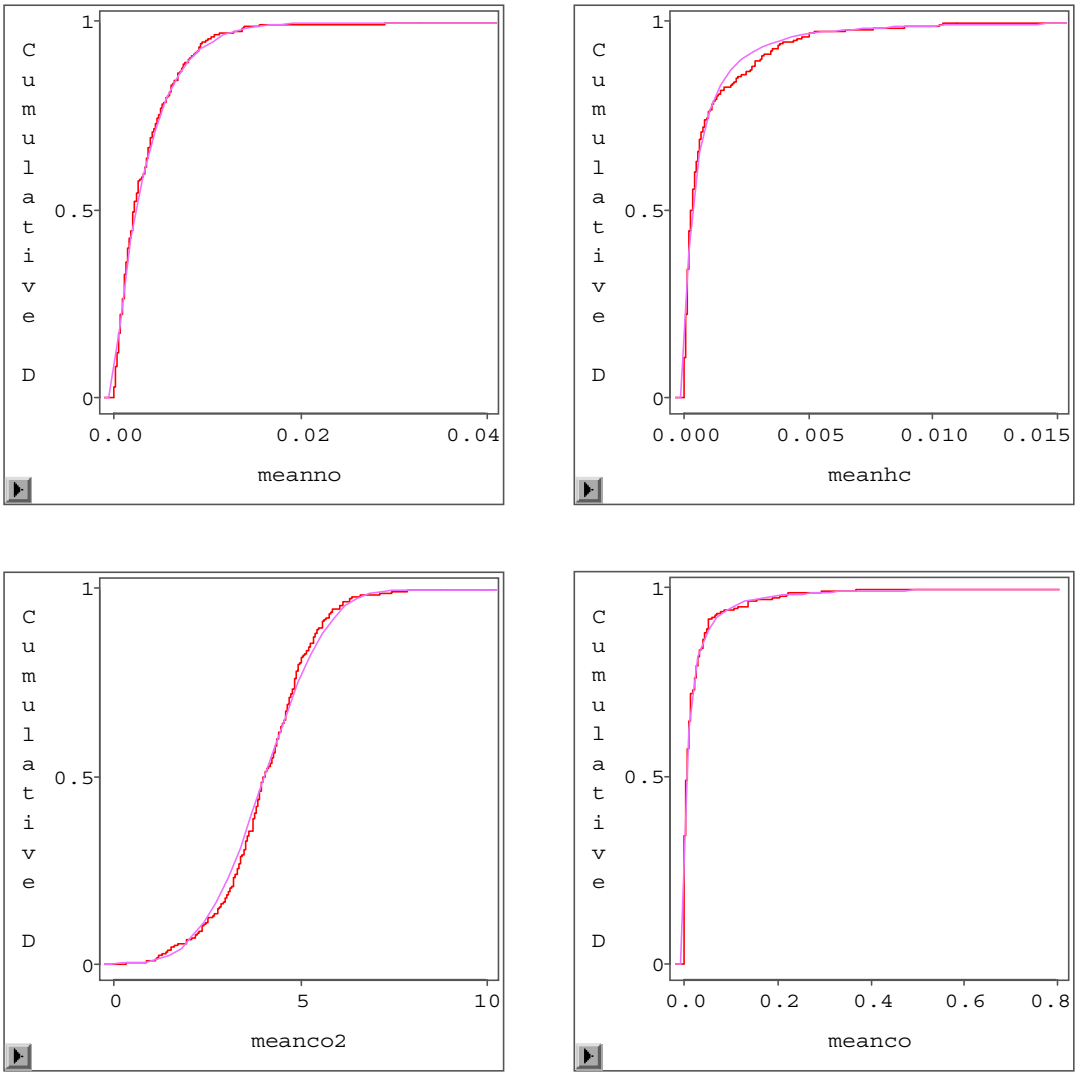
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	L	L	L	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-4. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #1 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Trip Average Means



Trip Average, VSP Bin 7

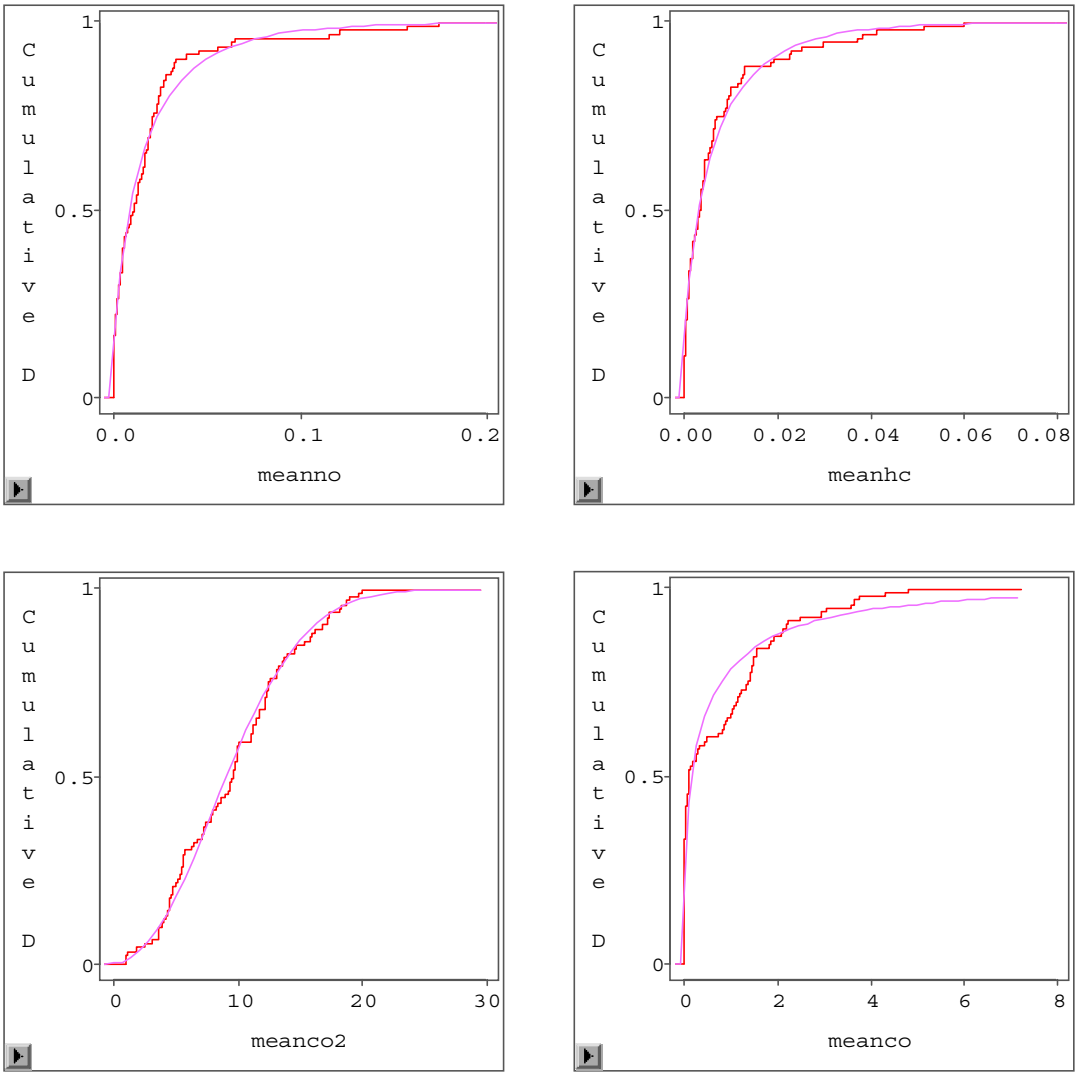
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	W	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-5. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #7 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Trip Average Means.



Trip Average, VSP Bin 14

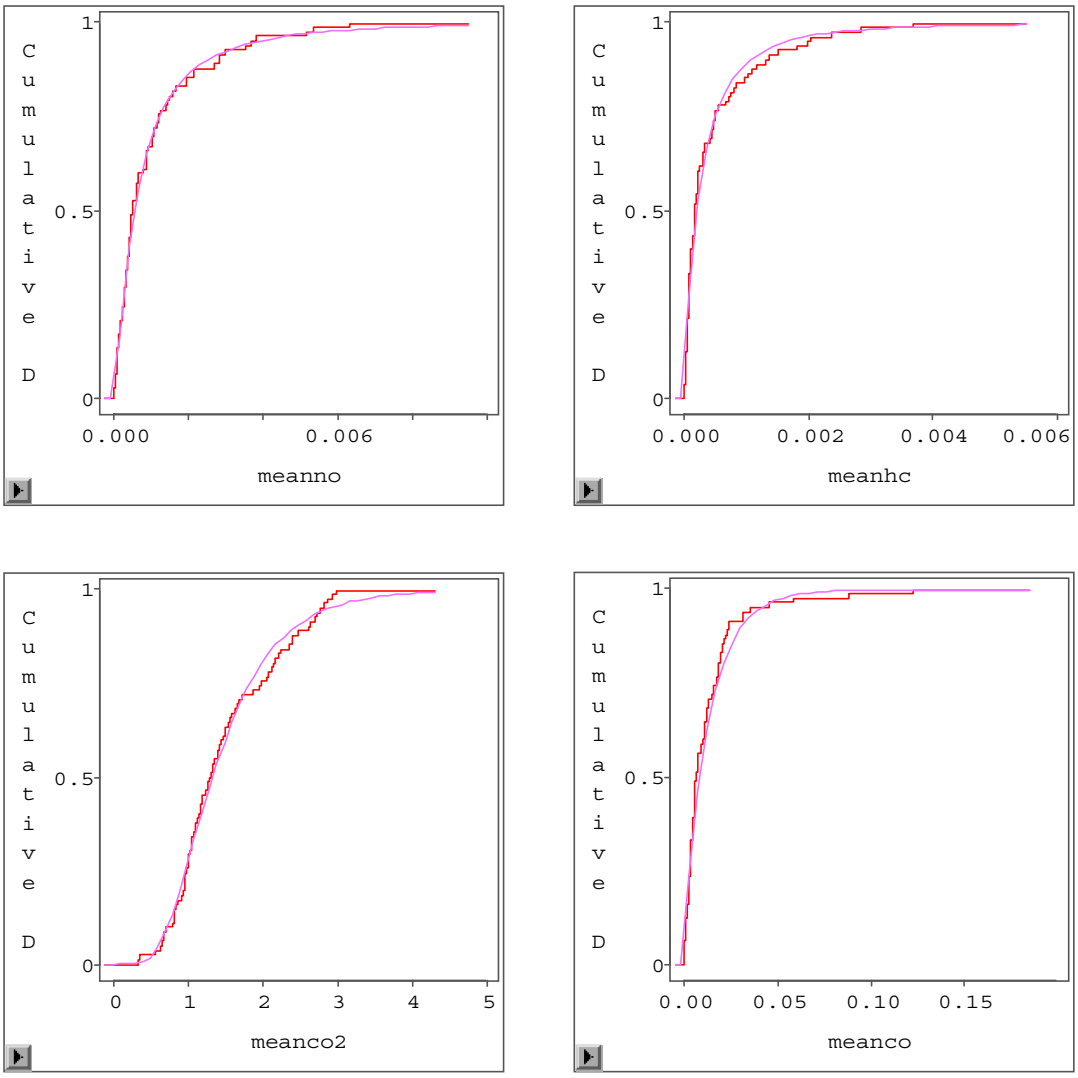
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	W	W	W

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-6. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #14 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Trip Average Means.



Vehicle Average, VSP Bin 1

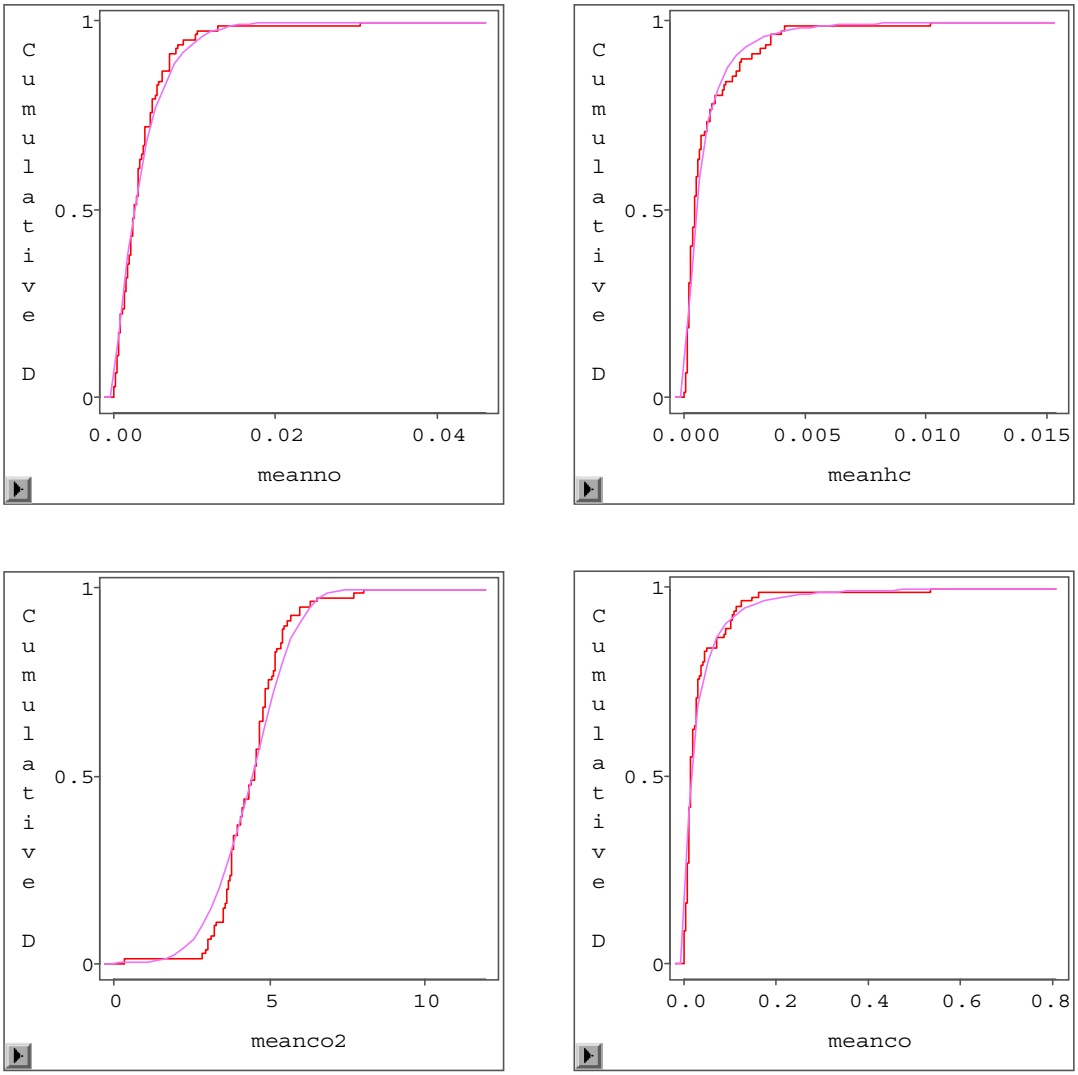
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	L	L	L	W

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-7. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #1 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Vehicle Average Means.



Vehicle Average, VSP Bin 7

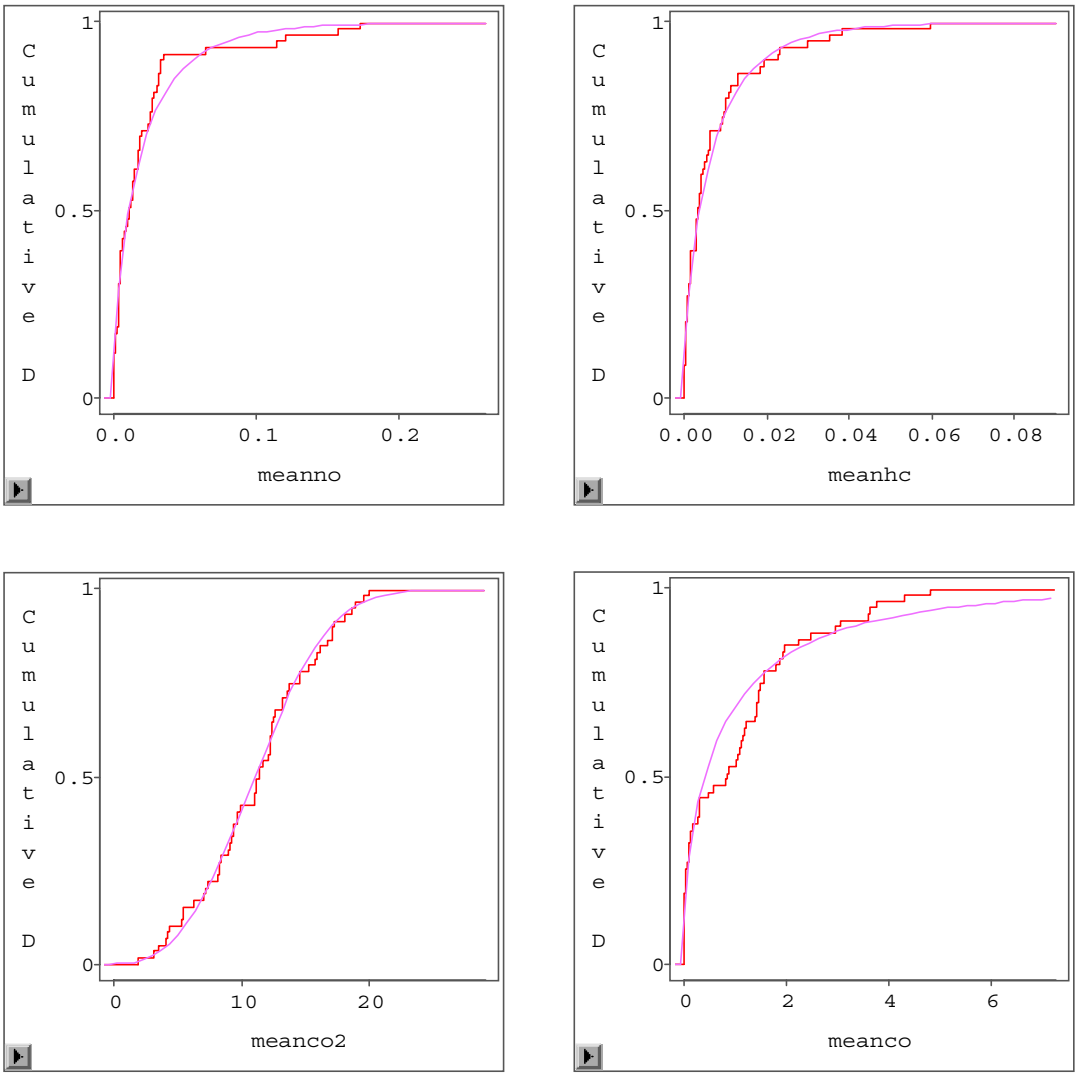
Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	W	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-8. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #7 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Vehicle Average Means.



Vehicle Average, VSP Bin 14

Pollutant	NO	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	W	W	W

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 6-9. Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Mode #14 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution for Vehicle Average Means.

Table 6-1. Summary of Fitted Parametric Probability Distributions for Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Bins for Trip Average Means

VSP Bins	NO			HC			CO_2			CO		
	Fit Para. Dist[a]	para 1	para 2	Fit Para. Dist[a]		Fit Para. Dist[a]	para 1	para 2	Fit Para. Dist[a]		Fit Para. Dist[a]	para 1
1	L	1.1746	-7.1968	L	1.4327	-8.4431	L	0.5305	0.5235	L	1.6843	-5.5881
2	L	1.2133	-7.222	L	1.5103	-8.6318	L	0.5001	0.5467	L	1.6961	-5.8367
3	L	1.1893	-7.5064	L	1.5108	-8.7568	L	0.4868	0.3599	L	1.5637	-6.1689
4	W	0.0021	1.0996	L	1.4482	-8.2217	L	0.3563	0.906	L	1.6522	-5.3273
5	W	0.0025	1.0771	L	1.3764	-8.0443	L	0.3256	1.0988	L	1.5545	-5.1264
6	W	0.0031	1.039	L	1.3421	-7.9055	W	3.9612	3.798	L	1.5702	-5.0068
7	W	0.0036	1.0137	L	1.3774	-7.8134	W	4.5374	3.5135	L	1.595	-4.8661
8	W	0.0046	0.9858	L	1.4163	-7.7013	W	5.1194	3.2378	L	1.6647	-4.7747
9	W	0.0055	0.9031	L	1.4125	-7.5305	W	5.773	2.9653	L	1.8428	-4.6522
10	W	0.0061	0.8227	L	1.5656	-7.4463	W	6.3325	2.5081	W	0.0283	0.5263
11	W	0.0072	0.6991	W	0.0018	0.6731	W	7.5883	2.3674	W	0.0518	0.5148
12	W	0.012	0.8189	W	0.0036	0.733	W	9.0917	2.5755	W	0.1501	0.5218
13	W	0.0129	0.8494	W	0.005	0.742	W	10.2248	2.679	W	0.2868	0.5092
14	W	0.0151	0.6942	W	0.0059	0.7189	W	10.925	2.1308	W	0.4011	0.4567

[a] W = Weibull; para 1 of Weibull is scale parameter and para 2 of Weibull is shape parameter;
L = lognormal; para 1 of lognormal is ϕ and para 2 of lognormal is ξ;
Parameters were calculated using SAS.

Table 6-2. Summary of Fitted Parametric Probability Distributions for Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Bins for Vehicle Average Means

VSP Bins	NO			HC			CO_2			CO		
	Fit Para. Dist[a]	para 1	para 2	Fit Para. Dist[a]		Fit Para. Dist[a]	para 1	para 2	Fit Para. Dist[a]		Fit Para. Dist[a]	para 1
1	L	1.162	-7.4631	L	1.223	-8.3866	L	0.4726	0.2934	W	0.0127	0.9102
2	W	0.001	0.8876	L	1.3677	-8.7468	L	0.4384	0.3477	L	1.4844	-5.6518
3	L	1.1366	-7.6305	L	1.313	-8.8287	L	0.3567	0.2279	L	1.3664	-6.0737
4	W	0.0016	1.1128	L	1.2155	-8.3183	W	2.5339	4.3527	L	1.22	-5.1105
5	W	0.0023	1.116	L	1.0873	-7.9406	W	3.2985	5.0571	L	1.1426	-4.7103
6	W	0.0031	1.117	L	1.0185	-7.6843	W	4.0899	4.7385	L	1.1543	-4.3078
7	W	0.0038	1.0844	L	1.0469	-7.4981	W	4.8834	4.2448	L	1.256	-4.0167
8	W	0.0048	1.0523	L	1.1083	-7.2772	W	5.6715	3.9835	L	1.4549	-3.7997
9	W	0.0059	1.0186	L	1.0985	-7.0789	W	6.4881	3.7832	L	1.5313	-3.5608
10	W	0.007	0.9649	L	1.0641	-6.8674	W	7.2909	3.4183	W	0.0886	0.7557
11	W	0.0098	0.9198	L	1.1483	-6.5547	W	8.7287	3.0995	W	0.1588	0.6969
12	W	0.0131	0.919	L	1.199	-6.1941	W	10.1588	2.8832	W	0.3065	0.68
13	W	0.0143	0.8884	L	1.2823	-5.8853	L	0.3453	2.2655	W	0.5212	0.6373
14	W	0.0185	0.7472	W	0.0065	0.7644	W	12.7194	2.7592	W	0.7882	0.5785

[a] W = Weibull; para 1 of Weibull is scale parameter and para 2 of Weibull is shape parameter;
L = lognormal; para 1 of lognormal is ϕ and para 2 of lognormal is ξ;
Parameters were calculated using SAS.

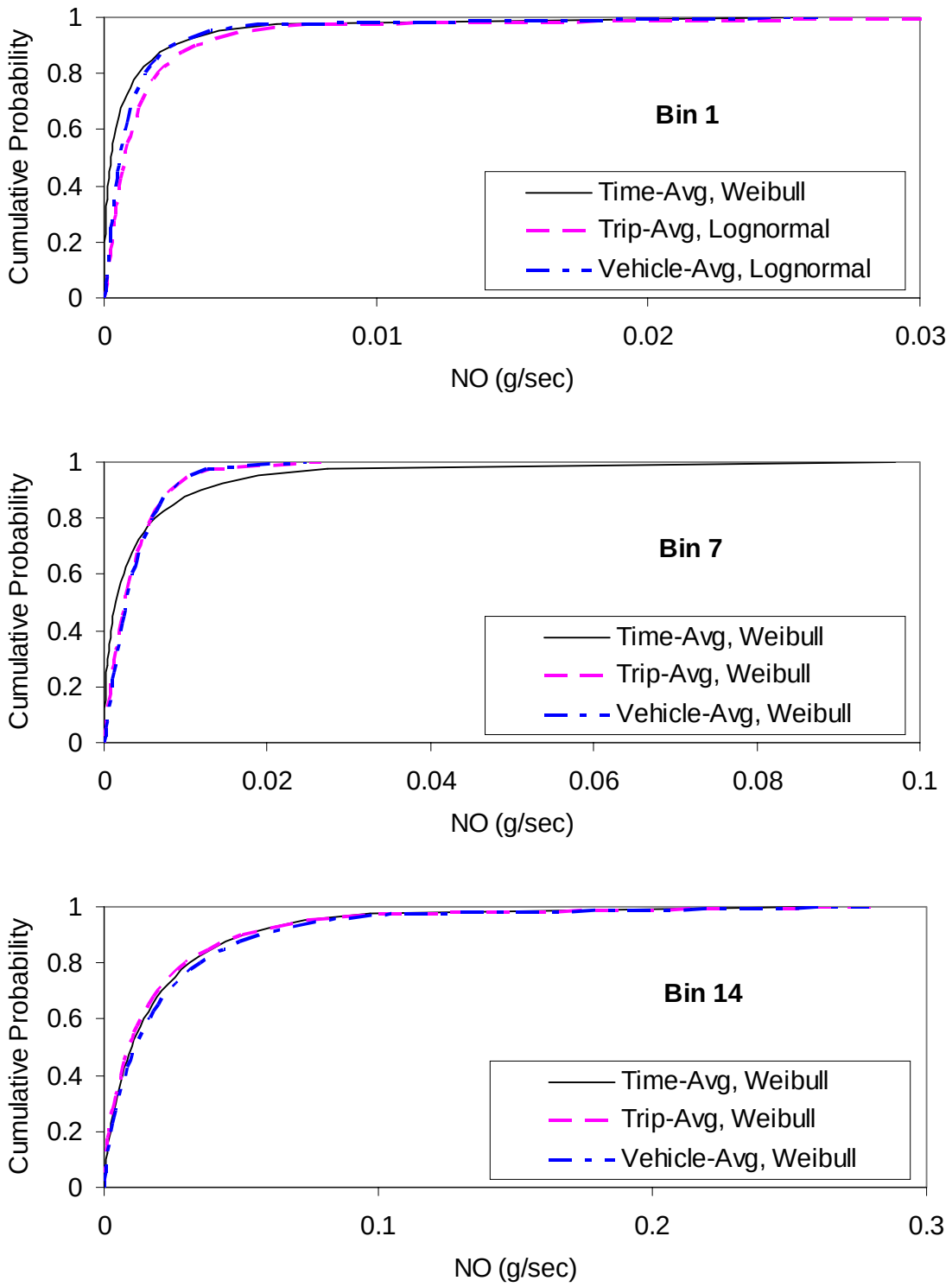


Figure 6-10. Comparison of Variability in NO_x Emissions for Time-Average, Trip-Average, and Vehicle-Average Approaches, Characterized by Parametric Probability Distributions, for VSP Modes #1, #7 and #14.

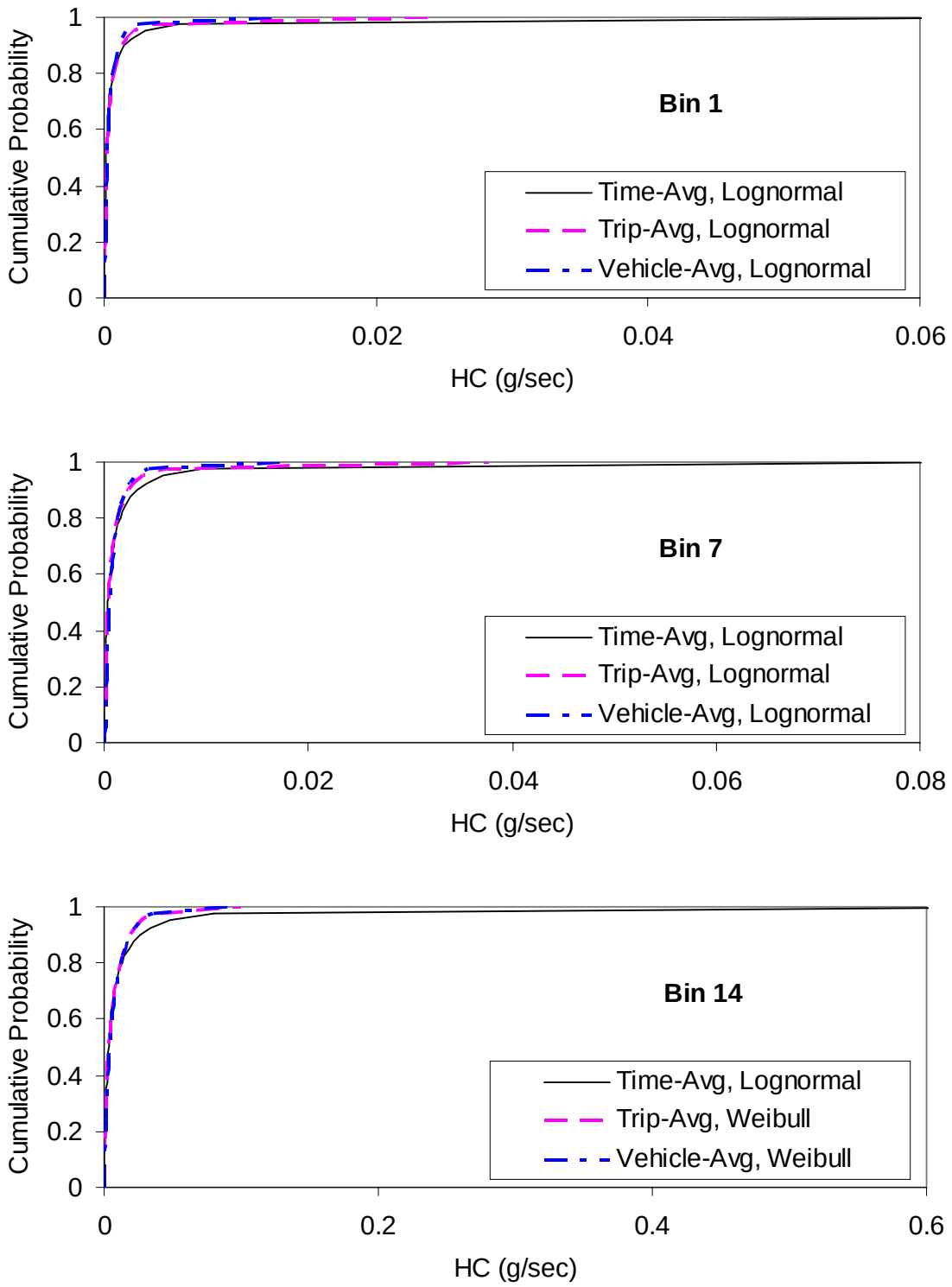


Figure 6-11. Comparison of Variability in HC Emissions for Time-Average, Trip-Average, and Vehicle-Average Approaches, Characterized by Parametric Probability Distributions, for VSP Modes #1, #7 and #14.

Because different types of averaging lead to different weighting of information in the database, the mean and standard deviation will differ depending upon which weighting approach is used. Table 6-3 summarizes how much the estimate of mean emissions changes within a mode for a given pollutant depending upon whether a trip-average or vehicle-average approach is used. The percentage changes shown in the table are with respect to the time-weighted mean values. The average value for the trip weighted approach can be either larger or smaller than that of the time-weighted approach for a given pollutant when comparing different modes. For example, the trip-weighted average for NO_x emissions for Mode 1 is 25 percent greater than for the time weighted approach, but for Mode 8 the trip-weighted average is 20 percent less than that of the time-weighted approach. Both the trip- and vehicle-weighted approaches have substantially different mean estimates in specific cases compared to the time weighted approach. These differences range from essentially no difference to an increase of over 100 percent or a decrease of as much as –42 percent. For NO_x, CO, and HC, the differences in means exceed 10 percent in magnitude for 80 percent of the pollutant/mode combinations. In contrast, for CO_2, a difference in mean values of more than 10 percent in magnitude occurred for only approximately 30 percent of the modes. Thus, while mean CO_2 emission estimates are more robust to the selection of averaging methods, the average emissions of NO_x, CO, and HC are dependent upon what method is selected.

A similar comparison is shown in Table 6-4 for the difference in standard deviations estimated based upon the three alternative weighting schemes. The magnitude of the relative differences is larger for the standard deviation than it is for the mean. However, unlike the differences in mean values, which may be higher or lower than the time-weighted approach, the standard deviations based upon either the trip- or vehicle-weighted approaches are generally substantially smaller than those based upon the time-weighted approach. This result is expected, since averaging will lead to a reduction in variability in the data. The reduction in the standard deviation is on the order of 30 to 60 percent. For most pollutant/mode combinations, the vehicle-weighted approach leads to more reduction in the standard deviation than does the trip weighted approach. This is because the database includes multiple trips for some vehicles.

The relative range of uncertainty in the mean modal emissions is given in Table 6-5 for time-averages, in Table 6-6 for trip-averages and in Table 6-7 for vehicle-averages. The relative ranges of uncertainty in the mean modal emissions for trip-averages and vehicle-averages can be compared with the time-weighted results. Because the sample size becomes smaller as second-by-second data are averaged, even though the variability in emissions decreases to some extent (as indicated by the results in Table 6-4), the uncertainty in the average increases when compared to the time based approach. For example, consider the range of uncertainty in average NO_x emissions for Mode 1. For the time-weighted approach, it is plus or minus 3 percent. For the trip-weighted approach, it is plus or minus 15 percent. For the vehicle weighted approach, it is plus or minus 26 percent.

The average emission rates and the 95 percent confidence intervals for the averages are compared graphically in Figure 6-12 for each of the four pollutants and for each mode.

Table 6-3. Comparison of Mean Emissions of NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Bins: Time-Average, Trip-Average, and Vehicle-Average Approaches.

Bin	NO[a]					HC[a]					CO_2[a]					CO[a]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
1	0.0011	0.0014	25	0.0011	-3	0.0007	0.0006	-9	0.0005	-28	1.6337	1.9294	18	1.4894	-9	0.0110	0.0151	37	0.0134	22
2	0.0009	0.0014	53	0.0010	12	0.0004	0.0006	35	0.0004	-6	1.5254	1.9498	28	1.5461	1	0.0065	0.0141	118	0.0100	54
3	0.0006	0.0011	91	0.0009	53	0.0007	0.0005	-17	0.0004	-42	1.2050	1.6322	35	1.3391	11	0.0051	0.0088	72	0.0062	22
4	0.0016	0.0020	21	0.0015	-7	0.0006	0.0008	21	0.0006	-14	2.3308	2.6267	13	2.3142	-1	0.0114	0.0186	64	0.0130	14
5	0.0025	0.0025	-1	0.0022	-13	0.0008	0.0008	3	0.0007	-16	3.0882	3.1464	2	3.0461	-1	0.0156	0.0217	39	0.0177	13
6	0.0034	0.0031	-10	0.0029	-14	0.0011	0.0009	-14	0.0008	-22	3.7963	3.5920	-5	3.7772	-1	0.0224	0.0219	-2	0.0263	17
7	0.0044	0.0036	-19	0.0036	-18	0.0013	0.0010	-21	0.0010	-24	4.4899	4.0968	-9	4.4868	0	0.0287	0.0258	-10	0.0374	30
8	0.0058	0.0046	-20	0.0047	-18	0.0016	0.0012	-27	0.0013	-20	5.0543	4.6024	-9	5.1861	3	0.0413	0.0333	-20	0.0573	39
9	0.0070	0.0058	-17	0.0059	-16	0.0019	0.0014	-28	0.0015	-20	5.6496	5.1663	-9	5.9128	5	0.0526	0.0418	-21	0.0766	46
10	0.0085	0.0068	-19	0.0071	-16	0.0023	0.0017	-26	0.0018	-20	6.1914	5.6271	-9	6.5947	7	0.0728	0.0553	-24	0.1074	48
11	0.0112	0.0092	-18	0.0102	-9	0.0031	0.0025	-19	0.0026	-17	7.1117	6.7425	-5	7.8458	10	0.1304	0.1047	-20	0.2036	56
12	0.0144	0.0134	-7	0.0137	-5	0.0045	0.0046	1	0.0039	-13	8.0558	8.0667	0	9.0446	12	0.2712	0.2701	0	0.3922	45
13	0.0171	0.0140	-18	0.0152	-11	0.0060	0.0064	6	0.0056	-5	9.2945	9.0835	-2	10.2076	10	0.4878	0.5091	4	0.6891	41
14	0.0198	0.0193	-3	0.0225	13	0.0098	0.0074	-25	0.0077	-21	9.9292	9.6832	-2	11.3174	14	0.8101	0.8049	-1	1.1002	36

[a] Unit of mean: g/sec; Unit of diff.: %.

Table 6-4. Comparison of Standard Deviations of Variability in NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Bins: Time-Average, Trip-Average, and Vehicle-Average Approaches.

Bin	NO[a]					HC[a]					CO_2[a]					CO[a]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	std. dev.	std. dev.	diff.	std. dev.	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
1	0.0029	0.0016	-44	0.0013	-56	0.0030	0.0013	-58	0.0007	-77	1.2557	1.0260	-18	0.6768	-46	0.0642	0.0389	-39	0.0184	-71
2	0.0028	0.0018	-37	0.0012	-57	0.0016	0.0014	-11	0.0007	-59	1.1395	1.0169	-11	0.6415	-44	0.0477	0.0457	-4	0.0196	-59
3	0.0020	0.0020	0	0.0013	-34	0.0024	0.0012	-48	0.0006	-74	0.7727	1.0000	29	0.5182	-33	0.0361	0.0261	-28	0.0121	-67
4	0.0037	0.0019	-48	0.0014	-62	0.0021	0.0016	-25	0.0009	-57	1.3014	0.9097	-30	0.5896	-55	0.0585	0.0409	-30	0.0254	-57
5	0.0051	0.0026	-49	0.0023	-54	0.0025	0.0015	-40	0.0010	-60	1.4529	0.9255	-36	0.6721	-54	0.0982	0.0536	-45	0.0300	-69
6	0.0067	0.0033	-51	0.0032	-53	0.0030	0.0015	-49	0.0012	-60	1.6444	1.0125	-38	0.8341	-49	0.1416	0.0459	-68	0.0453	-68
7	0.0079	0.0040	-49	0.0040	-49	0.0032	0.0017	-45	0.0014	-55	1.8382	1.2678	-31	1.0729	-42	0.1159	0.0567	-51	0.0667	-42
8	0.0092	0.0053	-42	0.0053	-43	0.0041	0.0020	-52	0.0019	-54	2.0072	1.5369	-23	1.3394	-33	0.1732	0.0836	-52	0.1086	-37
9	0.0116	0.0068	-41	0.0064	-45	0.0041	0.0023	-44	0.0020	-51	2.1765	1.8802	-14	1.6092	-26	0.1976	0.1020	-48	0.1446	-27
10	0.0135	0.0086	-36	0.0083	-39	0.0049	0.0029	-40	0.0025	-50	2.4519	2.4060	-2	2.0248	-17	0.2841	0.1282	-55	0.1793	-37
11	0.0174	0.0130	-25	0.0120	-31	0.0065	0.0048	-27	0.0035	-47	2.9053	3.0212	4	2.6930	-7	0.4291	0.2295	-47	0.3122	-27
12	0.0207	0.0168	-19	0.0159	-23	0.0097	0.0093	-5	0.0052	-47	3.2287	3.3547	4	3.4101	6	0.7115	0.4418	-38	0.5094	-28
13	0.0251	0.0169	-32	0.0187	-25	0.0118	0.0133	12	0.0074	-37	3.8763	3.6558	-6	3.4751	-10	0.9704	0.7430	-23	0.8259	-15
14	0.0278	0.0305	10	0.0357	28	0.0192	0.0113	-41	0.0111	-42	4.8908	4.8015	-2	4.5328	-7	1.4374	1.1124	-23	1.2247	-15

[a] Unit of diff.: %.

Table 6-5. Summary of Relative 95% Confidence Intervals for NO_x, HC, CO_2, and CO Mean Emissions for VSP Bins for the Time-Average Approach

VSP Bins	NO[a]			HC[a]			CO_2[a]			CO[a]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1	0.0011	-3	3	0.0007	-5	5	1.6337	-1	1	0.0110	-6	6
2	0.0009	-5	5	0.0004	-5	5	1.5254	-1	1	0.0065	-10	10
3	0.0006	-4	4	0.0007	-4	4	1.2050	-1	1	0.0051	-7	7
4	0.0016	-3	3	0.0006	-4	4	2.3308	-1	1	0.0114	-6	6
5	0.0025	-3	3	0.0008	-4	4	3.0882	-1	1	0.0156	-8	8
6	0.0034	-3	3	0.0011	-4	4	3.7963	-1	1	0.0224	-9	9
7	0.0044	-3	3	0.0013	-4	4	4.4899	-1	1	0.0287	-7	7
8	0.0058	-3	3	0.0016	-5	5	5.0543	-1	1	0.0413	-8	8
9	0.0070	-4	4	0.0019	-5	5	5.6496	-1	1	0.0526	-8	8
10	0.0085	-4	4	0.0023	-5	5	6.1914	-1	1	0.0728	-9	9
11	0.0112	-5	5	0.0031	-6	6	7.1117	-1	1	0.1304	-10	10
12	0.0144	-6	6	0.0045	-9	9	8.0558	-2	2	0.2712	-11	11
13	0.0171	-8	8	0.0060	-11	11	9.2945	-2	2	0.4878	-11	11
14	0.0198	-9	9	0.0098	-13	13	9.9292	-3	3	0.8101	-12	12

[a] Unit of mean: g/sec; Unit of lower and upper bound: %.

Table 6-6. Summary of Relative 95% Confidence Intervals for NO_x, HC, CO_2, and CO Mean Emissions for VSP Bins for the Trip-Average Approach.

VSP Bins	NO[a]			HC[a]			CO_2[a]			CO[a]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1	0.0014	-15	15	0.0006	-25	25	1.9294	-7	7	0.0151	-32	32
2	0.0014	-16	16	0.0006	-30	30	1.9498	-6	6	0.0141	-39	39
3	0.0011	-21	21	0.0005	-28	28	1.6322	-7	7	0.0088	-36	36
4	0.0020	-12	12	0.0008	-25	25	2.6267	-4	4	0.0186	-27	27
5	0.0025	-13	13	0.0008	-22	22	3.1464	-4	4	0.0217	-30	30
6	0.0031	-13	13	0.0009	-20	20	3.5920	-3	3	0.0219	-26	26
7	0.0036	-14	14	0.0010	-20	20	4.0968	-4	4	0.0258	-27	27
8	0.0046	-14	14	0.0012	-21	21	4.6024	-4	4	0.0333	-31	31
9	0.0058	-15	15	0.0014	-21	21	5.1663	-5	5	0.0418	-31	31
10	0.0068	-16	16	0.0017	-22	22	5.6271	-5	5	0.0553	-29	29
11	0.0092	-20	20	0.0025	-26	26	6.7425	-6	6	0.1047	-30	30
12	0.0134	-23	23	0.0046	-36	36	8.0667	-7	7	0.2701	-29	29
13	0.0140	-24	24	0.0064	-41	41	9.0835	-8	8	0.5091	-29	29
14	0.0193	-32	32	0.0074	-31	31	9.6832	-10	10	0.8049	-28	28

[a] Unit of mean: g/sec; Unit of lower and upper bound: %.

Table 6-7. Summary of Relative 95% Confidence Intervals for NO_x, HC, CO_2, and CO Mean Emissions for VSP Bins for the Vehicle-Average Approach

VSP Bins	NO[a]			HC[a]			CO_2[a]			CO[a]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1	0.0011	-26	26	0.0005	-31	31	1.4894	-10	10	0.0134	-30	30
2	0.0010	-26	26	0.0004	-35	35	1.5461	-9	9	0.0100	-42	42
3	0.0009	-31	31	0.0004	-36	36	1.3391	-8	8	0.0062	-42	42
4	0.0015	-20	20	0.0006	-35	35	2.3142	-6	6	0.0130	-42	42
5	0.0022	-23	23	0.0007	-31	31	3.0461	-5	5	0.0177	-37	37
6	0.0029	-23	23	0.0008	-31	31	3.7772	-5	5	0.0263	-37	37
7	0.0036	-24	24	0.0010	-31	31	4.4868	-5	5	0.0374	-39	39
8	0.0047	-24	24	0.0013	-32	32	5.1861	-6	6	0.0573	-41	41
9	0.0059	-24	24	0.0015	-29	29	5.9128	-6	6	0.0766	-41	41
10	0.0071	-25	25	0.0018	-29	29	6.5947	-7	7	0.1074	-36	36
11	0.0102	-26	26	0.0026	-29	29	7.8458	-7	7	0.2036	-33	33
12	0.0137	-27	27	0.0039	-30	30	9.0446	-9	9	0.3922	-30	30
13	0.0152	-30	30	0.0056	-32	32	10.2076	-8	8	0.6891	-29	29
14	0.0225	-40	40	0.0077	-37	37	11.3174	-10	10	1.1002	-28	28

[a] Unit of mean: g/sec; Unit of lower and upper bounds: %.

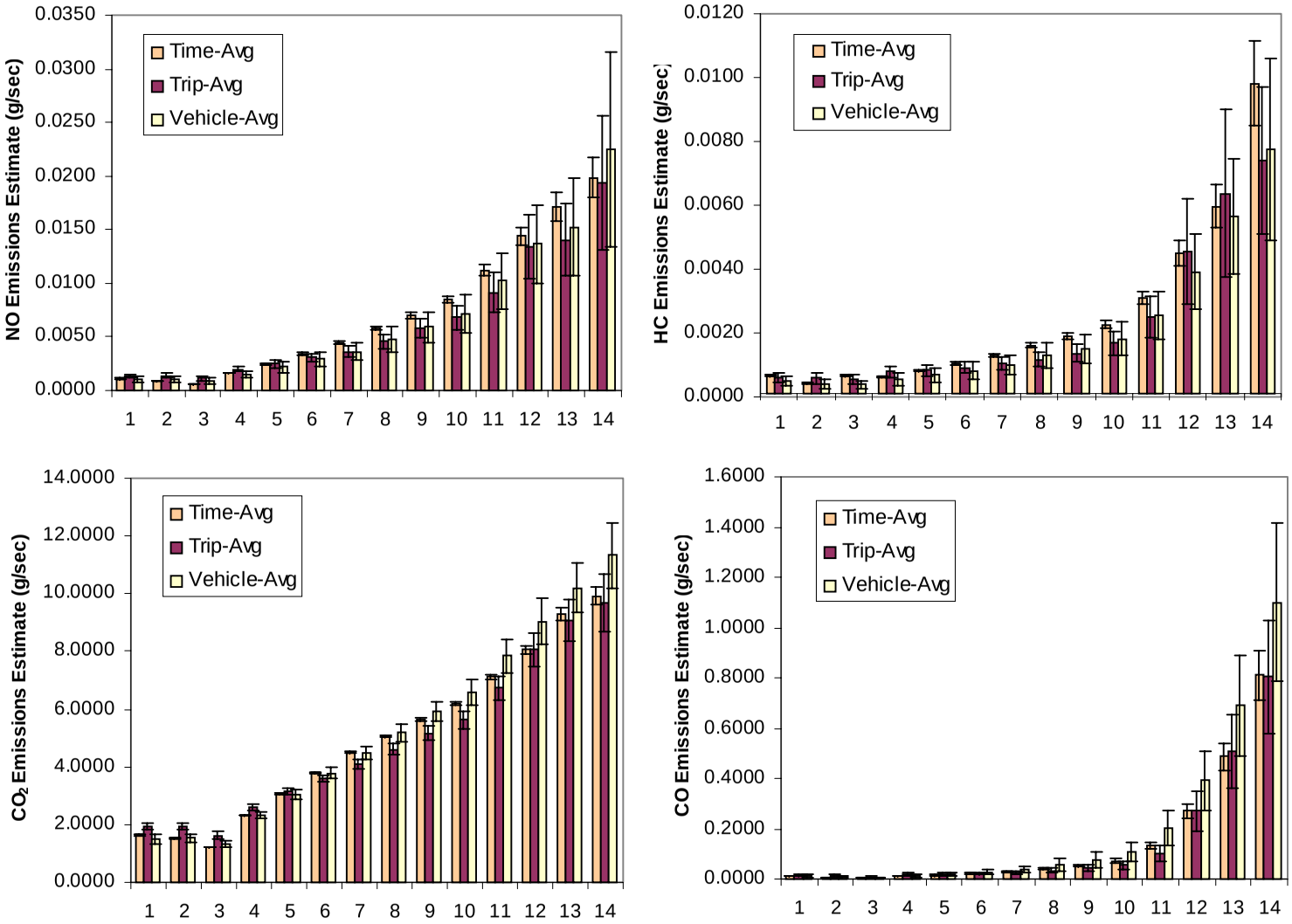


Figure 6-12. Comparison of Quantified Uncertainty in the Mean Emissions of NO_x, HC, CO_2, and CO for VSP Bins: Time-Average, Trip-Average, and Vehicle-Average Approaches.

The results for the “56-bin” approach given in the Appendix for the comparison of the three weighting approaches are qualitatively similar to those shown in this chapter for the 14 VSP bins.

6.3 Summary and Recommendation

The main findings from the comparison of the time, trip, and vehicle weighted approaches are as follows:

- Compared to time-weighted approach, the means for the trip and vehicle weighted approaches can be either higher or lower.
- The standard deviation decreases for the trip weighted approach, and further for the vehicle weighted approach, when compared to the time weighted approach.
- Averaging time varies for both the trip and vehicle weighted approaches; there is no standard averaging time
- The uncertainty in the average typically increases with more averaging over time, because of smaller sample size.
- The trip and vehicle weighted approaches disproportionately give emphasis to trips or vehicles with little data

Based upon these main findings, a judgment was made that the time weighted approach is the preferred basis for development of a conceptual emission estimation model. The time weighted approach offers flexibility in the future to weight the data by vehicle or trip if so desired. The time weighted approach is predicated upon the assumption that data for a given vehicle stratification (e.g., odometer reading and engine displacement) are representative of that strata. It is easier from a software design and from an analysis perspective to work with time weighted data, and such an approach will give more weight to vehicles or trips for which there are more data, which is intuitively appealing.

7 QUANTIFICATION OF VARIABILITY AND UNCERTAINTY

The estimation of uncertainty in the average emission rate for a mode depends upon the variability in data for the mode, the variance within the data, and the sample size. Key issues addressed in the analyses include the adequacy of selected parametric probability distribution models for representing variability in data, and whether the range of uncertainty in the mean values is sufficiently small that a normality approximately can be used to represent uncertainty in the mean. To provide insight into these issues, results are presented of analysis of both variability and uncertainty based upon the VSP modes for one-second average data. This chapter includes a review of methodological considerations, quantification of variability for individual modes, quantification of uncertainty for individual modes, and estimation of uncertainty for driving cycles or trips.

7.1 Methodological Considerations

In uncertainty analysis, there are several sources of uncertainty that must be considered. The first is the scenario being modeled. The second is the model itself. The third are the inputs to the model. In practice, the term "model uncertainty" is typically understood to mean uncertainty regarding the functional form of the model itself. Cullen and Frey (1999) address sources of model uncertainty in detail in Chapter 3. Since MOVES is anticipated to be a data-driven model, the uncertainty associated with model structure will be associated with the definitions of the bins. For example, suppose that average emissions are sensitive to variation in engine displacement, but that a bin-based approach is implemented without using engine displacement as one of the binning criteria. Then the "model" would fail to enable prediction of the sensitivity of average emissions with respect to different engine displacements. In this case, one could argue that there is uncertainty associated with an incomplete formulation of the model structure. Once the model structure is correctly specified, a technique can be applied for propagating uncertainty regarding emissions in each bin to predict uncertainty of the final model results. This latter approach addresses uncertainty in the inputs to the model (i.e. the data within each bin) but does not address uncertainty associated with the model structure. The main objective this task is to focus on a methodology for propagating uncertainty in the model input data (e.g., the data used in each bin, and the activity data used to weight the binned data) in order to predict uncertainty in the estimated emissions. Another consideration is that for the model predictions to be accurate, which means free of bias when comparing the average model predictions to the true average emissions in the real world, the model must be developed based upon a representative data set.

There are several key considerations pertaining to this task, which are briefly summarized in the following list, with more detailed discussion in the following text:

- Variability
- Uncertainty
- Choice of empirical versus parametric probability distribution models
- Averaging Time
- Bottom-Up versus Top-Down Approaches

7.1.1 Variability and Uncertainty

Variability refers to real differences in emissions, such as from one vehicle to another. Uncertainty refers to lack of knowledge regarding the true value of a quantity. Sources of variability include differences in vehicle/engine design, operating conditions, maintenance, fuel composition, and ambient conditions (as examples). Sources of uncertainty include random sampling error, measurement error, lack of representativeness, and lack of information. For emission factor purposes, we are typically interested in average emissions for a particular fleet of vehicles, rather than in trying to predict emissions for an individual vehicle. Therefore, we are typically more interested in characterizing uncertainty in the average emission estimate than in characterizing inter-vehicle variability in the estimate. The distinction between inter-vehicle variability and fleet average uncertainty has been demonstrated quantitatively in many recent studies based upon different sources of data, including dynamometer (bag) data, RSD, and on-board data (e.g., Kini and Frey, 1997; Frey, Bharvirkar, and Zheng, 1999; Frey and Zheng, 2002; Frey, Rouphail, Unal, and Colyar, 2001; Frey, Unal, and Chen, 2002; Frey and Eichenberger, 1997a&b; Frey, Rouphail, Unal, and Dalton, 2000).

7.1.2 Empirical Distributions

EPA has emphasized that it prefers a data-driven approach to development of MOVES. However, there is a trade-off between a purely data driven approach versus one that includes some abstraction and aggregation. Specifically, in the context of quantitative analysis of variability and uncertainty, there is a choice to be made regarding whether to base the analysis upon empirical distributions or upon parametric distributions. In the former, each data point in the database, such as for a single bin, is assigned a probability. Typically, data are assumed to be equally weighted but this need not be the case in all situations. Based upon the data values and the probability assigned to each data value, a step-wise empirical cumulative distribution function can be developed. An example of a step-wise empirical cumulative distribution function is given in Figure 7-1 for a data set with sample size of 10. A dataset such as this might represent inter-vehicle variability in emissions.

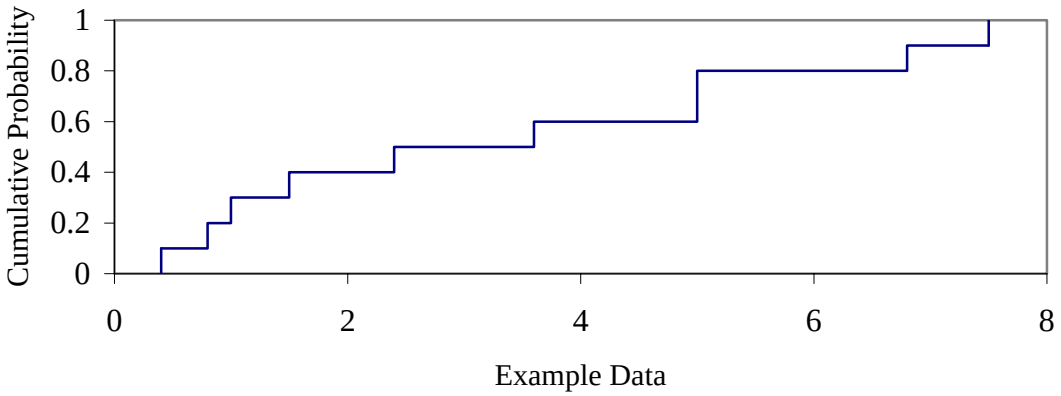


Figure 7-1. Example of a Stepwise Empirical Cumulative Distribution Function

The mean and standard deviation of the empirical distribution are calculated directly from the data. The empirical distribution has the advantage that it is "true" to the data. However, there are several important potential disadvantages: (1) there is no interpolation within the range of observed data (i.e. the distribution has only discrete values corresponding to the original data set, and there is zero probability of sampling any other value); (2) there is no plausible extrapolation beyond the range of observed data; and (3) one must retain all of the data in order to characterize the empirical distribution. Of these three potential disadvantages, the most important are the second and third ones. The second one is important especially for small data sets. With any data set, but especially smaller ones, it is unlikely that the observed highest value corresponds to the true highest value, and that the observed lowest value corresponds to the true lowest value. Thus, there is a possibility of failing to characterize the full range of variability. The third potential disadvantage is that one must retain all of the original data. This is not a problem for a very small data set, but for a very large data set this could be cumbersome.

7.1.3 Parametric Distributions

An alternative to empirical distributions is to use parametric probability distributions to represent variability. The most commonly used parametric distributions, such as lognormal, gamma, or Weibull, typically have only two parameters. The parameters are estimated using statistical estimation approaches such as the method of matching moments or maximum likelihood estimation. The distribution is fully specified once the values of its parameters are estimated. Frey and Zheng (2002) give details of these methods, and such methods are incorporated into the AuvTool software recently developed for EPA/ORD (Zheng and Frey, 2002). Thus, a data set of any size can be represented based upon the type of distribution selected (i.e. lognormal, gamma, Weibull) and the numerical values of its parameters.

Compared to empirical distributions, parametric distributions allow for interpolation within the range of observed data, and for extrapolation to the upper and lower tails of the fitted distribution. The latter is a potential advantage because it is likely that the observed range of variability is less than the true range of variability as previously discussed. Because parametric distributions provide a compact way of storing information regarding variability, the data storage requirements will be less than if the empirical data set must be retained. However, there are some key disadvantages to the use of parametric probability distributions in MOVES. If new data are obtained and must be used to update the distributions for variability, then it will be necessary to combine the new data with the previous data, and repeat the process of fitting a parametric distribution to the data. Alternatively, one could fit a distribution to the new data, and compare the distribution fitted to the new data with the one that was fitted to the previous data. If the two distributions are not significantly different from each other, then there would be no compelling need to update the previous distribution. If they are different, then one could create a new mixture distribution. For example, if the original fitted distribution was based upon 10,000 data values, and if the new distribution was estimated from a new set of 5,000 data values, a mixture distribution could be defined in which 2/3 weight is given to the first (older) distribution and 1/3 weight is given to the second (newer) distribution.

7.1.4 Averaging Time

The issue of averaging time must be explicitly considering regardless of the choice of the empirical or parametric approach to characterizing variability. The issue of averaging time is

also closely related to Subtask 1b and is addressed in Chapter 4 and implicitly in Chapter 6. For example, suppose that the most basic form of data in MOVES is the average over a five second time period. Any distribution developed directly from the 5-second data would represent variability in emissions from one 5-second averaging time to another.

The data within a bin may include multiple data values for each of many vehicles. If the objective is to estimate inter-vehicle variability, then all of the 5-second average data values for a given vehicle should be averaged to arrive at a best estimate of the average emissions for a 5-second period for a given bin for that vehicle. This calculation would be repeated for all vehicles in the bin. Then, the average values for each vehicle would be used to construct a distribution of inter-vehicle variability within that bin. The range of variability will be influenced by the fact that the calculations are based upon a 5-second time period. In contrast, if the objective were to estimate variability in emissions for a 10-second time period, then the range of inter-vehicle variability would tend to be somewhat smaller. Through simple calculations with the data, as long as there are sufficient data and as long as the data can reasonably be assumed to be statistically independent, it is easy to combine data for two or more averaging time periods to construct estimates of average emissions over longer time periods.

Calculation of inter-vehicle variability for different averaging times is conceptually straight-forward when all data are retained within a bin and if empirical distributions are employed. If parametric distributions are employed, then it is necessary to develop an analytical procedure for adjusting the distribution based upon different averaging times. As a conceptual example, Frey and Rhodes (1996) illustrated that the variability in power plant efficiency decreases as the averaging increases from one hour, to one day, to one week, and so on. By analyzing example data sets, it is possible to develop an estimate of how the variance of the data is expected to decrease as the averaging time increases. For example, the variance is a function of averaging time. The mean would not change. Thus, if a distribution were fitted to 5-second averaging time data, a new distribution could be estimated for 10-second averaging time assuming the same mean and using the empirically-derived function of variance versus averaging time. We have developed a conceptual example of an analytical averaging time adjustment method for the parametric approach.

7.1.5 Normal and High Emitters

Regardless of whether empirical or parametric distributions are used, all data within a bin represent the distribution for variability, including both “normal” and “high” emitters whose data fall into the given bin. Thus, there is no need for a discrete approach for normal and high emitters as has been used in the past. However, it is important to have a data set that is representative of both normal and high emitters when developing estimates of average emissions, of variability in emissions, and of uncertainty in average emissions. The average emission rate is calculated based upon all of the data within the bin, and therefore takes into account both normal and high emitters. Similarly, the standard deviation is calculated based upon all of the data within the bin, and therefore takes into account both normal and high emitters.

EPA implies that as part of future work, the effects of I/M programs on the distribution of emission will be evaluated, but this is not included as a task in this work. For example, an I/M program might identify vehicles with emissions above some cut-off, and result in modification or

repair of the vehicle so that its emissions are acceptable. The distribution of emissions can be recalculated using numerical methods by truncating the distribution and by resampling from within the range of acceptable emissions for those vehicles that successfully undergo repair or modification. The numerical method can also be developed to take into account repeated failures of some proportion of the vehicles and other considerations pertaining to IM programs.

7.1.6 Uncertainty Estimates for Final Model Results

A key objective of MOVES is to estimate uncertainty in final model results. To illustrate an approach for estimating uncertainty in final model results, consider a simple conceptual example. Suppose that we wish to know the fleet average tailpipe emissions for LDGVs operating on a particular corridor. As input assumptions, we specify information such as the typical speed profile (e.g., an average estimate of second-by-second speed), road grade at specific locations along the corridor, proportions of vehicles in different vehicle type categories, ambient conditions, and proportion of vehicles in different mileage accumulation categories for each vehicle type. Based upon this type of information, weights are calculated for each bin in the MOVES model. If we focus on a specific vehicle type and mileage accumulation category, we can narrow the discussion to consideration only of factors having to do with the speed profile and the road grade. For each bin, an average emission rate can be estimated. Suppose that the emissions are in units of grams per second. In order to estimate the total emissions associated with a given bin, there must be an estimate of the amount of time that the vehicle spends "in" the bin (figuratively speaking), which can be obtained based upon the known or assumed speed profile and based upon the road grade. For example, if a VSP approach is used, the speed profile and the road grade are used to estimate VSP, and the numerical value of VSP for a given segment of the trip is used to determine from which bin an emission estimate is needed. Thus, in this example, an emission estimate is a time-weighted average of the mass per time emission rates obtained from different bins. The amount of time allocated to each of the bins will differ.

The uncertainty in the average emissions for the trip is based upon the uncertainty in the average emission rates within each bin. Potentially, there could also be uncertainty regarding the amount of time (or weight) assigned to each bin.

The uncertainty in the average emission rate is typically influenced by the following key considerations: (1) random sampling error; (2) measurement error; and (3) lack of representativeness. The first of these three can be characterized based upon the variance in the data for variability and upon the sample size. For example, if normality conditions for the sampling distribution of the mean are satisfied, the standard error of the mean is given the by standard deviation for variability divided by the square root of the sample size. If normality conditions are not satisfied, then a more accurate result can be obtained using bootstrap simulation. For example, Frey and Rhodes (1996, 1998, 1999), Frey and Burmaster (1999), Frey, Bharvirkar, and Zheng (1999), Frey and Bammi (2002a&b), Frey and Eichenberger (1997b), and Frey and Zheng (2002a&b) have demonstrated the use of bootstrap simulation to characterize uncertainty in mean emission rates in situations when data are positively skewed and, in many cases, for small sample size. The range of uncertainty in the average emissions is typically asymmetric when there is a large amount of variability in the data and a small sample size. The use of a normality assumption in such situations can lead to uncertainty estimates for the mean that predict negative emission rates, which is physically impossible. Therefore, it is

important to employ an appropriate approach for quantifying uncertainty associated with random sampling error. We recommend the use of bootstrap techniques where appropriate, and we will also explore simplified solutions obtained based upon the results of bootstrap simulation. For example, we hypothesize that it is possible to develop generic solution algorithms for estimating asymmetric uncertainty ranges in the mean when the underlying data for variability can be fitted reasonably well by a standard parametric distribution and when the coefficient of variation (standard deviation divided by the mean) and the sample size of the original data are known. Such algorithms could be used to make a rapid estimate of uncertainty in average emissions without need to run a full bootstrap simulation in every case.

Random sampling error is typically the dominant source of uncertainty in the mean when the sample sizes are small. Random sampling error in the mean is relatively easy to quantify in practice because it can be inferred from the standard deviation and the sample size of the data, which are usually known.

Measurement error is a potentially important source of uncertainty and should be considered in developing MOVES. One drawback of estimating uncertainty based only upon random sampling error is that for very large sample sizes, the random sampling error in the mean becomes very small. If the measurement error has a random component, then the range of observed variability in the data is larger than the true range of variability in the actual emissions. Therefore, random measurement errors in the data are reflected in the range of uncertainty in the mean emission rates estimated using techniques for random sampling error. However, if measurement error has a systematic component (bias), statistical analysis alone will not detect this without comparison to some benchmark. Measurement error may not be well known, however. Therefore, this source of uncertainty can be difficult to quantify in practice. Since the random component of measurement error influences the estimate of uncertainty in the mean obtained from random sampling error-based estimated, the primary consideration in incorporating measurement error more fully into the analysis is to properly distinguish random measurement error from observed variability (e.g., Zheng, 2002) and to account for biases in measurements.

Uncertainty because of lack of representativeness cannot be quantified based upon statistical analysis of variation within a dataset obtained by only one method. In order to quantify nonrepresentativeness, which relates to bias (also referred to as systematic error or lack of accuracy), it is necessary to have a benchmark of the true value of the quantity. By using on-board data, a key goal of MOVES is to develop emission estimates based upon real-world on-road data. Thus, the fundamental basis of MOVES is to use representative, real world data. The validation aspects of this project also aim at testing the representativeness of the data used for model development. Overall, the focus of this project was on methods for quantifying uncertainty associated with random sampling error, which also is influenced by random measurement errors.

Monte Carlo simulation or similar numerical methods (e.g., Latin Hypercube Sampling) can be used to propagate distributions for uncertainty in average emissions for a bin to arrive at an estimate of uncertainty in the total emissions (e.g., Frey and Rhodes, 1996; Frey and Zheng,

2001; Zheng and Frey, 2002). In cases with linear models in which normality assumptions are reasonable, analytical solutions can also be used (Cullen and Frey, 1999).

7.1.7 Bottom-Up and Top-Down Approaches

In the shoot-out, NCSU illustrated both a bottom-up and top-down approach for estimating inter-vehicle variability and fleet average uncertainty in emissions. The bottom-up approach was based upon estimating variability or uncertainty for individual modes and using statistical formulas to estimate the variability or uncertainty in the total emissions. The top-down approach was based upon comparing trip emissions predictions of the model with the actual observed trip emissions. Based upon statistical analysis of the parity plots of predictions versus observations, a 95 percent probability prediction interval was estimated for inter-vehicle variability and a 95 percent confidence interval was estimated for uncertainty in the mean.

In principle, the bottom-up approach will be the more flexible and rigorous approach, and it will also have an advantage of allowing for identification of which bins contributed the most to uncertainty in the total emissions estimates. The top-down approach will typically be an easier but less flexible approach, and it will not provide any insight regarding key sources of uncertainty.

The primary approach explored in this chapter is the bottom-up approach. This approach is more consistent with the EPA objective of characterizing variability in emissions within bins. However, the top-down approach is illustrated in the validation comparisons of average driving cycle emissions, as discussed in Chapter 9.

7.1.8 Summary of Methodological Considerations

The focus here is to demonstrate a methodology for characterizing inter-vehicle variability in the binned data and uncertainty in the estimate of the final model result. The methodology was demonstrated for the pilot modal emission rates. The emphasis of the work was on a parametric distribution-based approach. The parametric approach was selected because of the attractiveness of compactly representing large data sets within a bin using only a distribution type and a few parameters. The adequacy of a purely parametric approach is assessed. A method for properly characterizing the effect of averaging time on variability (and, in turn, on uncertainty) is demonstrated.

7.2 Quantification of Variability

Parametric probability distribution models that were considered for fit to data include normal, lognormal and Weibull distributions. These distributions were selected because they often offer good fits to dataset. In particular, the lognormal distribution is often a good candidate for fitting to non-negative positively skewed data, and can be theoretically justified as a descriptor of emissions data because both emissions and the lognormal distribution are based upon multiplicative processes. The Weibull distribution can also be used to fit to nonnegative positively skewed data. However, the Weibull distribution has additional flexibility to take on different shapes and often has a shorter upper tail than the lognormal distribution does, when viewed as a cumulative distribution function. The less “tail-heavy” nature of the Weibull distribution often provides an empirically better fit than does the lognormal distribution. The

normal distribution often provides a good fit but is appropriate for use with non-negative data only if the ratio of the standard deviation to the mean is sufficiently small (e.g., around 0.2 or less). Otherwise, the normal distribution may lead to predictions of negative values with unacceptable frequency. In general, it is usually not appropriate to use the normal distribution to represent variability within a bin, but it is often appropriate to use the normal distribution to describe uncertainty in the average.

The probability density function (PDF) of the normal distribution is:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \qquad -\infty < x < \infty \qquad (7\text{-}1)$$

The PDF of lognormal distribution:

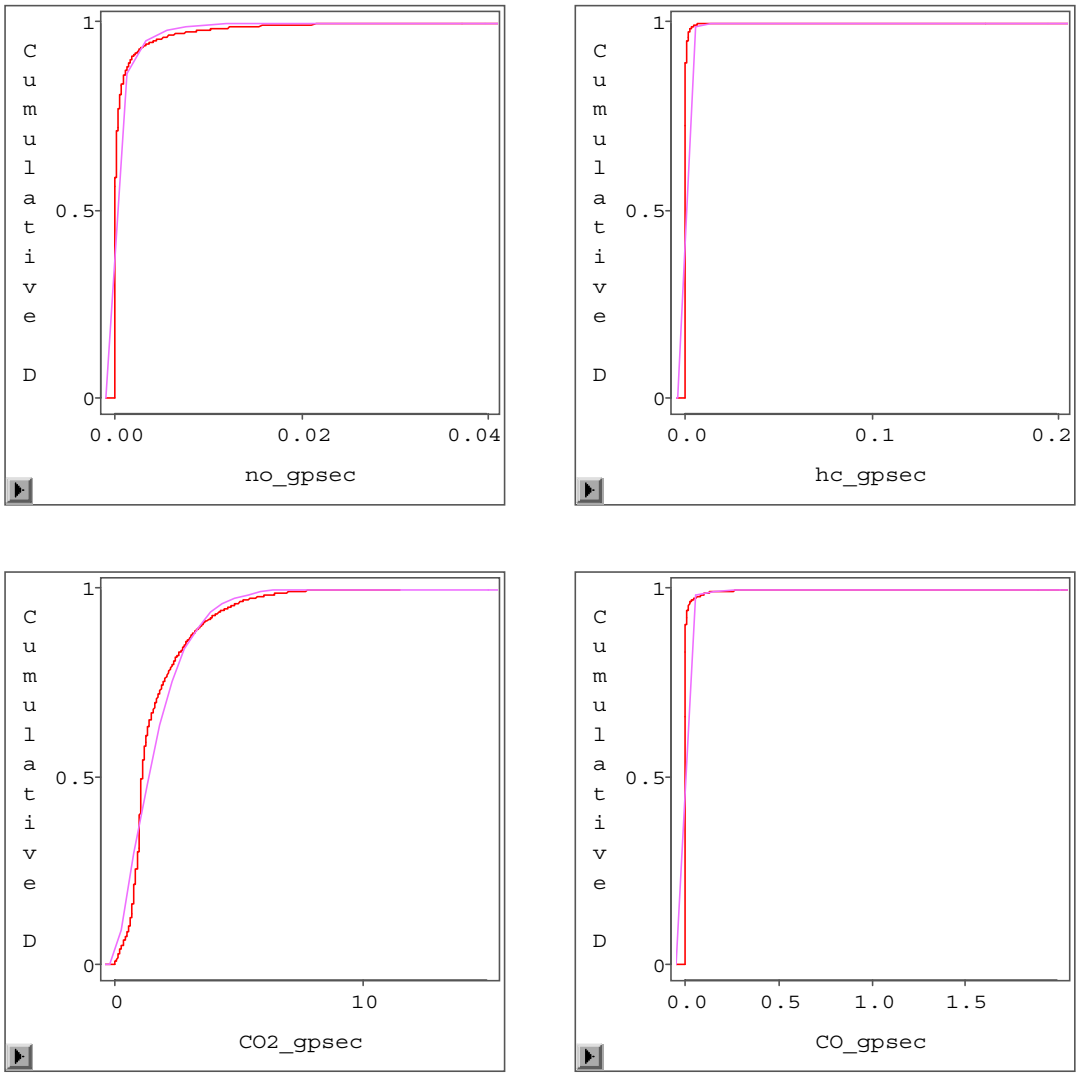
$$f(x) = \frac{1}{\sqrt{2\pi}\phi} \frac{1}{x} e^{\frac{-(\ln x-\xi)^2}{2\phi^2}} \qquad 0 < x < \infty \qquad (7\text{-}2)$$

The PDF of the Weibull distribution, shape parameter *k* and scale parameter *c*:

$$f(x) = \frac{k}{c^k} x^{k-1} e^{-(\frac{x}{c})^k} \qquad 0 \le x < \infty \qquad (7\text{-}3)$$

Fitting of parametric distributions to data was conducted using "SAS" software. Criteria for selecting a best fit are inherently subjective, but can be aided by the use of statistical goodness-of-fit tests (e.g., Cullen and Frey, 1999). Each such test emphasizes a particular criterion for a good fit, which may or may not be relevant to the needs of a particular analyst or assessment. Furthermore, with very large sample sizes, which are often the case for data sets based upon second-by-second data, the goodness-of-fit (GOF) tests are very sensitive and may reject a distribution that in other respects would be acceptable. For example, a visual comparison of the distribution and the data may indicate that the distribution provides a "good" fit even though the fit was rejected by the GOF test.

As examples, results of fitting parametric distributions to VSP mode data are shown for NO_x, HC, CO_2, and CO in Figures 7-1, 7-2, 7-3 and 7-4 for VSP Modes 1, 4, 8 and 12, respectively. The purpose here is to present representative results. Graphical analysis was done, however, for all bins, even though not all graphs are shown here. The graphs were generated using SAS. For VSP Mode 1, the Weibull distribution fitted to the NO_x data appears to adequately describe the general characteristics of the data, including the central tendency, the upper tail, and the positive skewness. However, there are some deviances in the fit that are noticeable, such between the 50th and 80th percentiles. Similarly, the lognormal distribution fit to the CO_2 data offers a qualitatively good fit, but deviates from the data in some respects. The deviations of the fitted distribution from the data in these two cases are not large in an absolute sense, and are likely to be acceptable. In contrast, the fitted distributions for HC and CO for Mode 1 do not appear to offer good fits. For Mode 4, all the distributions fitted appear to capture the key trends in the data for all four pollutants. For Mode 8, the fits are generally good for all four pollutants, especially for NO. For Mode 12, the fitted distributions appear to agree with the data.



Sec-By-Sec, VSP Bin 1

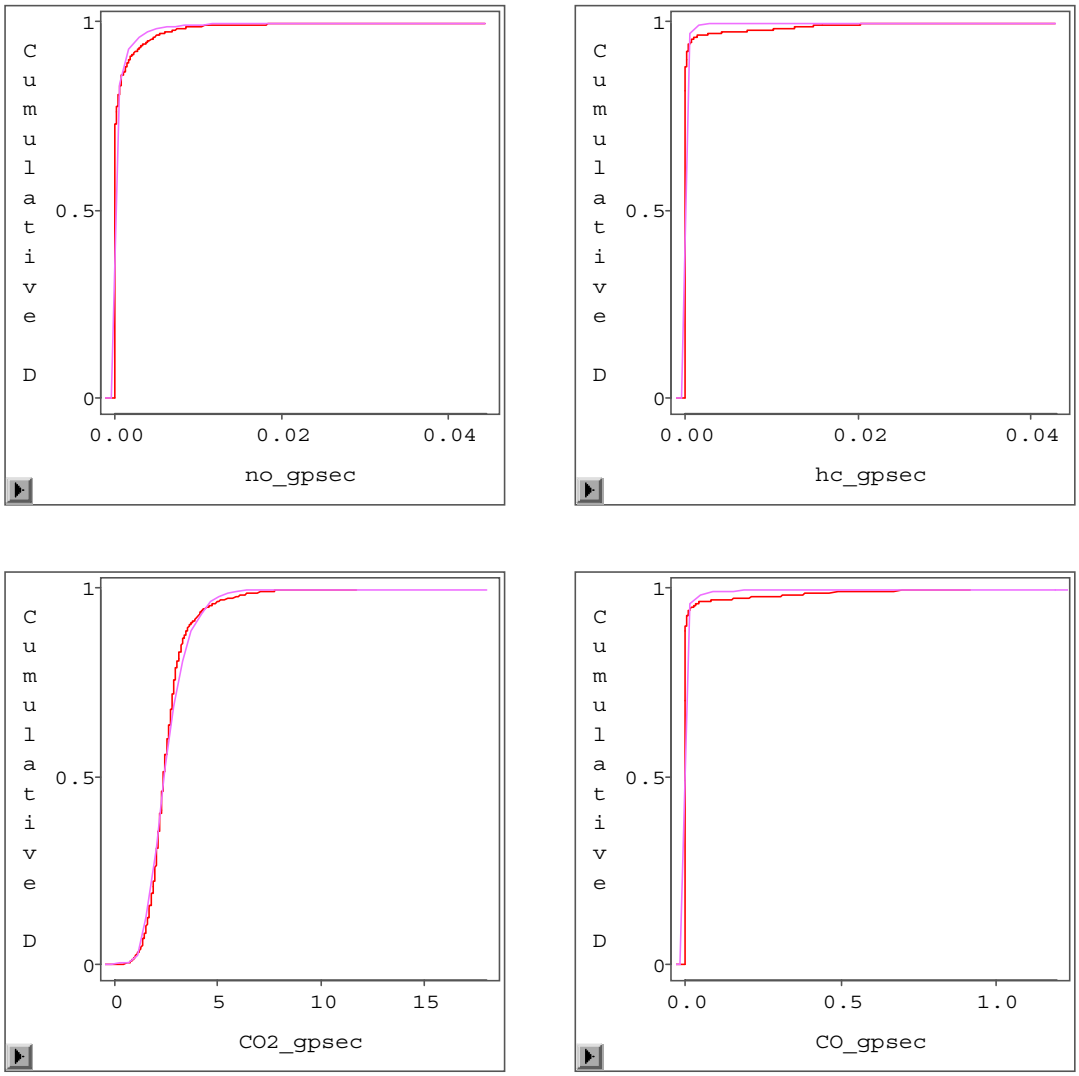
Pollutant	NO_x	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	W	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 7-1. Variability in NO_x, HC, CO_2, and CO Emissions for VSP Mode #1 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution, Time Average, Odometer reading < 50,000 miles, Engine Displacement < 3.5 liters.



Sec-By-Sec, VSP Bin 4

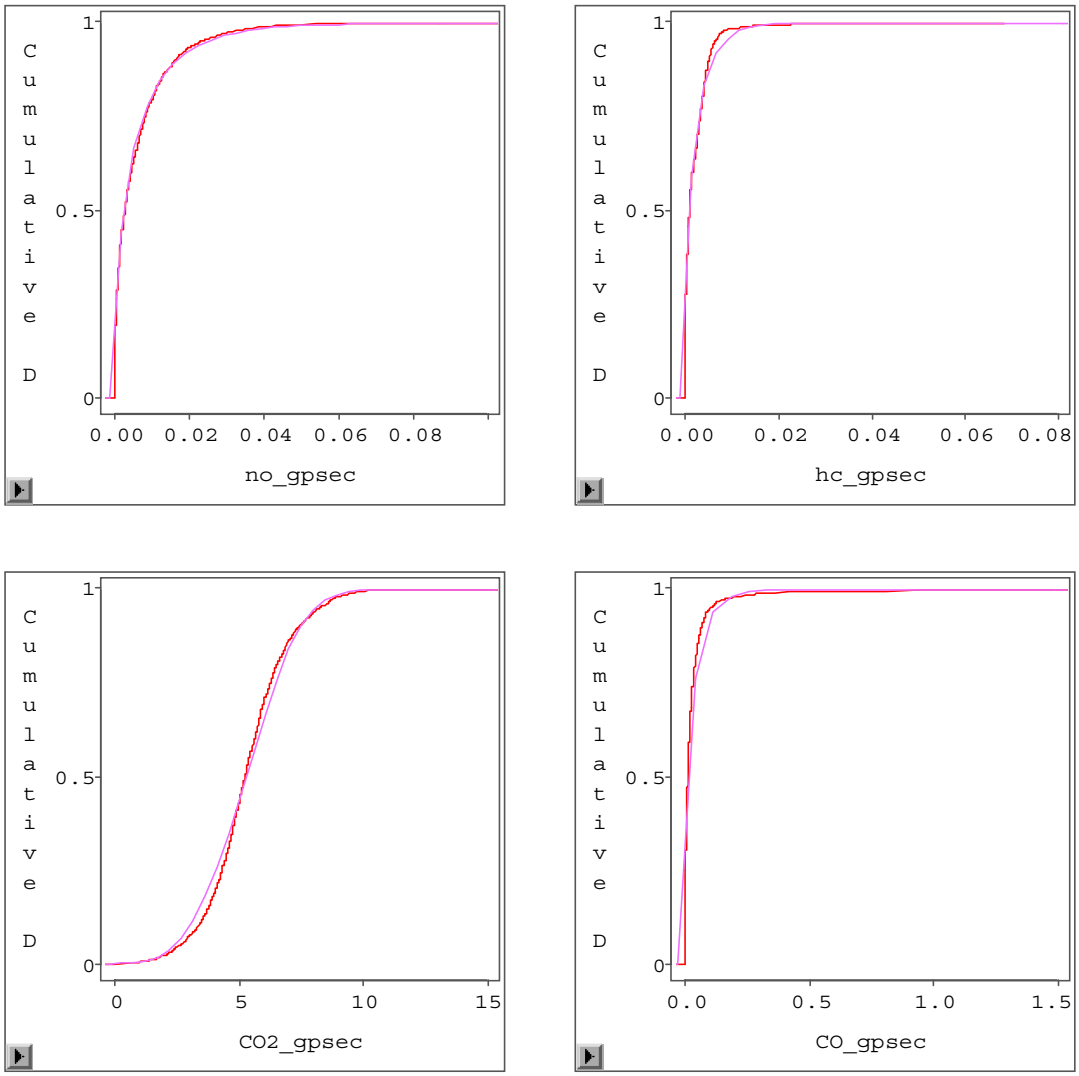
Pollutant	NO_x	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	L	L	L

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 7-2. Variability in NO_x, HC, CO_2, and CO Emissions for VSP Mode #4 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution, Time Average, Odometer reading < 50,000 miles, Engine Displacement > 3.5 liters.



Sec-By-Sec, VSP Bin 8

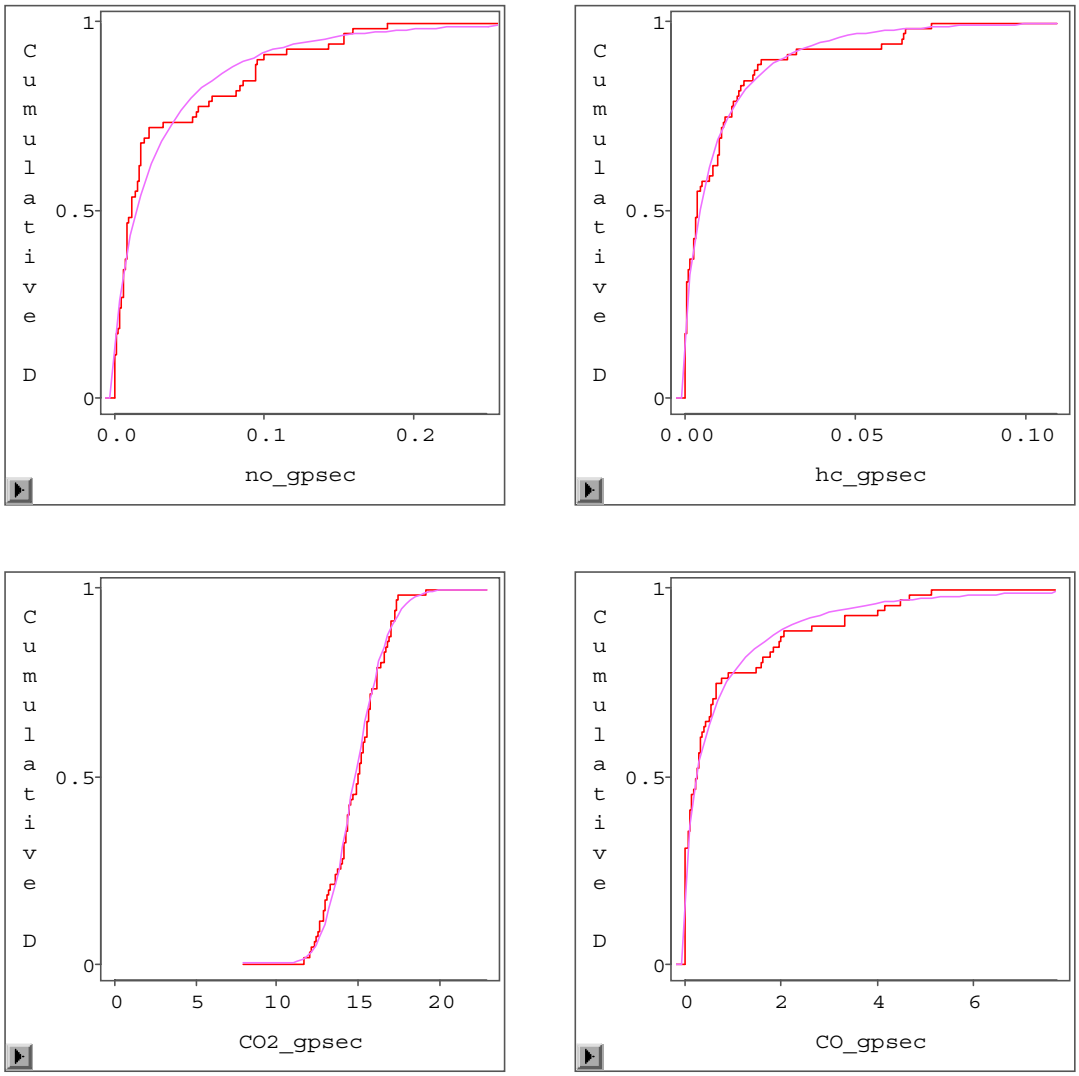
Pollutant	NO_x	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	W	W	W

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 7-3. Variability in NO_x, HC, CO_2, and CO Emissions for VSP Mode #8 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution, Time Average, Odometer reading > 50,000 miles, Engine Displacement < 3.5 liters.



Sec-By-Sec, VSP Bin 12

Pollutant	NO_x	HC	CO_2	CO
Fitted Parametric Distribution[a]	W	W	L	W

[a] N = normal; L = lognormal; W = Weibull.

Empirical CDF

Fitted Parametric Distribution

Figure 7-4. Variability in NO_x, HC, CO_2, and CO Emissions for VSP Mode #12 Characterized by Empirical Probability Distribution and Fitted Parametric Probability Distribution, Time Average, Odometer reading > 50,000 miles, Engine Displacement > 3.5 liters.

Overall, in most cases, the fitted distributions appear to compare well with the data. Because statistical GOF tests are too sensitive, from a practical perspective, when the sample size becomes large, alternative criteria for evaluating goodness-of-fit were sought. One such criterion is to evaluate the absolute difference between the mean of the data and the mean of the fitted distribution. A second criterion is to evaluate the absolute difference of the standard deviation of the data versus that of the fitted distribution. Therefore, these absolute differences were calculated for each of the 14 VSP modes, for each of the four strata by engine displacement and odometer reading reading, and for each of the four pollutants.

The distributions were fitted to the data using Maximum Likelihood Estimation (MLE). The choice of MLE was made on the basis that MLE is commonly used and is considered to be a more statistically efficient method than other approaches, such as the Method of Matching Moments (MoMM) (Cullen and Frey, 2002). However, MLE has a potential disadvantage in that the central moments of the fitted distribution (e.g., the mean and standard deviation) may not be the same as those of the data to which the distribution was fit. In contrast, for MoMM estimates of the distribution parameters, the fitted distribution will have a mean and standard deviation the same as that of the data. In most cases, the difference of the means and standard deviations between fitted distributions and the data are not large in an absolute sense, as shown in Tables 7-1 and 7-2, respectively. For example, for VSP Bins 1101 through 1114, which represent data for odometer reading < 50,000 miles, and engine displacement < 3.5 liters, the largest absolute deviation in the mean values for NO_x is for Mode 12 of this strata (identified as VSP Bin 1112 in Table 7-1), with an absolute difference of 0.0004 g/sec. This difference is in comparison to a mean from the data set of 0.0121 g/sec, and a mean from the fitted distribution of 0.0125 g/sec. Therefore, on a relative basis, this difference is only approximately three percent of the mean of the data. For the other 13 modes for this pollutant and strata, the absolute differences are smaller. However, in some cases, the relative differences are very large. For example, for Mode 1104, the absolute difference is -0.00028 g/sec compared to a data mean of 0.00117. Thus, the relative difference in this case is -24 percent. However, the absolute difference in the mean for Mode 1104 is only 70 percent of the absolute difference for Mode 1112. Typically, the largest absolute differences are small compared to the highest average emission rates among the modes for given pollutant and strata, although there are some exceptions (e.g., Mode 1211 for CO). The exceptions typically point to situations in which a single component distribution cannot provide a good fit because the data are inherently some type of mixture distributions.

Based upon a review of the results in Tables 7-1 and 7-2, criteria for discriminating good and bad fit were proposed for different pollutants. These criteria are shown in the second column of Table 7-3. For example, for NO_x, if the absolute difference in the mean of the MLE fitted distribution versus that of the data is larger than the magnitude of the criteria value, which is 0.001 g/sec, the fit is judged not to be good. When the absolute differences in the mean of the fitted distribution is less than the criteria value, the fit was also judged to be acceptable. Of the 56 modes, 49 of the modes for NO_x have differences in the mean between the data and the fitted distribution of less than the criteria value. For CO, 48 of the modes satisfy the criteria value, for HC 54 of the modes satisfy the critera, and for CO_2 all 56 modes satisfy the criteria value.

Table 7-1. Comparison of Mean between Empirical Data Set and Fitted Parametric Distributions, Absolute Basis

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
1101	0.000901	0.000714	-0.000187	0.000450	0.000460	0.0000103	1.67	1.68	0.00901	0.00781	0.00644	-0.00136
1102	0.000628	0.000554	-0.0000745	0.000257	0.000187	-0.0000701	1.46	1.45	-0.0122	0.00391	0.00248	-0.00143
1103	0.000346	0.000221	-0.000124	0.000406	0.000290	-0.000116	1.14	1.11	-0.0213	0.00335	0.00232	-0.00103
1104	0.00117	0.000894	-0.000279	0.000432	0.000357	-0.0000748	2.23	2.26	0.0223	0.00834	0.00877	0.000437
1105	0.00171	0.00167	-0.0000384	0.000530	0.000506	-0.0000242	2.92	2.92	0.00448	0.0110	0.00693	-0.00403
1106	0.00237	0.00234	-0.0000288	0.000705	0.000709	0.00000383	3.53	3.52	-0.00774	0.0170	0.0101	-0.00691
1107	0.00310	0.00303	-0.0000746	0.000822	0.000947	0.000124	4.11	4.09	-0.0135	0.0200	0.0134	-0.00662
1108	0.00423	0.00440	0.000162	0.000976	0.00121	0.000235	4.64	4.62	-0.0192	0.0292	0.0182	-0.0110
1109	0.00507	0.00509	0.0000255	0.00111	0.00137	0.000261	5.16	5.13	-0.0280	0.0355	0.0230	-0.0125
1110	0.00587	0.00601	0.000146	0.00144	0.00184	0.000396	5.63	5.60	-0.0295	0.0551	0.0823	0.0272
1111	0.00762	0.00776	0.000135	0.00206	0.00200	-0.0000595	6.53	6.52	-0.0160	0.114	0.177	0.0630
1112	0.0121	0.0125	0.000398	0.00337	0.00309	-0.000285	7.59	7.58	-0.00516	0.208	0.381	0.174
1113	0.0155	0.0152	-0.000267	0.00486	0.00564	0.000787	9.02	9.02	-0.00434	0.442	2.08	1.63
1114	0.0179	0.0180	0.000167	0.0109	0.0185	0.00759	10.1	10.1	0.00887	0.882	15.8	15.0
1201	0.000290	0.000176	-0.000113	0.000548	0.000161	-0.000387	1.57	1.56	-0.00525	0.0177	0.00883	-0.00886
1202	0.000223	0.000112	-0.000111	0.000222	0.0000357	-0.000187	1.44	1.38	-0.0685	0.00861	0.00109	-0.00752
1203	0.000174	0.0000733	-0.000101	0.000272	0.0000441	-0.000228	1.47	1.43	-0.0426	0.00848	0.00219	-0.00629
1204	0.000719	0.000682	-0.0000374	0.000472	0.000125	-0.000347	2.61	2.61	-0.00628	0.0145	0.00560	-0.00894

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Table 7-1. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
1205	0.00114	0.00106	-0.0000757	0.000754	0.000261	-0.000493	3.52	3.49	-0.0305	0.0257	0.0125	-0.0132
1206	0.00159	0.00140	-0.000185	0.000702	0.000477	-0.000225	4.65	4.62	-0.0306	0.0252	0.0418	0.0166
1207	0.00237	0.00234	-0.0000344	0.000944	0.00102	0.0000781	5.64	5.57	-0.0612	0.0411	0.0954	0.0543
1208	0.00410	0.00427	0.000169	0.00144	0.00128	-0.000161	6.60	6.57	-0.0311	0.0766	0.243	0.166
1209	0.00612	0.00609	-0.0000310	0.00171	0.00163	-0.0000792	7.65	7.59	-0.0594	0.129	0.280	0.151
1210	0.00731	0.00735	0.0000373	0.00261	0.00240	-0.000207	8.81	8.75	-0.0629	0.151	0.210	0.0592
1211	0.0132	0.0133	0.000155	0.00352	0.00441	0.000884	11.7	11.6	-0.0625	0.355	1.57	1.22
1212	0.0127	0.0122	-0.000503	0.00765	0.00918	0.00152	14.5	14.5	-0.00549	0.882	0.967	0.0856
1213	0.0154	0.0175	0.00210	0.00667	0.00664	-0.0000266	15.7	15.6	-0.0425	0.755	0.834	0.0788
1214	0.0203	0.0277	0.00742	0.00657	0.00658	0.00000652	17.4	17.4	0.00448	0.905	0.930	0.0256
2101	0.00101	0.000933	-0.0000812	0.000901	0.000827	-0.0000746	1.54	1.54	-0.00782	0.0110	0.00921	-0.00182
2102	0.00104	0.000888	-0.000154	0.000901	0.000880	-0.0000215	1.60	1.61	0.00584	0.00872	0.0155	0.00680
2103	0.000423	0.000416	-0.00000691	0.000835	0.000936	0.000100	1.13	1.10	-0.0352	0.00468	0.00459	-0.0000939
2104	0.00161	0.00171	0.0000994	0.00103	0.00113	0.000103	2.39	2.39	0.00229	0.0122	0.0107	-0.00149
2105	0.00264	0.00270	0.0000615	0.00125	0.00151	0.000262	3.21	3.21	-0.00404	0.0167	0.0148	-0.00194
2106	0.00379	0.00386	0.0000704	0.00166	0.00156	-0.000100	3.96	3.94	-0.0216	0.0233	0.0209	-0.00236
2107	0.00510	0.00514	0.0000440	0.00209	0.00209	-0.0000000742	4.75	4.74	-0.0167	0.0293	0.0275	-0.00179

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Table 7-1. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
2108	0.00637	0.00652	0.000146	0.00233	0.00232	-0.0000162	5.37	5.34	-0.0317	0.0369	0.0344	-0.00255
2109	0.00766	0.00775	0.0000836	0.00282	0.00280	-0.0000195	5.94	5.92	-0.0168	0.0495	0.0557	0.00617
2110	0.00991	0.0100	0.000115	0.00298	0.00303	0.0000464	6.43	6.39	-0.0347	0.0638	0.0652	0.00148
2111	0.0127	0.0130	0.000290	0.00379	0.00380	0.0000159	7.07	7.04	-0.0240	0.105	0.0834	-0.0220
2112	0.0144	0.0145	0.000105	0.00457	0.00462	0.0000482	7.62	7.60	-0.0149	0.248	0.170	-0.0775
2113	0.0160	0.0162	0.000209	0.00570	0.00569	-0.0000096	8.32	8.30	-0.0204	0.413	0.375	-0.0381
2114	0.0167	0.0170	0.000242	0.00716	0.00721	0.0000479	8.48	8.46	-0.0145	0.625	0.701	0.0762
2201	0.000725	0.000619	-0.000106	0.000863	0.000530	-0.000333	1.65	1.63	-0.0178	0.0203	0.0216	0.00136
2202	0.000504	0.000489	-0.0000148	0.000300	0.000219	-0.0000813	1.76	1.68	-0.0833	0.00818	0.00332	-0.00486
2203	0.000661	0.000754	0.0000929	0.000323	0.000266	-0.0000575	1.56	1.48	-0.0815	0.00483	0.00211	-0.00272
2204	0.00252	0.00292	0.000406	0.000449	0.000409	-0.0000398	2.95	2.94	-0.00368	0.0123	0.0139	0.00157
2205	0.00585	0.00695	0.00110	0.000818	0.000637	-0.000181	4.13	4.12	-0.00309	0.0220	0.0209	-0.00115
2206	0.00836	0.00928	0.000919	0.00122	0.00106	-0.000155	5.34	5.34	-0.00370	0.0451	0.0447	-0.000326
2207	0.0106	0.0113	0.000694	0.00211	0.00200	-0.000108	6.51	6.50	-0.00441	0.0775	0.0765	-0.00100
2208	0.0145	0.0155	0.00106	0.00439	0.00453	0.000134	7.60	7.60	-0.00391	0.167	0.152	-0.0144
2209	0.0164	0.0175	0.00110	0.00464	0.00450	-0.000133	8.77	8.77	-0.00112	0.170	0.167	-0.00262

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Table 7-1. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
2210	0.0198	0.0213	0.00154	0.00496	0.00461	-0.000356	10.4	10.4	-0.00409	0.264	0.248	-0.0153
2211	0.0305	0.0326	0.00209	0.00663	0.00643	-0.000203	12.8	12.8	-0.00133	0.339	0.363	0.0242
2212	0.0342	0.0341	-0.0000985	0.0109	0.0107	-0.000221	15.0	15.0	0.00141	0.825	0.823	-0.00141
2213	0.0434	0.0433	-0.000115	0.0166	0.0166	0.0000243	16.9	16.9	0.00567	1.44	0.242	-1.20
2214	0.0690	0.0688	-0.000151	0.0271	0.0275	0.000473	18.9	18.9	0.00168	2.18	2.40	0.223

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.
[b] Unit of mean: g/sec; Unit of diff.: g/sec.

Table 7-2. Comparison of Standard Deviation between Empirical Data Set and Fitted Parametric Distributions, Absolute Basis

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
1101	0.00295	0.00181	-0.00114	0.00283	0.00257	-0.000259	1.39	1.27	-0.118	0.0589	0.0873	0.0284
1102	0.00256	0.00155	-0.00101	0.00112	0.000921	-0.000202	1.21	1.20	-0.0122	0.0367	0.0307	-0.00602
1103	0.00154	0.000544	-0.00100	0.00150	0.00157	0.0000668	0.816	0.832	0.0155	0.0216	0.0267	0.00509
1104	0.00343	0.00262	-0.000809	0.00141	0.00170	0.000290	1.38	1.48	0.0925	0.0519	0.164	0.112
1105	0.00442	0.00469	0.000269	0.00160	0.00223	0.000630	1.53	1.52	-0.00811	0.0968	0.0195	-0.0774
1106	0.00567	0.00629	0.000621	0.00237	0.00308	0.000714	1.67	1.68	0.0161	0.155	0.0291	-0.126
1107	0.00671	0.00799	0.00128	0.00240	0.00419	0.00179	1.77	1.79	0.0204	0.106	0.0378	-0.0684
1108	0.00794	0.0109	0.00298	0.00281	0.00542	0.00260	1.94	1.97	0.0319	0.152	0.0536	-0.0987
1109	0.0101	0.0127	0.00259	0.00267	0.00559	0.00292	2.09	2.13	0.0378	0.165	0.0674	-0.0981
1110	0.0110	0.0142	0.00318	0.00369	0.00845	0.00477	2.35	2.40	0.0502	0.252	2.40	2.15
1111	0.0147	0.0166	0.00196	0.00545	0.00335	-0.00210	2.72	2.66	-0.0570	0.396	5.86	5.46
1112	0.0201	0.0240	0.00394	0.0104	0.00507	-0.00534	2.99	3.00	0.00935	0.571	13.4	12.8
1113	0.0247	0.0240	-0.000653	0.0133	0.0210	0.00769	3.64	3.64	-0.00180	0.906	173	172
1114	0.0277	0.0304	0.00269	0.0249	0.195	0.170	5.37	5.35	-0.0248	1.52	6426	6424
1201	0.00135	0.000495	-0.000858	0.00246	0.00102	-0.00145	0.752	0.775	0.0226	0.0876	0.240	0.153
1202	0.00142	0.000303	-0.00112	0.00177	0.0000879	-0.00169	0.730	0.990	0.260	0.0764	0.00895	-0.0674
1203	0.00125	0.000185	-0.00107	0.00194	0.000121	-0.00182	0.784	0.862	0.0785	0.0697	0.0296	-0.0401
1204	0.00228	0.00217	-0.000105	0.00246	0.000475	-0.00199	1.08	0.981	-0.100	0.0803	0.0868	0.00648

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Table 7-2. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
1205	0.00334	0.00345	0.000116	0.00360	0.00121	-0.00239	1.21	1.32	0.116	0.139	0.260	0.121
1206	0.00440	0.00454	0.000145	0.00277	0.00269	-0.0000782	1.79	1.86	0.0780	0.113	1.19	1.08
1207	0.00552	0.00628	0.000753	0.00278	0.00726	0.00448	2.31	2.44	0.132	0.166	3.05	2.89
1208	0.00813	0.0104	0.00225	0.00722	0.00729	0.0000726	2.64	2.75	0.110	0.286	15.5	15.2
1209	0.0140	0.0138	-0.000243	0.00443	0.00691	0.00248	2.51	2.66	0.155	0.411	11.4	11.0
1210	0.0145	0.0151	0.000630	0.00909	0.0107	0.00159	2.80	2.94	0.138	0.475	3.65	3.18
1211	0.0245	0.0281	0.00358	0.00699	0.0218	0.0148	3.38	3.45	0.0633	0.934	126	125
1212	0.0230	0.0187	-0.00433	0.0117	0.0375	0.0258	2.53	2.36	-0.168	1.45	2.78	1.34
1213	0.0359	0.0766	0.0408	0.00917	0.00937	0.000205	1.95	2.02	0.0729	1.10	1.75	0.650
1214	0.0378	0.122	0.0846	0.00769	0.00744	-0.000244	2.21	2.22	0.0116	1.18	1.41	0.234
2101	0.00229	0.00198	-0.000316	0.00225	0.00158	-0.000666	1.11	1.09	-0.0207	0.0471	0.0220	-0.0251
2102	0.00257	0.00215	-0.000424	0.00228	0.00178	-0.000505	1.11	1.05	-0.0655	0.0371	0.225	0.188
2103	0.00168	0.000959	-0.000724	0.00312	0.00689	0.00377	0.713	0.870	0.157	0.0286	0.0477	0.0191
2104	0.00334	0.00442	0.00108	0.00287	0.00614	0.00327	1.17	1.18	0.00910	0.0501	0.0226	-0.0274
2105	0.00467	0.00587	0.00120	0.00294	0.00717	0.00423	1.29	1.33	0.0447	0.0669	0.0279	-0.0390
2106	0.00658	0.00751	0.000929	0.00377	0.00260	-0.00117	1.36	1.44	0.0770	0.0828	0.0353	-0.0475
2107	0.00802	0.00859	0.000563	0.00403	0.00317	-0.000860	1.50	1.57	0.0697	0.0809	0.0424	-0.0385

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Table 7-2. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
2108	0.00901	0.0101	0.00109	0.00355	0.00323	-0.000321	1.64	1.72	0.0744	0.102	0.0511	-0.0507
2109	0.0107	0.0114	0.000657	0.00520	0.00390	-0.00130	1.81	1.87	0.0537	0.147	0.177	0.0300
2110	0.0135	0.0145	0.000959	0.00484	0.00420	-0.000640	1.96	2.05	0.0877	0.209	0.207	-0.00169
2111	0.0163	0.0182	0.00187	0.00687	0.00513	-0.00175	2.30	2.38	0.0775	0.331	0.242	-0.0896
2112	0.0166	0.0185	0.00182	0.00707	0.00621	-0.000863	2.45	2.56	0.101	0.665	0.614	-0.0508
2113	0.0186	0.0214	0.00278	0.00814	0.00765	-0.000490	3.00	3.09	0.0927	0.918	2.27	1.35
2114	0.0182	0.0213	0.00313	0.0100	0.00945	-0.000532	3.19	3.25	0.0524	1.26	6.02	4.76
2201	0.00203	0.00142	-0.000610	0.00572	0.00192	-0.00380	0.614	0.685	0.0715	0.114	0.489	0.375
2202	0.00137	0.00126	-0.000111	0.00132	0.000455	-0.000860	0.676	0.856	0.181	0.0762	0.0510	-0.0252
2203	0.00181	0.00161	-0.000202	0.00249	0.000568	-0.00192	0.662	1.13	0.464	0.0835	0.0219	-0.0615
2204	0.00402	0.00713	0.00311	0.000901	0.000634	-0.000267	0.735	0.676	-0.0582	0.0623	0.163	0.101
2205	0.00834	0.0186	0.0102	0.00430	0.00106	-0.00324	0.886	0.836	-0.0500	0.0699	0.0493	-0.0206
2206	0.0117	0.0206	0.00890	0.00249	0.00211	-0.000377	1.08	1.02	-0.0627	0.120	0.102	-0.0183
2207	0.0133	0.0211	0.00785	0.00404	0.00531	0.00128	1.35	1.26	-0.0835	0.196	0.157	-0.0396
2208	0.0178	0.0287	0.0109	0.0111	0.0172	0.00608	1.44	1.36	-0.0803	0.430	0.294	-0.136
2209	0.0200	0.0315	0.0115	0.00739	0.00671	-0.000680	1.50	1.47	-0.0298	0.329	0.270	-0.0596

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Table 7-2. Continued.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
2210	0.0261	0.0422	0.0161	0.00948	0.00751	-0.00196	1.83	1.74	-0.0961	0.651	0.909	0.257
2211	0.0330	0.0521	0.0192	0.0106	0.00980	-0.000809	2.14	2.08	-0.0507	0.706	1.28	0.577
2212	0.0466	0.0518	0.00521	0.0168	0.0164	-0.000441	1.62	1.65	0.0221	1.29	1.57	0.272
2213	0.0493	0.0484	-0.000869	0.0179	0.0202	0.00228	2.39	2.44	0.0568	1.43	0.369	-1.06
2214	0.0572	0.0630	0.00582	0.0327	0.0406	0.00795	2.10	2.07	-0.0313	2.05	3.80	1.75

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.
[b] Unit of mean: g/sec; Unit of diff.: g/sec.

Table 7-3. Comparisons of Empirical Data Set and Fitted Parametric Distributions, Average Difference for Good Fits, Fitting Based upon MLE

Pollutant	Criteria (g/sec)[a]	No. of good fits	Mean			Standard deviation		
			Empirical (g/sec)	Abs. diff (g/sec)	Rel. diff (%)	Empirical (g/sec)	Abs. diff (g/sec)	Rel. diff (%)
NO_x	0.001	49	0.00812	0.0000404	0.50	0.0116	0.00119	10
HC	0.001	54	0.00302	-0.0000192	-0.64	0.00570	0.000611	11
CO_2	0.1	56	6.27	-0.0186	-0.30	1.81	0.0372	2.1
CO	0.1	48	0.140	0.00511	3.6	0.304	0.500	160

[a] A fit is good when its absolute difference in the mean is smaller than criteria value.

Table 7-4. Comparisons of Empirical Data Set, Fitted Lognormal Distributions Based upon MLE, and Fitted Lognormal Distributions Based upon MoMM, for the Two Worst MLE Fits for CO.

VSP Bin[a]	MLE						MoMM					
	Mean			Standard Deviation			Mean			Standard Deviation		
	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff	empirical	fitted dist	diff
1113	0.442	2.08	1.63	0.906	173	172	0.442	0.442	0	0.906	0.906	0
1114	0.882	15.8	15.0	1.52	6426	6424	0.882	0.882	0	1.52	1.52	0

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters.

From Table 7-3, it is apparent that the relative difference in the mean values of the fitted distribution and the data is less than one percent for NO_x, HC, and CO_2 for the vast majority of the modes, and less than four percent for the majority of the modes in the case of CO. The estimated standard deviation tends to be more sensitive to deviations of the fitted distribution from the data than does the estimated mean. For most of the modes and pollutants, the relative difference between the standard deviation of the fitted distribution versus that of the data is less than 10 percent, but there are some examples for CO in which the difference is substantially larger.

In this study, MLE was used to estimate parameters of fitted parametric distributions for representing variability in population. If MoMM was used, there would have been no difference in the mean and standard deviation between the empirical sample data and fitted distribution, as shown for selected examples in Table 7-4. In these two examples, which represent the worst fits of parametric distributions to modal data for CO, the MoMM fitted distribution is confirmed to have the same mean and standard deviation as the original data, whereas both the mean and standard deviations of the distribution fitted using MLE are substantially different than the values estimated directly from the data. However, it is not likely that the mean and the standard deviation of population will be exactly the same as those of sample. The basis for fitting a distribution using MLE is to estimate a distribution from which the data were most likely to have been a sample, which is a different criterion than that for estimating a distribution using MoMM.

Table 7-5. Recommendation of Mixture Distributions for Two Worst Fits

Bin[a]	Pollutant	Dist. 1	Dist. 2	Weight	Dist. 1[b]		Dist. 2[b]	
					Para 1	Para 2	Para 1	Para 2
1113	CO	Lognormal	Lognormal	0.7878	2.3619	-4.7782	0.6782	0.329
1114	CO	Lognormal	Lognormal	0.6367	2.1368	-5.4363	0.7358	0.6043

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters.
[b] Para 1 of lognormal is ϕ and Para 2 of lognormal is ξ.

Even though MoMM results in the same estimates of the mean and standard deviation as the original data set, MoMM does not always provide a good fit. For example, distributions fitted using both MLE and MoMM for the case of CO emissions for odometer reading < 50,000 miles, and engine displacement < 3.5 Liters, are shown in comparison to the empirical distribution of the data for VSP Mode 14 in Figure 7-5. A similar example is given for Mode 13, for CO for the same odometer reading and engine displacement category in Figure 7-6. Figures 7-5 and 7-6 suggest that neither MLE nor MoMM provides an ideal fit compared to the data. When comparing MLE and MoMM fits for these two cases, it appears that MLE provides a better fit for the lower percentiles of the distribution and MoMM provides a better fit for the upper tail of the distribution. However, it is also clear in these examples that the data are not well represented by a single component parametric distribution, especially in the central portion of the distribution. A key question is whether occasional disagreements between fitted distributions and data, such as these, can be tolerated in the model. Alternatively, either mixture distributions or empirical distributions can be used to represent data such as these. For the same data as shown in Figure 7-5, an illustration of the use of a fitted mixture distribution is shown in Figure 7-7. Similarly, for the same data as shown in Figure 7-6, an illustration of the use of a fitted mixture distribution is given in Figure 7-8. The parameters of the mixture distributions shown in Figures 7-7 and 7-8 are given in Table 7-5. The mixture distributions comprised of only two lognormal components are shown to agree very well with the empirical data in both cases. The mixture distributions were estimated using MLE as described by Zheng (2002) using a modified version of AuvTool. These example case studies illustrate that mixture distributions can be an effective approach for achieving a good fit when a single component distribution is not adequate. These case studies also suggest that the data in these modes may be comprised of two or more subpopulations that might reflect different activity patterns or different vehicle characteristics.

Table 7-6 summarizes the type of parametric distribution and the parameters of the distribution fitted to the data for each pollutant and mode based upon MLE approach.

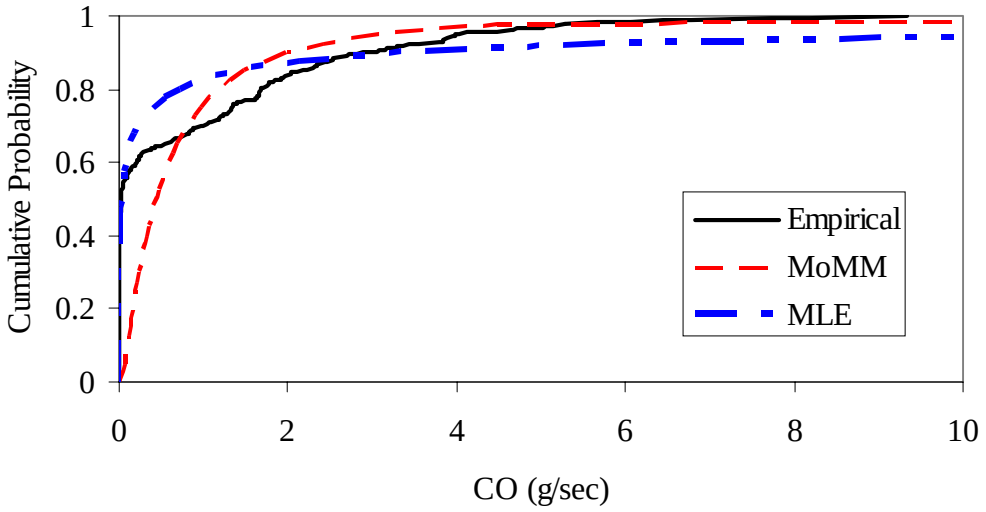

Figure 7-5. Comparison of Fitted Parametric Distribution Based upon Method of Matching Moment and Maximum Likelihood Estimation, Mode 14 CO Emissions, Odometer reading < 50,000 miles, Engine Displacement < 3.5 liters.

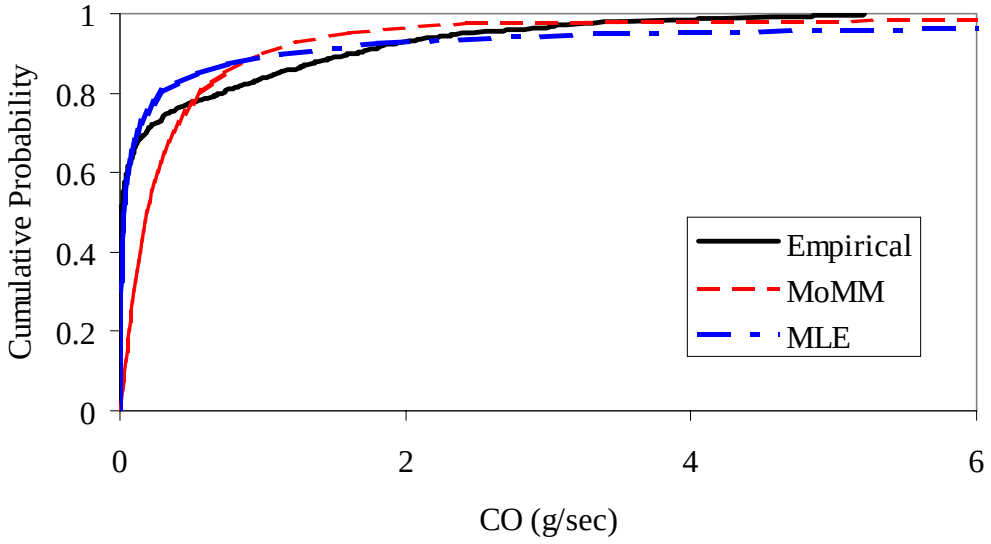

Figure 7-6. Comparison of Fitted Parametric Distribution Based upon Method of Matching Moment and Maximum Likelihood Estimation, Mode 13 CO Emissions, Odometer reading < 50,000 miles, Engine Displacement < 3.5 liters

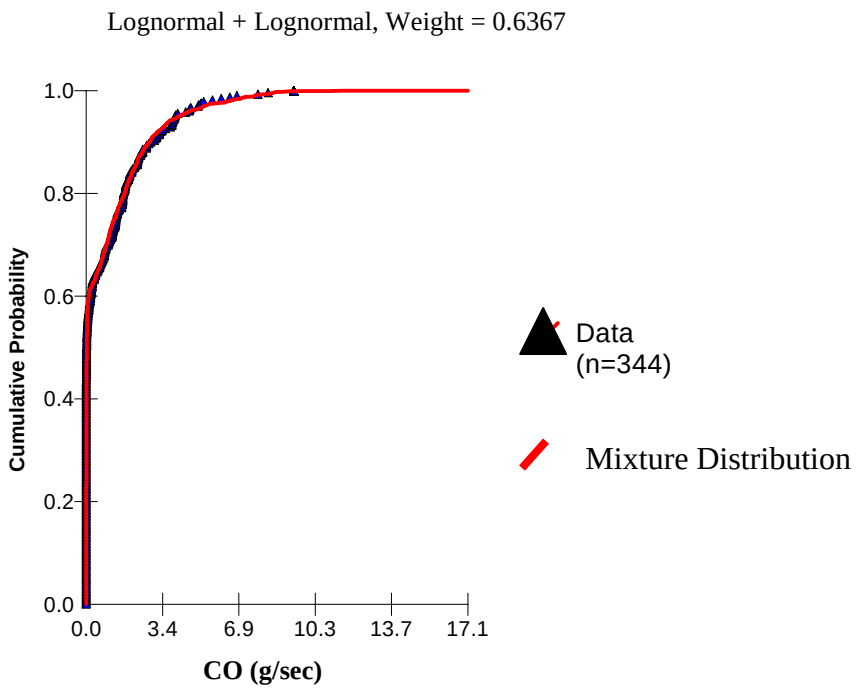

Figure 7-7. Mixture Distribution Comprised of Two Lognormal Components Fitted to Data for Mode 14 CO Emissions for Odometer Reading < 50,000 miles and Engine Displacement < 3.5 Liters.

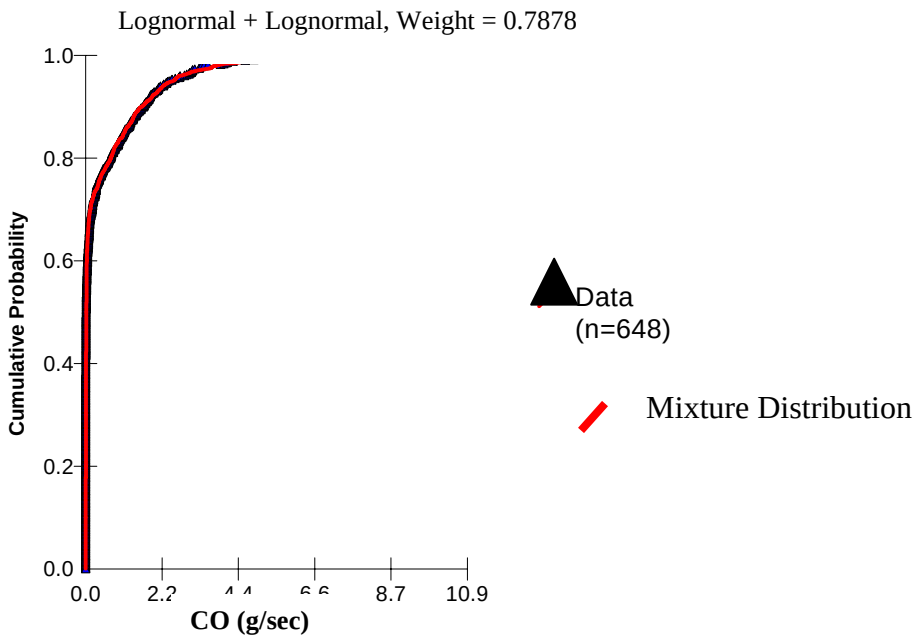

Figure 7-8. Mixture Distribution Comprised of Two Lognormal Components Fitted to Data for Mode 13 CO Emissions for Odometer Reading < 50,000 miles and Engine Displacement < 3.5 Liters.

Table 7-6. Summary of Single Component Parametric Probability Distributions Fitted Using MLE for Variability in VSP Modes for NO_x, HC, CO_2, and CO for Vehicles of Different Engine Displacement and Odometer Reading.

VSP Bin[a]	NO_x			HC			CO_2			CO		
	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2
1101	W	3.00E-04	4.58E-01	L	1.86E+00	-9.42E+00	W	1.83E+00	1.34E+00	L	2.28E+00	-7.65E+00
1102	W	2.00E-04	4.29E-01	L	1.80E+00	-1.02E+01	W	1.54E+00	1.21E+00	L	2.24E+00	-8.52E+00
1103	W	9.74E-05	4.68E-01	L	1.85E+00	-9.85E+00	W	1.22E+00	1.35E+00	L	2.21E+00	-8.52E+00
1104	W	3.00E-04	4.17E-01	L	1.78E+00	-9.52E+00	L	5.97E-01	6.35E-01	L	2.42E+00	-7.66E+00
1105	W	6.00E-04	4.29E-01	L	1.74E+00	-9.10E+00	W	3.30E+00	2.01E+00	W	2.50E-03	4.29E-01
1106	W	9.00E-04	4.41E-01	L	1.73E+00	-8.75E+00	W	3.97E+00	2.21E+00	W	3.50E-03	4.22E-01
1107	W	1.20E-03	4.46E-01	L	1.74E+00	-8.47E+00	W	4.62E+00	2.43E+00	W	4.80E-03	4.28E-01
1108	W	1.90E-03	4.65E-01	L	1.74E+00	-8.24E+00	W	5.20E+00	2.51E+00	W	6.10E-03	4.16E-01
1109	W	2.20E-03	4.64E-01	L	1.69E+00	-8.02E+00	W	5.78E+00	2.59E+00	W	7.80E-03	4.18E-01
1110	W	2.80E-03	4.82E-01	L	1.76E+00	-7.85E+00	W	6.32E+00	2.49E+00	L	2.60E+00	-5.87E+00
1111	W	4.10E-03	5.16E-01	W	1.40E-03	6.25E-01	W	7.34E+00	2.63E+00	L	2.65E+00	-5.23E+00
1112	W	7.60E-03	5.61E-01	W	2.20E-03	6.35E-01	W	8.52E+00	2.73E+00	L	2.67E+00	-4.52E+00
1113	W	1.12E-02	6.54E-01	L	1.64E+00	-6.52E+00	W	1.01E+01	2.67E+00	L	2.97E+00	-3.69E+00

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Table 7-6. Continued.

VSP Bin[a]	NO_x			HC			CO_2			CO		
	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2
1114	W	1.25E-02	6.20E-01	L	2.17E+00	-6.35E+00	W	1.14E+01	1.97E+00	L	3.47E+00	-3.24E+00
1201	W	6.36E-05	4.29E-01	L	1.93E+00	-1.06E+01	W	1.76E+00	2.12E+00	L	2.57E+00	-8.03E+00
1202	W	4.28E-05	4.39E-01	L	1.40E+00	-1.12E+01	W	1.51E+00	1.41E+00	L	2.06E+00	-8.94E+00
1203	W	3.10E-05	4.60E-01	L	1.46E+00	-1.11E+01	W	1.60E+00	1.71E+00	L	2.28E+00	-8.73E+00
1204	W	2.00E-04	3.96E-01	L	1.65E+00	-1.04E+01	L	3.64E-01	8.91E-01	L	2.34E+00	-7.93E+00
1205	W	3.00E-04	3.91E-01	L	1.76E+00	-9.81E+00	W	3.92E+00	2.87E+00	L	2.46E+00	-7.42E+00
1206	W	4.00E-04	3.93E-01	L	1.87E+00	-9.39E+00	W	5.20E+00	2.67E+00	L	2.59E+00	-6.52E+00
1207	W	9.00E-04	4.41E-01	L	1.99E+00	-8.86E+00	W	6.29E+00	2.44E+00	L	2.63E+00	-5.82E+00
1208	W	1.90E-03	4.71E-01	L	1.87E+00	-8.41E+00	W	7.40E+00	2.57E+00	L	2.88E+00	-5.57E+00
1209	W	3.00E-03	4.96E-01	L	1.72E+00	-7.89E+00	W	8.48E+00	3.12E+00	L	2.72E+00	-4.98E+00
1210	W	4.10E-03	5.32E-01	L	1.74E+00	-7.55E+00	W	9.75E+00	3.28E+00	L	2.39E+00	-4.42E+00
1211	W	7.20E-03	5.22E-01	L	1.80E+00	-7.04E+00	W	1.29E+01	3.76E+00	L	2.96E+00	-3.93E+00
1212	W	9.20E-03	6.70E-01	L	1.70E+00	-6.13E+00	L	1.62E-01	2.66E+00	W	3.36E-01	4.22E-01

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Table 7-6. Continued.

VSP Bin[a]	NO_x			HC			CO_2			CO		
	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2
1213	L	1.73E+00	-5.55E+00	W	5.40E-03	7.22E-01	W	1.65E+01	9.25E+00	W	4.52E-01	5.23E-01
1214	L	1.74E+00	-5.10E+00	W	6.20E-03	8.86E-01	L	1.27E-01	2.85E+00	W	7.13E-01	6.78E-01
2101	W	5.00E-04	5.20E-01	W	5.00E-04	5.61E-01	W	1.69E+00	1.43E+00	W	4.20E-03	4.77E-01
2102	W	4.00E-04	4.74E-01	W	5.00E-04	5.39E-01	W	1.79E+00	1.57E+00	L	2.31E+00	-6.84E+00
2103	W	2.00E-04	4.90E-01	L	2.00E+00	-8.98E+00	W	1.18E+00	1.27E+00	L	2.17E+00	-7.73E+00
2104	W	7.00E-04	4.53E-01	L	1.85E+00	-8.49E+00	W	2.70E+00	2.13E+00	W	5.70E-03	5.19E-01
2105	W	1.40E-03	5.10E-01	L	1.78E+00	-8.07E+00	W	3.61E+00	2.58E+00	W	9.10E-03	5.67E-01
2106	W	2.30E-03	5.55E-01	W	1.10E-03	6.28E-01	W	4.41E+00	2.98E+00	W	1.45E-02	6.21E-01
2107	W	3.60E-03	6.26E-01	W	1.60E-03	6.78E-01	W	5.28E+00	3.33E+00	W	2.08E-02	6.70E-01
2108	W	4.90E-03	6.66E-01	W	1.90E-03	7.30E-01	W	5.94E+00	3.44E+00	W	2.68E-02	6.90E-01
2109	W	6.10E-03	6.98E-01	W	2.30E-03	7.31E-01	W	6.58E+00	3.52E+00	L	1.55E+00	-4.09E+00
2110	W	8.00E-03	7.07E-01	W	2.50E-03	7.34E-01	W	7.11E+00	3.45E+00	L	1.55E+00	-3.93E+00
2111	W	1.06E-02	7.26E-01	W	3.20E-03	7.52E-01	W	7.86E+00	3.25E+00	L	1.50E+00	-3.60E+00

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Table 7-6. Continued.

VSP Bin[a]	NO_x			HC			CO_2			CO		
	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2
2112	W	1.27E-02	7.92E-01	W	3.90E-03	7.54E-01	W	8.48E+00	3.27E+00	L	1.62E+00	-3.09E+00
2113	W	1.38E-02	7.65E-01	W	4.80E-03	7.54E-01	W	9.31E+00	2.92E+00	L	1.91E+00	-2.80E+00
2114	W	1.50E-02	8.02E-01	W	6.20E-03	7.72E-01	W	9.50E+00	2.82E+00	L	2.08E+00	-2.51E+00
2201	W	3.00E-04	4.92E-01	L	1.63E+00	-8.87E+00	W	1.84E+00	2.55E+00	L	2.50E+00	-6.95E+00
2202	W	2.00E-04	4.53E-01	L	1.29E+00	-9.27E+00	W	1.90E+00	2.06E+00	L	2.34E+00	-8.44E+00
2203	W	4.00E-04	5.17E-01	L	1.31E+00	-9.09E+00	W	1.60E+00	1.32E+00	L	2.17E+00	-8.50E+00
2204	W	1.30E-03	4.71E-01	L	1.11E+00	-8.41E+00	L	2.27E-01	1.05E+00	L	2.22E+00	-6.75E+00
2205	W	2.70E-03	4.43E-01	L	1.15E+00	-8.02E+00	L	2.01E-01	1.40E+00	W	9.70E-03	4.81E-01
2206	W	4.70E-03	5.04E-01	L	1.26E+00	-7.65E+00	L	1.89E-01	1.66E+00	W	2.18E-02	4.93E-01
2207	W	7.00E-03	5.71E-01	L	1.44E+00	-7.26E+00	L	1.93E-01	1.85E+00	W	4.28E-02	5.33E-01
2208	W	9.80E-03	5.77E-01	L	1.65E+00	-6.76E+00	L	1.78E-01	2.01E+00	W	9.13E-02	5.58E-01
2209	W	1.13E-02	5.88E-01	W	3.50E-03	6.89E-01	L	1.66E-01	2.16E+00	W	1.21E-01	6.44E-01
2210	W	1.24E-02	5.47E-01	W	3.30E-03	6.38E-01	L	1.66E-01	2.32E+00	L	1.63E+00	-2.73E+00

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Table 7-6. Continued.

VSP Bin[a]	NO_x			HC			CO_2			CO		
	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2	Dist[b]	para 1	para 2
2211	W	2.38E-02	6.49E-01	W	4.90E-03	6.75E-01	L	1.61E-01	2.54E+00	L	1.61E+00	-2.31E+00
2212	W	2.61E-02	6.78E-01	W	8.10E-03	6.72E-01	L	1.09E-01	2.70E+00	W	5.02E-01	5.64E-01
2213	W	4.10E-02	8.95E-01	W	1.50E-02	8.28E-01	L	1.44E-01	2.82E+00	W	1.85E-01	6.76E-01
2214	W	7.12E-02	1.09E+00	W	2.16E-02	6.95E-01	L	1.09E-01	2.94E+00	W	1.77E+00	6.53E-01

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.

[b] W = Weibull; para 1 of Weibull is scale parameter and para 2 of Weibull is shape parameter; L = lognormal; para 1 of lognormal is ϕ and para 2 of lognormal is ξ; Parameters were calculated using SAS.

7.3 Quantification of Uncertainty in Mean Emission Rates

A particular concern in this study is whether a normality approximation can be used to represent uncertainty in the mean. A normality assumption is convenient because it is easy to calculate the range of uncertainty in the mean in such situations. When a normality assumption is not applicable, a numerical method, known as bootstrap simulation, was used to quantify uncertainty in the mean. Typically, the normality assumption is influenced by the sample size, sample mean, and standard error of mean (SEM). When either sample size $n < 40$, or when the SEM divided by the mean was greater than 20, then bootstrap simulation was done to estimate the sampling distribution of the mean. Overall, in most cases, a normality assumption was applicable. Table 7-7 indicates situations for which a normality assumption was suspected to be inadequate. These situations include VSP Modes 12 (NO_x), 13 (NO_x and CO), and 14 (All Pollutants) for odometer reading < 50,000 miles and engine displacement > 3.5 liters, and Mode 14 (All Pollutants) for odometer reading > 50,000 miles and engine displacement > 3.5 liters. In each of these cases, either the sample size is less than 40 or the relative standard error of the mean is greater than 0.2. Therefore, in these cases, bootstrap simulation was used to quantify uncertainty in the mean. Uncertainty estimates for all other modes and strata were based upon application of the normality assumption.

Table 7-7. VSP Modes for Which Uncertainty in the Mean Was Quantified by Bootstrap Simulation.

Bin[a]	NO	HC	CO_2	CO
1212	$\frac{SEM}{mean} = 0.21$, $n = 77$	n/a	n/a	n/a
1213	$\frac{SEM}{mean} = 0.32$, $n = 52$	n/a	n/a	$\frac{SEM}{mean} = 0.20$, $n = 52$
1214	$\frac{SEM}{mean} = 0.30$, $n = 39$	$\frac{SEM}{mean} = 0.19$, $n = 39$	$\frac{SEM}{mean} = 0.020$, $n = 39$	$\frac{SEM}{mean} = 0.21$, $n = 39$
2214	$\frac{SEM}{mean} = 0.14$, $n = 34$	$\frac{SEM}{mean} = 0.21$, $n = 34$	$\frac{SEM}{mean} = 0.019$, $n = 34$	$\frac{SEM}{mean} = 0.16$, $n = 34$

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.

The absolute range of uncertainty in the mean values for each pollutant and VSP-based mode is given in Figure 7-9 for NO_x and HC and in Figure 7-10 for CO and CO_2. The relative range of uncertainty in the mean values for each pollutant and VSP-based mode is given in Table 7-8. The relative range of uncertainty is typically less than plus or minus 50 percent for most cases. For CO_2, the range of uncertainty is less than plus or minus 5 percent in nearly all cases. The relative range of uncertainty is generally smaller for the strata which have larger sample sizes. For example, for vehicles with engine displacement less than 3.5 liters and odometer reading less than 50,000 miles, the typical range of uncertainty is less than plus or minus 10 percent for 12 of 14 modes for modal NO_x emissions, less than plus or minus 10 percent for 10 of 14 modes for HC, less than plus or minus three percent for CO_2 for all modes, and less than plus or minus 20 percent for all modes for CO. However, for vehicles with engine displacement greater than 3.5 liters in the same odometer reading category, the typical range of uncertainty is plus or minus 30 percent for NO_x, 40 percent for HC, 7 percent for CO_2, and 40 percent for CO. The latter category has a much smaller sample size than the former.

In the several cases identified in Table 7-7 for which the normality assumption was suspected to be inapplicable, it was confirmed based upon the results of bootstrap simulation that the sampling distributions of the means were not normal. For example, for NO_x emissions for Mode 13 for odometer reading < 50,000 miles and engine displacement > 3.5 liters, uncertainty in the mean was quantified by bootstrap simulation based upon the empirical distribution of data. The relative 95 percent confidence interval was found to be minus 48 percent to plus 73 percent. The confidence interval is positively skewed and the wide range of uncertainty in this case is attributed to a large SEM relative to the mean. In Table 7-8, uncertainty estimates based upon bootstrap simulation are highlighted in bold. For the cases in which uncertainties in the means were quantified by bootstrap simulation, parametric distributions were fit to the sampling distributions of the means using the AuvTool software. As an example, a graphical comparison is given in Figure 7-11 of the empirical distribution of the bootstrap replications of the mean and a fitted parametric distribution is given for NO_x emission of Mode 12 based upon an odometer reading < 50,000 miles and engine displacement > 3.5 liters. A summary of parameters for parametric distributions fitted to the bootstrap replications of the means is given in Table 7-9.

Normal, lognormal, Weibull, beta and gamma distributions were considered as possible fits for the sampling distributions. The PDFs of the normal, lognormal, and Weibull distributions have previously been given in Equations (7-1), (7-2), and (7-3), respectively. The PDF of the beta distribution is:

$$f(x) = \frac{1}{B(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1} \qquad B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \tag{7-4}$$

The PDF of gamma distribution is:

$$f(x) = \frac{\lambda^r x^{r-1} e^{-\lambda x}}{\Gamma(r)} \qquad \Gamma(r) = \int_0^\infty x^{r-1} e^{-x} dx \qquad 0 \le x < \infty \tag{7-5}$$

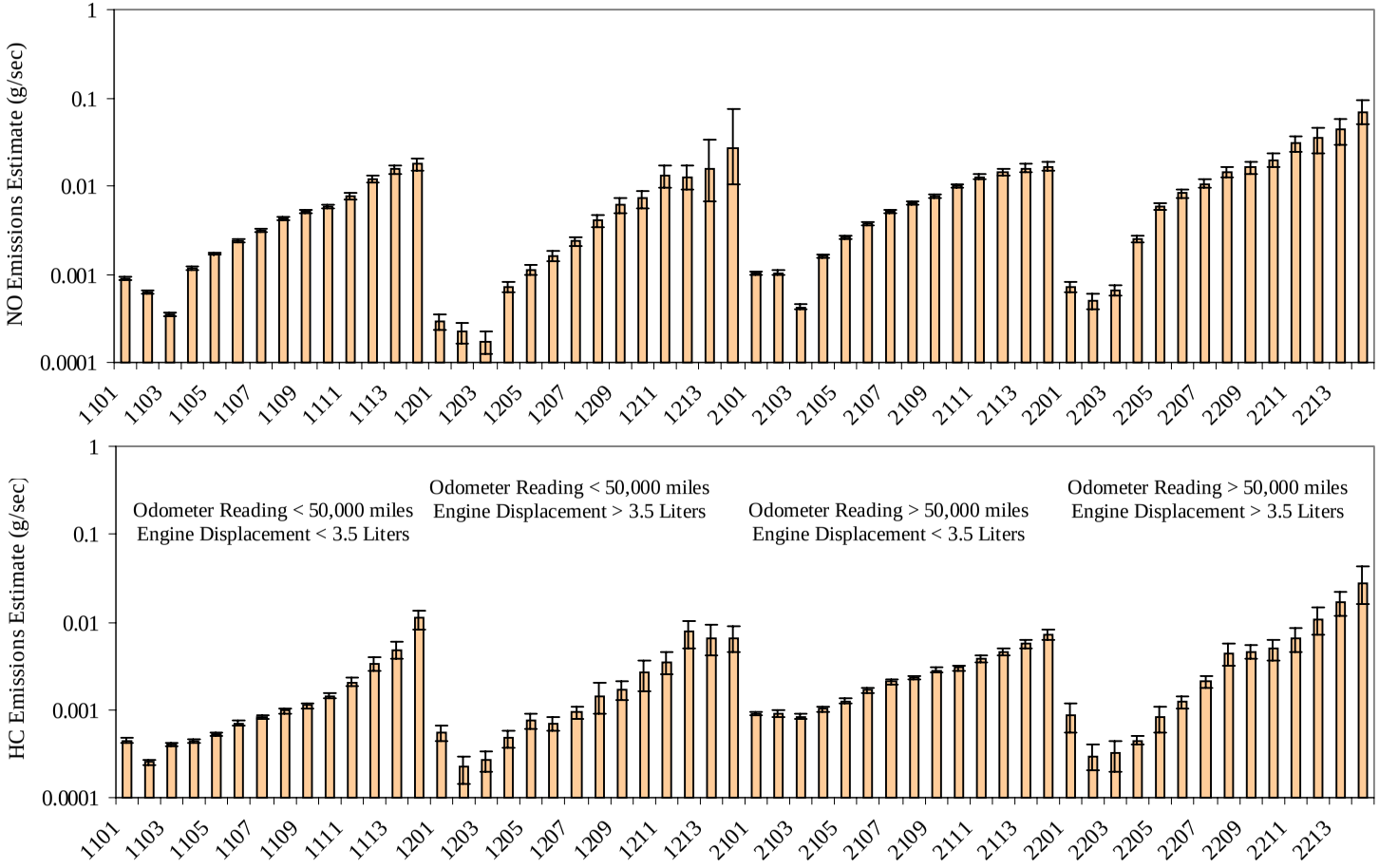

Figure 7-9. Quantified Uncertainty in the NO_x and HC Mean Emissions (g/sec) of VSP Modes.
First two digit of VSP Bins: 11: odometerreading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.

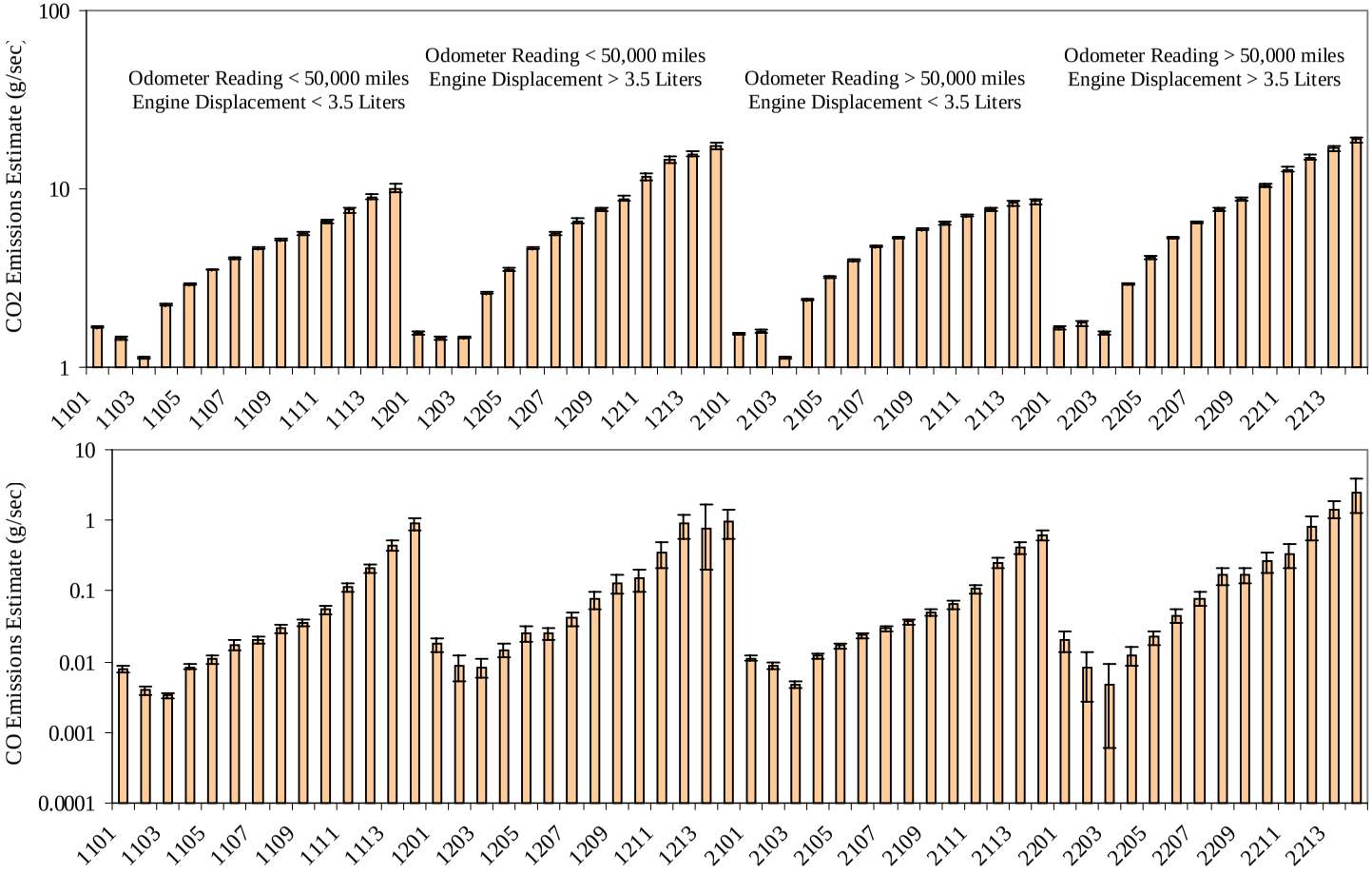

Figure 7-10. Quantified Uncertainty in the CO_2 and CO Mean Emissions (g/sec) of VSP Modes
First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.)

Table 7-8. Summary of Mean Values and Relative 95% Confidence Intervals in the Mean for NO_x, HC, CO_2, and CO Emissions (g/sec) for VSP Modes for Vehicles of Different Odometer Reading and Engine Displacement.

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1101	0.000901	-4	4	0.000450	-8	8	1.671078	-1	1	0.007807	-10	10
1102	0.000628	-6	6	0.000257	-7	7	1.457983	-1	1	0.003908	-15	15
1103	0.000346	-5	5	0.000406	-4	4	1.135362	-1	1	0.003347	-8	8
1104	0.001173	-4	4	0.000432	-5	5	2.233264	-1	1	0.008335	-9	9
1105	0.001706	-4	4	0.000530	-5	5	2.919890	-1	1	0.010959	-14	14
1106	0.002368	-4	4	0.000705	-6	6	3.525303	-1	1	0.017013	-16	16
1107	0.003103	-4	4	0.000822	-6	6	4.107483	-1	1	0.020026	-11	11
1108	0.004234	-4	4	0.000976	-7	7	4.635048	-1	1	0.029222	-12	12
1109	0.005069	-5	5	0.001112	-7	7	5.160731	-1	1	0.035531	-13	13
1110	0.005865	-6	6	0.001443	-8	8	5.632545	-1	1	0.055068	-14	14
1111	0.007623	-8	8	0.002061	-11	11	6.534780	-2	2	0.113824	-14	14
1112	0.012149	-10	10	0.003373	-18	18	7.585213	-2	2	0.207586	-16	16
1113	0.015456	-12	12	0.004857	-21	21	9.024217	-3	3	0.441775	-16	16

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Table 7-8. Continued

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1114	0.017863	-16	16	0.010948	-24	24	10.088390	-6	6	0.882300	-18	18
1201	0.000290	-19	19	0.000548	-19	19	1.566819	-2	2	0.017699	-21	21
1202	0.000223	-28	28	0.000222	-35	35	1.443564	-2	2	0.008608	-39	39
1203	0.000174	-27	27	0.000272	-27	27	1.470553	-2	2	0.008479	-31	31
1204	0.000719	-12	12	0.000472	-20	20	2.611318	-2	2	0.014548	-22	22
1205	0.001136	-13	13	0.000754	-22	22	3.523681	-2	2	0.025709	-25	25
1206	0.001587	-13	13	0.000702	-19	19	4.650741	-2	2	0.025212	-22	22
1207	0.002370	-13	13	0.000944	-16	16	5.635386	-2	2	0.041130	-22	22
1208	0.004098	-15	15	0.001443	-38	38	6.599677	-3	3	0.076601	-28	28
1209	0.006124	-21	21	0.001708	-24	24	7.647334	-3	3	0.129248	-29	29
1210	0.007313	-22	22	0.002605	-39	39	8.808448	-4	4	0.150578	-35	35
1211	0.013178	-27	27	0.003523	-29	29	11.670609	-4	4	0.355223	-39	39
1212	**0.012179**	**-38**	**46**	0.007653	-34	34	14.520355	-4	4	0.881642	-37	37

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Table 7-8. Continued

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
1213	**0.016506**	**-48**	**73**	0.006667	-37	37	15.653272	-3	3	**1.059857**	**-25**	**27**
1214	**0.027225**	**-36**	**49**	**0.006593**	**-33**	**39**	**17.35699**	**-7**	**5**	**0.934715**	**-36**	**44**
2101	0.001014	-4	4	0.000901	-5	5	1.543686	-1	1	0.011030	-8	8
2102	0.001042	-7	7	0.000901	-7	7	1.604406	-2	2	0.008723	-13	13
2103	0.000423	-7	7	0.000835	-6	6	1.130833	-1	1	0.004682	-10	10
2104	0.001613	-5	5	0.001027	-6	6	2.386260	-1	1	0.012154	-9	9
2105	0.002638	-4	4	0.001253	-6	6	3.210249	-1	1	0.016731	-10	10
2106	0.003793	-5	5	0.001664	-6	6	3.957732	-1	1	0.023269	-10	10
2107	0.005098	-5	5	0.002089	-6	6	4.752012	-1	1	0.029322	-8	8
2108	0.006373	-5	5	0.002332	-5	5	5.374221	-1	1	0.036942	-9	9
2109	0.007664	-5	5	0.002818	-7	7	5.940051	-1	1	0.049513	-11	11
2110	0.009913	-5	5	0.002985	-6	6	6.427506	-1	1	0.063759	-13	13
2111	0.012685	-6	6	0.003786	-8	8	7.065985	-2	2	0.105380	-15	15

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Table 7-8. Continued

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
2112	0.014384	-7	7	0.004573	-9	9	7.617703	-2	2	0.247810	-16	16
2113	0.015967	-10	10	0.005700	-12	12	8.322442	-3	3	0.413069	-18	18
2114	0.016717	-10	10	0.007164	-13	13	8.475028	-3	3	0.624663	-19	19
2201	0.000725	-15	15	0.000863	-36	36	1.649427	-2	2	0.020282	-31	31
2202	0.000504	-20	20	0.000300	-32	32	1.762407	-3	3	0.008183	-68	68
2203	0.000661	-14	14	0.000323	-39	39	1.557773	-2	2	0.004830	-87	87
2204	0.002518	-9	9	0.000449	-11	11	2.946419	-1	1	0.012308	-28	28
2205	0.005847	-9	9	0.000818	-34	34	4.127492	-1	1	0.022033	-20	20
2206	0.008361	-11	11	0.001216	-16	16	5.343656	-2	2	0.045073	-20	20
2207	0.010582	-11	11	0.002110	-16	16	6.507179	-2	2	0.077496	-22	22
2208	0.014473	-14	14	0.004394	-28	28	7.602431	-2	2	0.166593	-28	28
2209	0.016372	-15	15	0.004635	-19	19	8.773093	-2	2	0.170018	-24	24
2210	0.019758	-17	17	0.004961	-25	25	10.365910	-2	2	0.263544	-33	33

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Table 7-8. Continued

VSP Bin[a]	NO_x[b]			HC[b]			CO_2[b]			CO[b]		
	mean	lower	upper	mean	lower	upper	mean	lower	upper	mean	lower	upper
2211	0.030507	-20	20	0.006631	-30	30	12.849389	-3	3	0.338962	-39	39
2212	0.034219	-32	32	0.010900	-36	36	15.030303	-3	3	0.824829	-36	36
2213	0.043387	-31	31	0.016573	-30	30	16.861726	-4	4	1.444311	-27	27
2214	**0.068743**	**-27**	**27**	**0.027174**	**-35**	**36**	**18.92916**	**-13**	**10**	**2.420786**	**-27**	**28**

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.
[b] Unit of mean: g/sec; Unit of lower and upper bound: %.

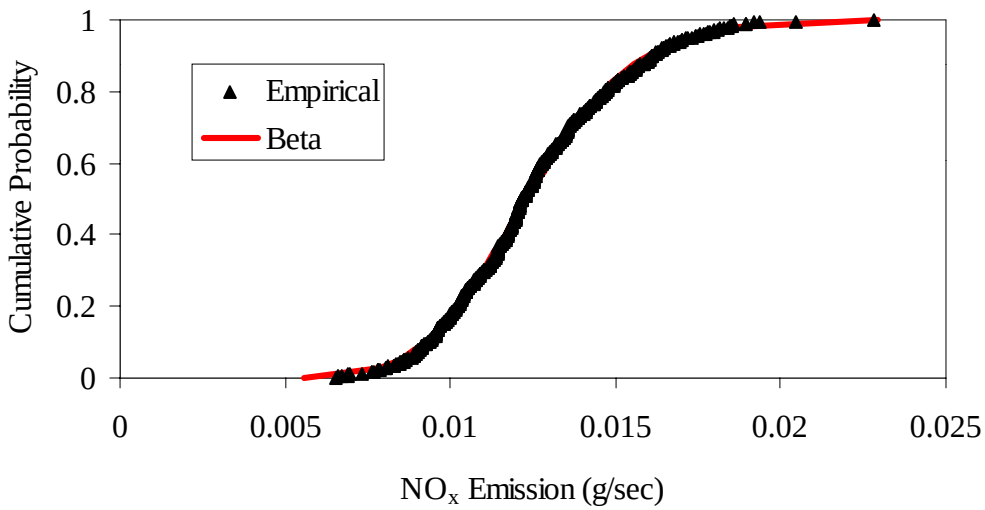

Figure 7-11. Empirical Distribution of Bootstrap Replications of Mean Values and Fitted Beta Distribution for Uncertainty in the Mean for NO_x Emissions (g/sec) of Mode 12, Odometer Reading < 50,000 miles, Engine Displacement > 3.5 Liters.

Table 7-9. Parameters of Parametric Probability Distribution Fit to the Bootstrap Replications of the Means for Selected Modes, Strata, and Pollutants, Based upon Empirical Bootstrap Simulation

VSP Bin	Odometer reading (miles)	Engine displacement (liters)	Pollutant	Distribution[a]	First Para.	Second Para
12	< 50,000	> 3.5	NO_x	Beta	22.275	1761.856
13	< 50,000	> 3.5	NO_x	Beta	3.431	96.093
13	< 50,000	> 3.5	CO	Gamma	25.328	0.029
14	< 50,000	> 3.5	NO_x	Beta	10.482	511.286
14	< 50,000	> 3.5	HC	Beta	25.413	3911.552
14	< 50,000	> 3.5	CO_2	Weibull	17.169	39.735
14	< 50,000	> 3.5	CO	Normal	0.895	0.191
14	> 50,000	> 3.5	NO_x	Beta	42.992	595.202
14	> 50,000	> 3.5	HC	Beta	21.873	805.28
14	> 50,000	> 3.5	CO_2	Weibull	18.658	33.446
14	> 50,000	> 3.5	CO	Gamma	36.591	0.058

[a] Beta: first parameter is α, second parameter is β; gamma: first parameter is γ, second parameter is λ; Weibull: first parameter is k, second parameter is c; Normal: first parameter is μ, second parameter is σ.

The parametric distributions fit to the bootstrap replications of the means generally offered an excellent fit. The use of parametric distributions to describe uncertainty in the mean offers the key advantage of compactness and eliminates the requirement to save the bootstrap replications of the mean. There was one case shown in Table 7-9 for which a normal distribution was found to provide the best fit. However, for the other 10 cases shown, beta, gamma, or Weibull distributions offered the best fit and captured the skewness in the sampling distributions of the mean.

7.4 Uncertainty Correction Factor for Averaging Time

Uncertainty in the mean emission rate based upon a 1-second time period was quantified for each bin. However, the range of uncertainty varies depending upon the averaging time of the data. The objective of this section is to demonstrate how the range of uncertainty varies with averaging time and to demonstrate an approach for adjusting estimates of uncertainty in the mean emission rates for a one second averaging time to other averaging times.

Uncertainty in the mean is related to the Standard Error of Mean (SEM). Therefore, it is convenient to develop a correction factor to adjust the SEM for different averaging times. To evaluate the relative change of the SEM, a correction factor for a t-second time period was defined as Equation (7-6):

$$CF_{t-\sec} = \frac{SEM_{t-\sec}}{SEM_{1-\sec}} \tag{7-6}$$

where: $CF_{t\text{-}sec}$: correction factor for t-second time period, no unit
$SEM_{t\text{-}sec}$: standard error of mean for t-second time period, g/sec
$SEM_{1\text{-}sec}$: standard error of mean for 1-second time period, g/sec

Using a relative correction factor enables a straight-forward adjustment of the uncertainty range for different time periods. For example, if the absolute 95 percent confidence interval of mean for a 1-second period is minus 0.1 gram/sec to plus 0.1 gram/sec, then the absolute 95 percent confidence interval of mean for 5-second period can be calculated as minus $0.1CF_{5\text{-}sec}$ gram/sec to plus $0.1CF_{5\text{-}sec}$ gram/sec. If the correction factor has a value of 2, then the uncertainty in the mean for the 5-second averaging time would be from minus 0.2 g/sec to plus 0.2 g/sec in this example.

In Figures 7-12 to 7-15, for each of four vehicle strata (combinations of odometer reading reading and engine displacement categories), respectively, the relative standard error of the mean (or correction factor defined in Equation 7-6) is plotted with respect to averaging time. The data for this analysis was obtained from the data set used to evaluate 10-second consecutive averages as a basis for model development. For each 10-second averaging time, there are two five-second averages and ten 1-second averages that can be compared in order to evaluate the range of uncertainty for each of these three averaging times. Each graph in each figure displays the standard error of the mean for the five-second averaging time divided by that for the 1-second averaging time, for each of 14 VSP modes. Similar data are shown for the 10-second averaging time. A simplified correction factor was estimated by fitting a polynomial regression through the data in the graphs. Although the analysis could be extended to averaging times longer than 10

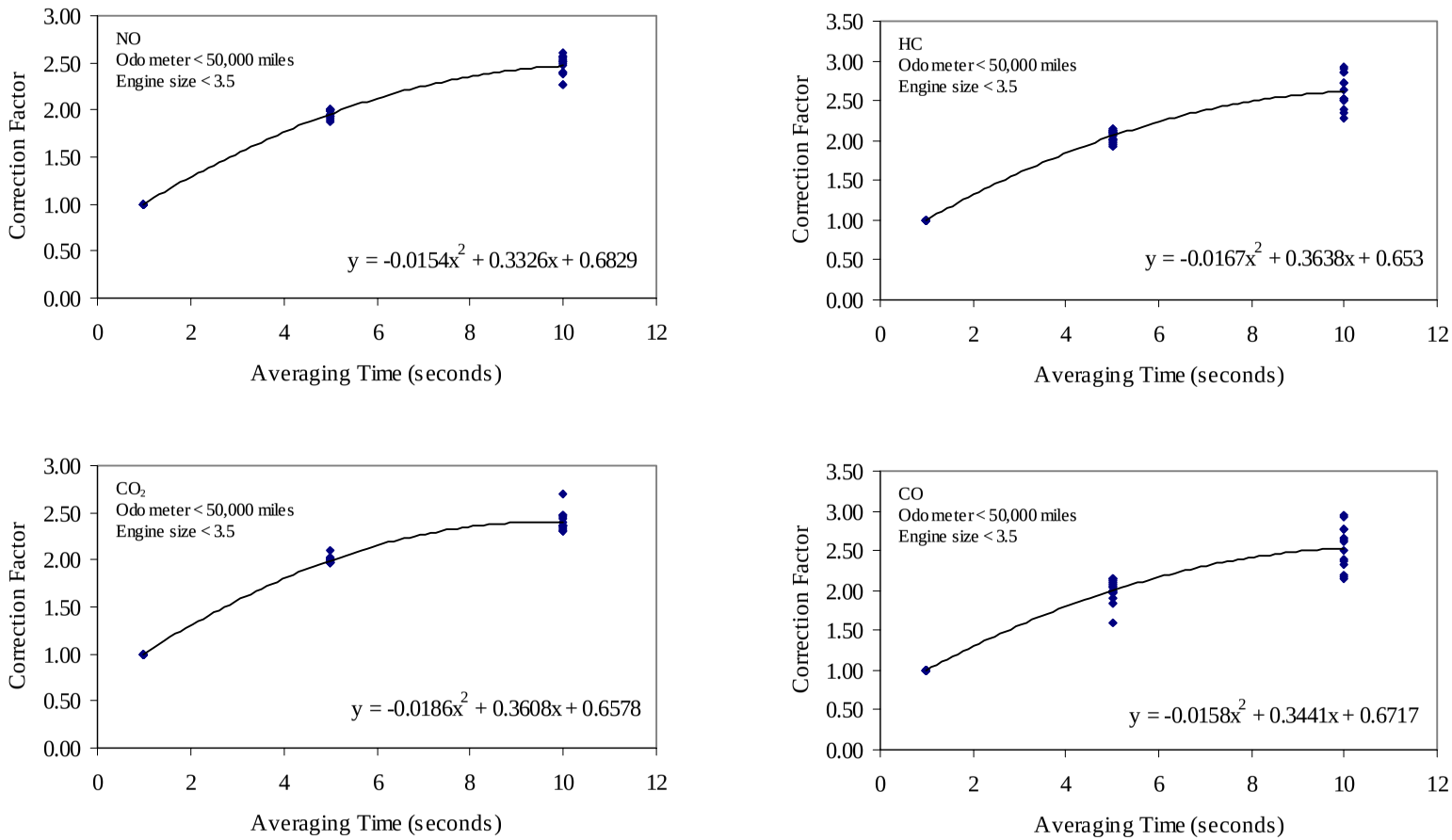

Figure 7-12. Estimation of Correction Factors for the Relative Standard Error of the Mean (SEM/Mean) Versus Averaging Times of 1, 5, and 10 seconds for NO_x, HC, CO_2, and CO Emissions (g/sec) for Odometer Reading < 50,000 Miles and Engine Displacement < 3.5 Liters.

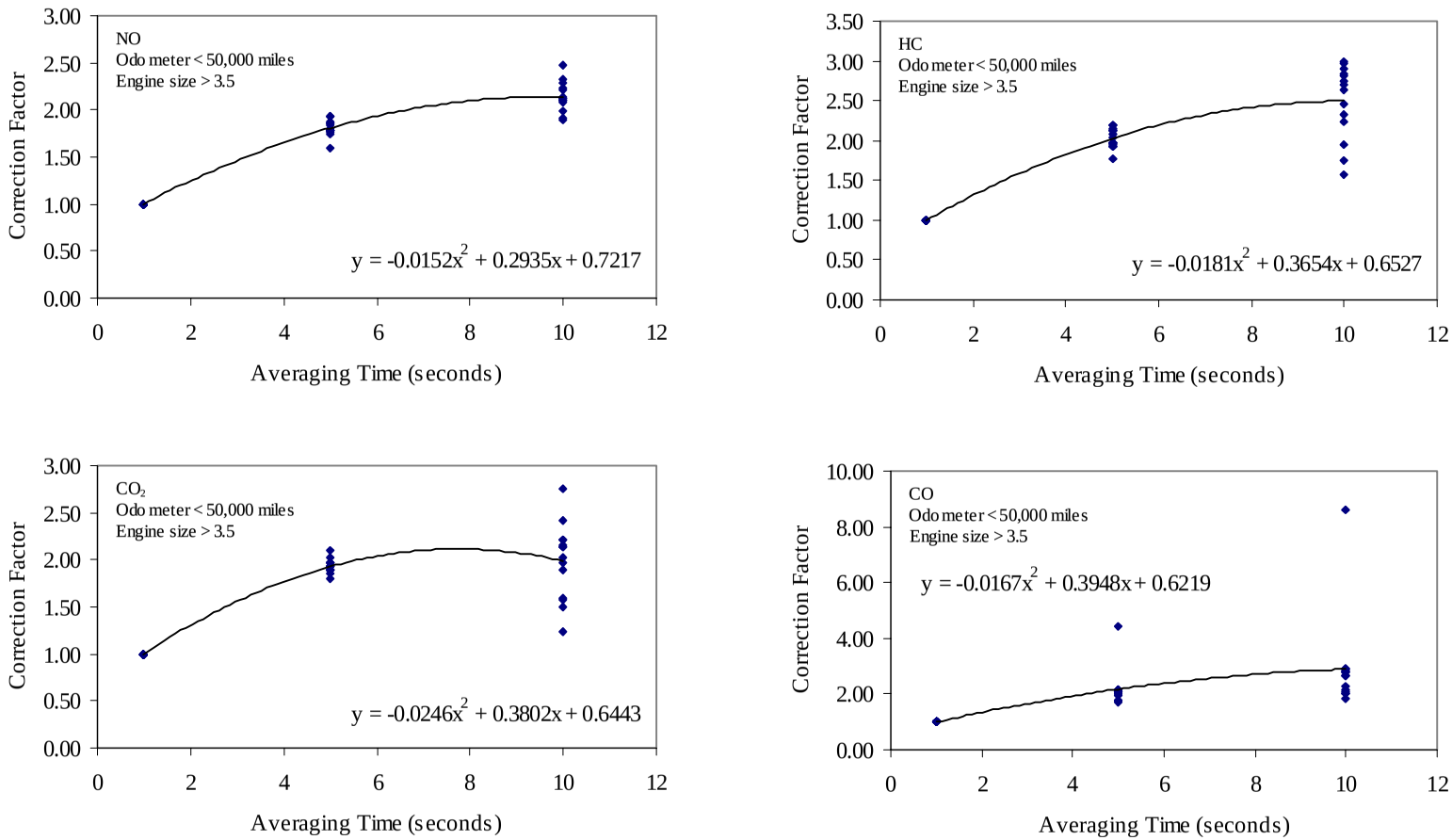

Figure 7-13. Estimation of Correction Factors for the Relative Standard Error of the Mean (SEM/Mean) Versus Averaging Times of 1, 5, and 10 seconds for NO_x, HC, CO_2, and CO Emissions (g/sec) for Odometer Reading < 50,000 Miles and Engine Displacement > 3.5 Liters.

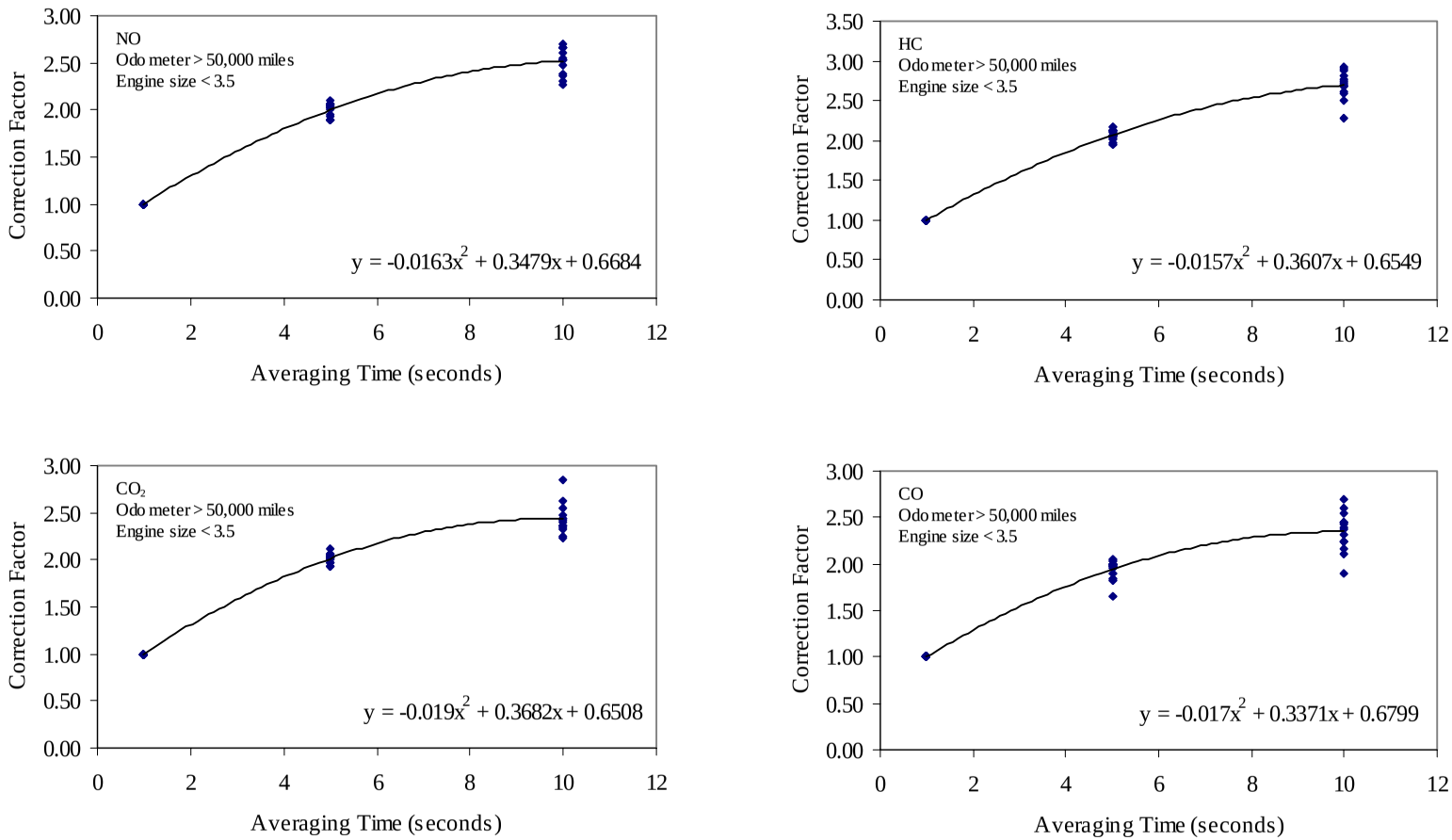

Figure 7-14. Estimation of Correction Factors for the Relative Standard Error of the Mean (SEM/Mean) Versus Averaging Times of 1, 5, and 10 seconds for NO_x, HC, CO_2, and CO Emissions (g/sec) for Odometer Reading > 50,000 Miles and Engine Displacement < 3.5 Liters.

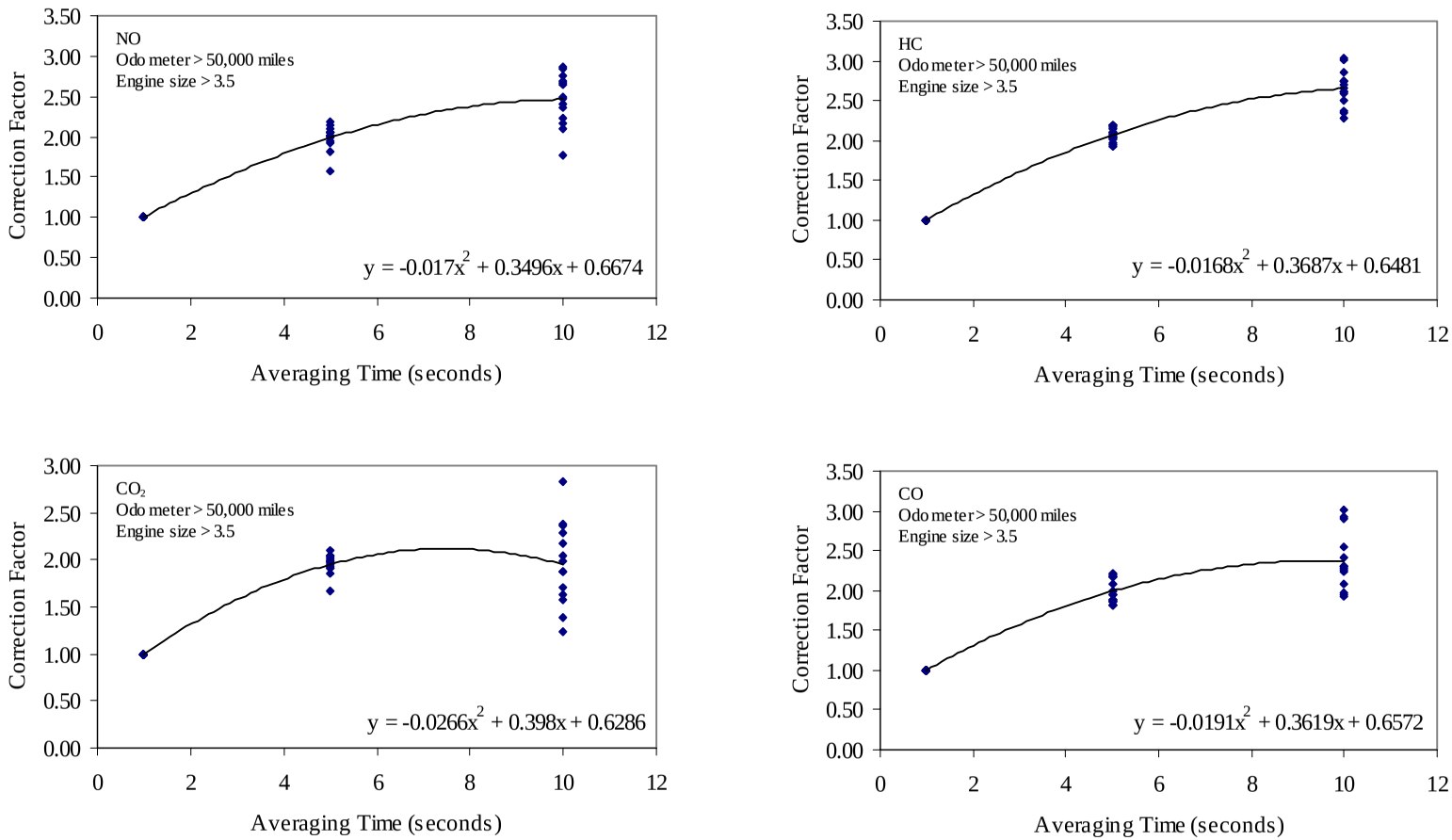

Figure 7-15. Estimation of Correction Factors for the Relative Standard Error of the Mean (SEM/Mean) Versus Averaging Times of 1, 5, and 10 seconds for NO_x, HC, CO_2, and CO Emissions (g/sec) for Odometer Reading > 50,000 Miles and Engine Displacement > 3.5 Liters.

seconds, as the averaging time increases, the sample size decreases. Therefore, for demonstration purposes, the largest averaging time considered was ten seconds. As an example, Figure 7-11 shows that the correction factor increases as the averaging time increases. However, the marginal change becomes smaller as the averaging time increases. We hypothesize that the correction factor may reach a plateau or a maximum at some averaging time larger than 10-seconds; however, we also hypothesize that such a plateau or maximum may not be much larger than the correction factor estimated at 10-seconds. Therefore, as an initial estimate pending further analysis in future studies, we suggest that the correction factor applied to averaging times greater than 10-seconds be the same as that for 10 seconds.

Of the 16 graphs shown in Figures 7-12 through 7-15, 14 of them display the same general characteristic of a reduction in the marginal increase in the correction factor as the averaging time increases. For only two cases, which are both for CO_2 emissions for odometer reading and engine displacement strata for which the sample size is relatively small, the correction factor appears to reach a peak at approximately 8 seconds averaging time and decreases from 8 seconds to 10 seconds averaging times. Thus, for these two case, shown in Figures 7-13 and 7-15, the correction factor for the 10 second averaging time is not substantially different from the correction factor for the 5 second averaging time. Although it is possible that the correction factor for these two cases might decrease as averaging time increases beyond 10 seconds, as a conservative assumption the value of the correction factor at 10 seconds is suggested for use for averaging times longer than 10 seconds. For CO as shown in Figure 7-13, there appears to be some data that may represent outliers, leading to an estimate of the correction factor for an individual mode as large as approximately 9.0 for the 10 second averaging time. This potential outlier may be because of a small sample size for that particular mode.

Table 7-10 summarizes the polynomial regression models fit to the data shown in Figures 7-12 through 7-15. Also shown in the table is the value of the correction factor at the 10 second averaging time for each pollutant and each odometer reading and engine displacement strata. These values are recommended for use for averaging times greater than 10 seconds. For NO_x, the correction factors for 10 seconds or greater averaging time range from 2.14 to 2.54 among the four strata. The corresponding ranges for HC, CO_2, and CO are 2.50 to 2.70, 1.99 to 2.43, and 2.35 to 2.90. Thus, a typical value of these correction factors at 10 seconds or greater averaging time is approximately 2.5, implying that the range of uncertainty for averaging times of 10 seconds or more is a factor of approximately 2.5 greater than that at 1 second. This difference is substantial and illustrates the importance of properly accounting for averaging time when performing uncertainty analysis.

As observed in Figures 7-12 through 7-15, there is variability in the value of the correction factor at the 10 second averaging time when comparing results for each of the 14 modes. It was hypothesized that perhaps a portion of the inter-mode variability in the correction factor for a given averaging time could be explained based upon VSP. Therefore, the values of the correction factors at 10 seconds were normalized with respect to the average correction factor at 10 seconds (as shown in the last four columns of Table 7-10), and the normalized correction factors, which are described here as “bin adjustment factors,” were plotted versus mode as shown in Figures 7-16 through 7-19 for four different odometer reading and engine displacement strata.

Table 7-10. Averaging Time Correction Factors for Uncertainty in VSP Bins for NO_x, HC, CO_2, and CO Emissions (g/sec) for Four Strata With Respect to Odometer Reading and Engine Displacement.

Strata[a]	< 10 seconds[b]				> 10 seconds			
	NO_x	HC	CO_2	CO	NO_x	HC	CO_2	CO
11	$y = -0.0154x^2 + 0.3326x + 0.6829$	$y = -0.0167x^2 + 0.3638x + 0.653$	$y = -0.0186x^2 + 0.3608x + 0.6578$	$y = -0.0158x^2 + 0.3441x + 0.6717$	2.47	2.62	2.40	2.53
12	$y = -0.0152x^2 + 0.2935x + 0.7217$	$y = -0.0181x^2 + 0.3654x + 0.6527$	$y = -0.0246x^2 + 0.3802x + 0.6443$	$y = -0.0167x^2 + 0.3948x + 0.6219$	2.14	2.50	1.99	2.90
21	$y = -0.0163x^2 + 0.3479x + 0.6684$	$y = -0.0157x^2 + 0.3607x + 0.6549$	$y = -0.019x^2 + 0.3682x + 0.6508$	$y = -0.017x^2 + 0.3371x + 0.6799$	2.52	2.70	2.43	2.35
22	$y = -0.017x^2 + 0.3496x + 0.6674$	$y = -0.0168x^2 + 0.3687x + 0.6481$	$y = -0.0266x^2 + 0.398x + 0.6286$	$y = -0.0191x^2 + 0.3619x + 0.6572$	2.46	2.65	1.95	2.37

[a] 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters; 12: odometer reading < 50,000 miles and engine displacement > 3.5 liters; 21: odometer reading > 50,000 miles and engine displacement < 3.5 liters; 22: odometer reading > 50,000 miles and engine displacement > 3.5 liters.
[b] y, correction factor (no unit), x, time (second)

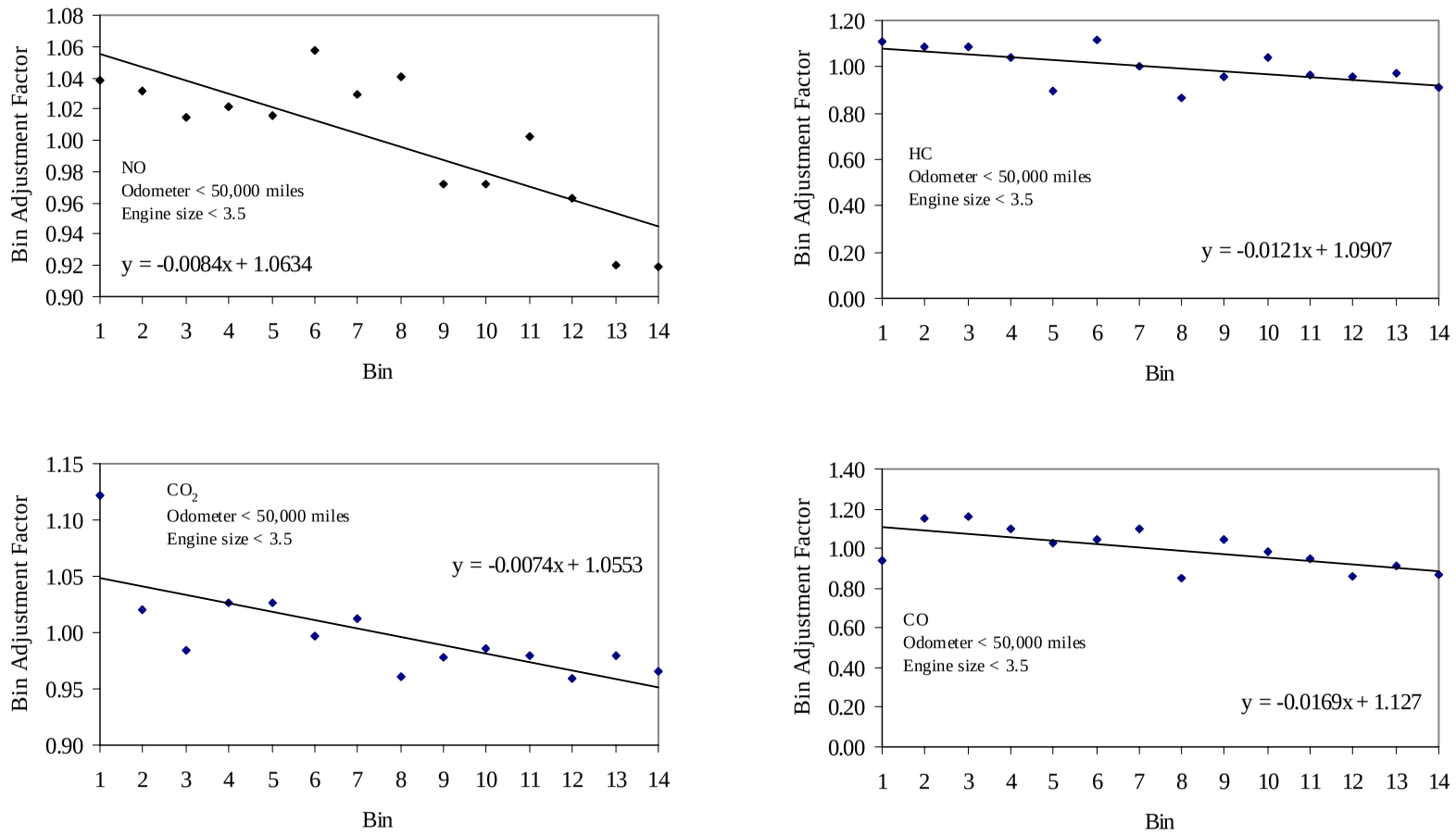

Figure 7-16. Bin Adjustment Factors for the Uncertainty Correction Factor at "≥ 10 seconds" of NO_x, HC, CO_2, and CO for Odometer Reading < 50,000 miles and Engine Displacement < 3.5 Liters.

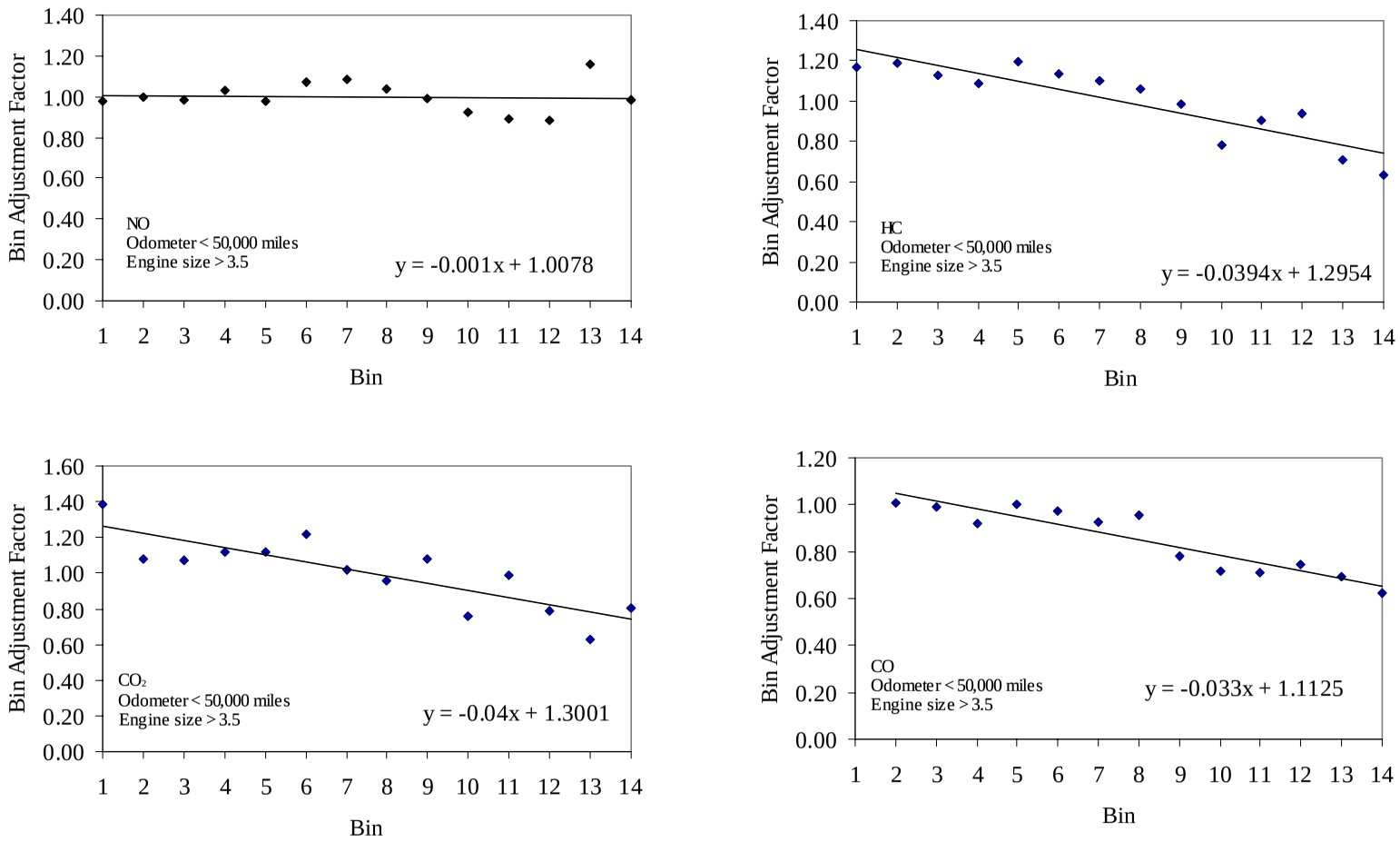

Figure 7-17. Bin Adjustment Factors for the Uncertainty Correction Factor at "≥ 10 seconds" of NO_x, HC, CO_2, and CO for Odometer Reading < 50,000 miles and Engine Displacement > 3.5 Liters.

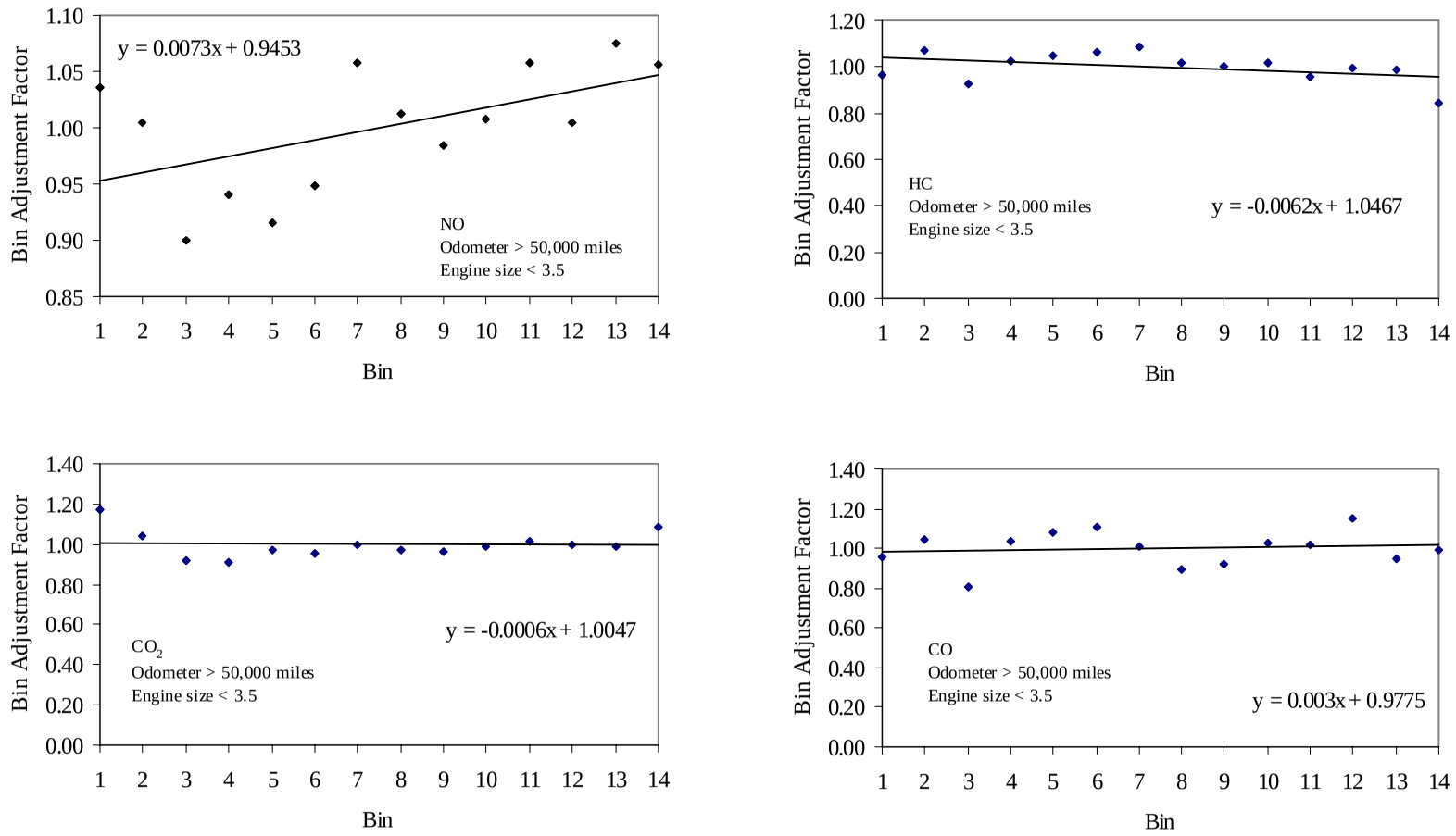

Figure 7-18. Bin Adjustment Factors for the Uncertainty Correction Factor at "≥ 10 seconds" of NO_x, HC, CO_2, and CO for Odometer Reading > 50,000 miles and Engine Displacement < 3.5 Liters.

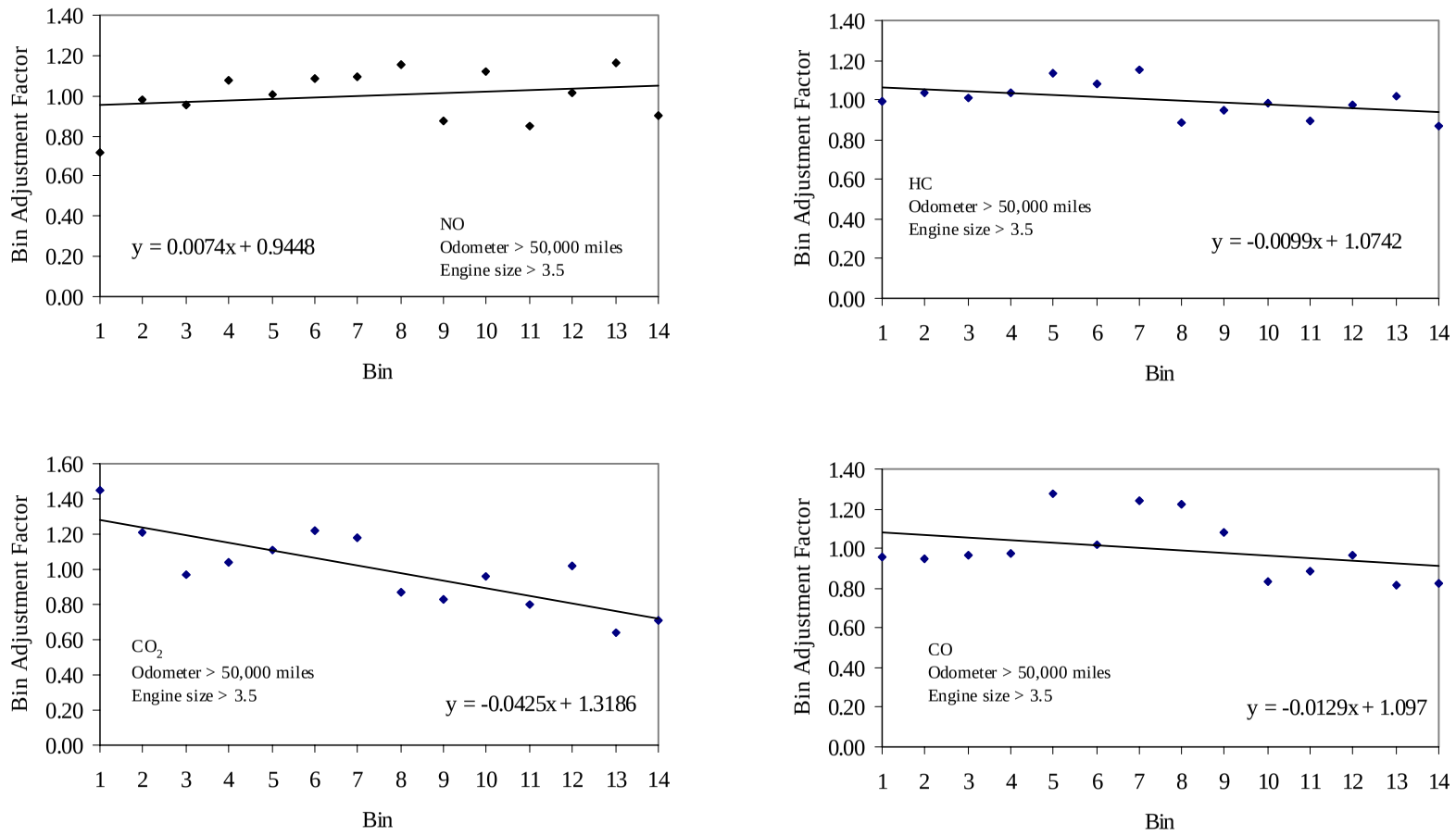

Figure 7-19. Bin Adjustment Factors for the Uncertainty Correction Factor at "≥ 10 seconds" of NO_x, HC, CO_2, and CO for Odometer Reading >50,000 miles and Engine Displacement > 3.5 Liters.

The bin adjustment factor (BAF) for a given bin is given by:

$$BAF_k = \frac{CF_{10-\sec,k}}{ACF_{10-\sec}} \tag{7-7}$$

Where:

BAF_k, Bin Adjustment Factor for Bin k at 10 second;
$CF_{10\text{-}sec,k}$, Correction Factor for Bin t at 10 second;
$ACF_{10\text{-}sec}$, Average Correction Factor for Bin 1 to Bin 14 at 10 second.

The data shown in Figures 7-16 through 7-19 indicate that typically the bin correction factor is smaller for the larger VSP modes than for the lower VSP modes, although there are exceptions. For example, for NO_x emissions for higher mileage vehicles, it appears that the bin correction factor increases as VSP increases. For 13 of the 16 graphs shown in the four figures, the typical range of variation of the bin adjustment factor is approximately plus or minus five percent or less. For vehicles with larger engine displacement, there are three cases in which the range of variation of the bin adjustment factor is approximately plus or minus 20 percent or more, including HC and CO_2 emissions for vehicles with odometer reading less than 50,000 miles and CO_2 for vehicles with odometer reading greater than 50,000 miles. It is possible that this apparent difference for the larger engine vehicles compared to the smaller engine vehicles represents a real difference or possibly it could be an artifact of having smaller sample sizes for the larger engine vehicles. In general, while the linear curve fits capture the overall trends of the data among the 14 modes, it is clear that the variation of the bin adjustment factor with respect to VSP mode is not truly linear in all cases. In future work, it may be worth exploring other curve fits to these data and/or exploring the use of other explanatory variables, such as the mid point value of VSP for each mode instead of the mode number, in order to improve the estimation of the bin adjustment factor.

A summary of the Bin Adjustment Factors developed based upon the data and curve fits shown in Figures 7-16 through 7-19 is given in Table 7-11.

7.5 Estimation of Uncertainty in Model Results

In this section, two methods are evaluated and compared for estimating uncertainty in the total emissions for a trip or driving cycle. These methods include the numerical method of Monte Carlo simulation and an analytical method based upon a linear model and normality assumptions for uncertainty in individual modes. These two methods are illustrated for a case study example of predicting uncertainty in total trip emissions for the IM240 driving cycle. This case study is followed by case studies for uncertainty in total emissions for several different driving cycles and then by a case study for multiple vehicles on a selected driving cycle.

7.5.1 Estimation of Uncertainty in Total Emissions Based Upon the IM240 Driving Cycle: Comparison of Monte Carlo Simulation and Analytical Approaches

This example demonstrates the prediction of total emissions from IM240 cycle. The prediction was based upon quantified uncertainty in VSP modes in which the uncertainty was adjusted for

Table 7-11. Bin Adjustment Factors for Correction Factor of Time Adjustment at "≥ 10 seconds" for NO_x, HC, CO_2, and CO and for Four Odometer Reading and Engine Displacement Strata.

Odometer reading (mile)	Engine displacement (liters)	NO_x[a]	HC[a]	CO_2[a]	CO[a]
< 50,000	< 3.5	y = -0.0084x + 1.0634	y = -0.0121x + 1.0907	y = -0.0074x + 1.0553	y = -0.0169x + 1.127
< 50,000	> 3.5	y = -0.001x + 1.0078	y = -0.0394x + 1.2954	y = -0.04x + 1.3001	y = -0.033x + 1.1125
> 50,000	< 3.5	y = 0.0073x + 0.9453	y = -0.0062x + 1.0467	y = -0.0006x + 1.0047	y = 0.003x + 0.9775
> 50,000	> 3.5	y = 0.0074x + 0.9448	y = -0.0099x + 1.0742	y = -0.0425x + 1.3186	y = -0.0129x + 1.097

[a] y: bin adjustment factor (no unit); x, bin number (from 1 to 14)

averaging time using the correction factors for averaging time adjustment. The standard IM240 cycle contains 240 seconds. The temporal allocation of the IM240 cycle into VSP modes is given in Table 7-12. Most of the time spend in the IM240 cycle is represented by VSP modes 1 through 8. Only 10 seconds are spent in Modes 9 through 11, combined, and no time is spent in the highest VSP modes 12, 13, or 14.

Table 7-12. Allocation of the Standard IM240 Driving Cycle Into VSP Modes With Respect to Time Spent in Each Mode.

VSP Mode Number	Total Seconds
1	41
2	24
3	16
4	37
5	47
6	19
7	29
8	17
9	4
10	3
11	3
12	None
13	None
14	None

Thus, total emissions from IM240 cycle are calculated based upon a sum of emission from each bin, based upon summing the products of the time spent in each mode multiplied by the respective mode average emission rate:

$$\begin{aligned} TE = \; & 41\times EF_{mode1} + 24\times EF_{mode2} + 16\times EF_{mode3} + 37\times EF_{mode4} + \\ & 47\times EF_{mode5} + 19\times EF_{mode6} + 29\times EF_{mode7} + 17\times EF_{mode8} + \\ & 4\times EF_{mode9} + 3\times EF_{mode10} + 3\times EF_{mode11} \end{aligned} \qquad (7\text{-}8)$$

where:

TE: total emissions, g

EF: 1-second based emission factor for each VSP mode (g/sec)

As an illustrative example, uncertainty in total NO_x emissions from the IM240 cycle for a vehicle with odometer reading < 50,000 miles and engine displacement < 3.5 liters was predicted. For Modes 1 through 11 applied to the IM240 cycle for this particular pollutant and vehicle strata, the quantified uncertainty in the 1-second average modal emissions can reasonably be based upon a normality assumption. To estimate uncertainty in total emissions, the quantified uncertainty in the 1-second average emissions of each mode was adjusted based upon the total amount of time spent in the mode using the averaging time correction factor previously described. The input assumptions for prediction of uncertainty in total emissions are given in Table 7-13. These assumptions include the probability distribution assumed for uncertainty in the mean for each mode, the mean modal emission rate, the standard deviation of the distribution for uncertainty in the mean (i.e. the standard error of the mean), the numerical value of the correction factor applied, and the numerical value of the bin adjustment factor applied. For Modes 1 through 8, 10 or more seconds were spent in each mode. Therefore, the correction factor applicable to 10 or more seconds is used for these modes. For Modes 9, 10 and 11, less than 10 seconds were spent in each mode. Therefore, the correction factor was estimated from the polynomial curve fits presented in Table 7-10. For cases in which the averaging time was less than 10 seconds, a bin adjustment factor was not applied. The correction factor and bin adjustment factor were multiplied with the standard deviation of the modal emission rate to arrive at a new standard deviation for the modal emission rate appropriate for the particular averaging time of each mode. For example, for Mode 1, the corrected standard deviation was ($1.97\text{x}10^{-5}$ g/sec) x (2.47) x (1.0248) = $4.99\text{x}10^{-5}$ g/sec.

Monte Carlo simulation was used to propagate uncertainty in each modal emission rate, using Equation (7-8), in order to estimate uncertainty in total emissions. For the Monte Carlo simulation, a sample size of 10,000 was selected. When performing Monte Carlo simulation, the selection of sample size is typically based upon a compromise between the precision of the estimated uncertainty for the model output versus the computational burden. A sample size of 10,000 is not necessary in every case. Smaller sample sizes may provide adequate results. Moreover, other methods aside from Monte Carlo simulation, such as Latin Hypercube Sampling, can be used to obtain precise estimates of the distribution of a model output using smaller sample sizes than required for Monte Carlo simulation. Cullen and Frey (1999) and Morgan and Henrion (1990) provide more discussion on criteria and methods for selecting sample sizes for Monte Carlo simulation and for Latin Hypercube Sampling. The results from Monte Carlo simulation are shown in Table 7-14 and in Figure 7-20.

Table 7-13. Input Assumptions for Prediction of Uncertainty in Total NO_x Emissions for a Cast Study of the IM240 cycle, for Vehicles with Odometer Reading < 50,000 Miles and Engine Displacement < 3.5 Liters.

	NO_x Emission Factor				
Mode Number	Input Distribution	Mean Modal Emission Rate (g/sec)	Standard Deviation of Mean Modal Emission Rate (g/sec)	Correction Factor	Bin Adjustment Factor
1	Normal	0.000901	1.97E-05	2.47	1.025
2	Normal	0.000628	2.04E-05	2.47	1.03
3	Normal	0.000346	9.26E-06	2.47	1.033
4	Normal	0.001173	2.46E-05	2.47	1.033
5	Normal	0.001706	3.56E-05	2.47	1.031
6	Normal	0.002368	5.12E-05	2.47	1.027
7	Normal	0.003103	6.86E-05	2.47	1.02
8	Normal	0.004234	9.44E-05	2.47	1.011
9	Normal	0.005069	0.000141	1.77	None[a]
10	Normal	0.005865	0.00017	1.54	None[a]
11	Normal	0.007623	0.000301	1.54	None[a]

[a] no Bin Adjustment Factor is needed because time period is smaller than 10 seconds.

Table 7-14. Example Prediction of Uncertainty in Total Emissions for NO_x Emissions From the IM240 Cycle for Vehicles with Odometer Reading < 50,000 Miles and Engine Displacement < 3.5 Liters Based upon Monte Carlo Simulation

Cycle		IM240
Vehicle		Odometer reading < 50,000 miles, engine displacement < 3.5 liters
Pollutant		NO_x
mean[a, b]		0.45 g
Absolute 95% CI[a, b]	Lower	-0.02 g
	Upper	0.02 g
Relative 95% CI[a, c]	Lower	-4.4 %
	Upper	4.4 %

[a] based upon Monte Carlo Simulation results of 10,000 runs
[b] unit: gram
[c] unit: %

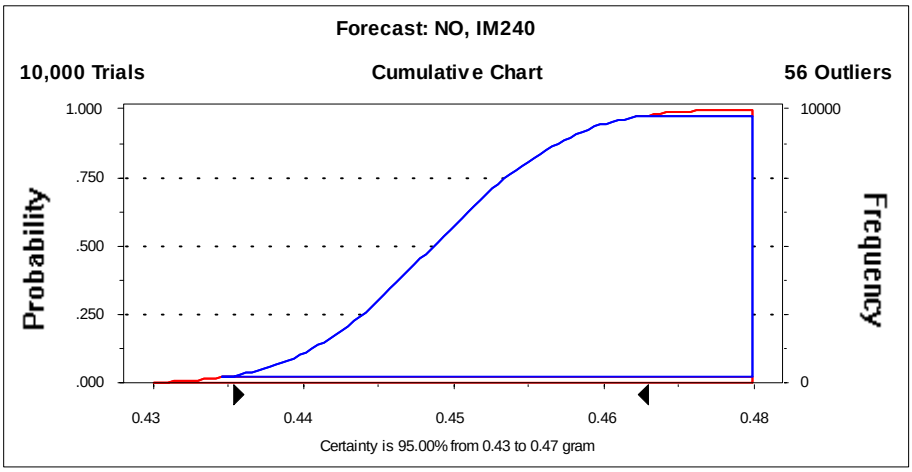

Figure 7-20. Quantified Uncertainty in Total NO_x Emissions from the IM240 Cycle for Vehicles with Odometer Reading < 50,000 Miles and Engine Displacement < 3.5 Liters Based upon Monte Carlo Simulation.

The results from the Monte Carlo simulation are a total NO_x emissions mean estimate of 0.45 grams with a 95 percent range of uncertainty of plus or minus 0.02 grams, or plus or minus 4.4 percent of the mean. In this particular case, even with the correction factor for averaging time adjustment and the bin adjustment factor applied to each mode, the range of uncertainty in the estimated average total emissions was sufficiently narrow that a normality assumption would be justifiable.

As an alternative to Monte Carlo simulation, an analytical solution was developed. For a linear model and for an assumption of normality for uncertainty in each modal emission rate, the uncertainty in the total emissions can be estimated as follows:

$$U_{total} = \sqrt{\sum_{i}^{n} (U_i \times W_i)^2} \tag{7-9}$$

Where:

U_{total}: Uncertainty in the sum of the quantities (i.e. half the 95% CI)
U_i: Uncertainties associated with each quantity, (i.e. half the 95% CI)
W_i: Weight associated with each quantity

The weight is the fraction of total time spent in each mode. The analytical solution for the IM240 cycle is that the average total emissions are 0.45 grams and the uncertainty is approximate minus or plus 0.018 grams for a 95% confidence interval, corresponding a relative range of minus or plus 4 percent, which is similar to numerical simulation results.

The analytical method offers the advantage of reduced computing resources required to estimate total uncertainty in emissions, when compared to the Monte Carlo simulation approach. However, the analytical method is limited to situations in which there are a linear combination of normal distributions. Therefore, if in the future there was a need to include uncertainty in not

Table 7-15. Allocation of the ART-EF, IM240, FTP (Bags 2 and 3) and US06 Driving Cycles Into VSP Modes With Respect to Time Spent in Each Mode.

VSP Mode	Seconds Spent in Each Mode by Driving Cycle			
	ART-EF	IM240	FTP	US06
1	85	41	201	113
2	51	24	119	19
3	196	16	336	69
4	66	37	294	26
5	40	47	212	40
6	31	19	105	55
7	18	29	60	64
8	10	17	27	61
9	5	4	8	45
10	2	3	5	56
11		3	3	32
12				9
13				21
14				11

only the modal emission rate but also in the fraction of time spent it each mode, the analytical method presented here would not be applicable. Cullen and Frey (1999) provide an overview of approximate analytical methods for propagating the standard deviation of distributions for model inputs through a model in order to estimate the standard deviation of the model output.

7.5.2 Estimation of Uncertainty in Total Emissions of Selected Driving Cycles

In this section, uncertainty estimates are developed for total emissions of NO_x, HC, CO_2, and CO for four selected driving cycles, including ART-EF, IM240, FTP, and US06. These four cycles represent different ranges of VSP and of total emissions. The uncertainty in total emissions was quantified using the analytical method explained in the previous section. The distribution of the total time of each cycle by VSP mode is given in Table 7-15. For the ART-EF cycle, over 90 percent of the total cycle time is spent in Modes 1 through 6, and there is no representation of Modes 11 through 14. As previously discussed, for the IM240 cycle most of the activity occurs in Modes 1 through 8. The FTP is similar to the IM240 cycle in that most of the time is spent in Modes 1 through 8. The US06 cycle is more widely distributed over the 14 modes compared to the other three cycles.

The results of the uncertainty analysis for the IM240, ART-EF, FTP, and US06 cycles are shown in Tables 7-16 through 7-19, respectively. Each table shows results for the mean total emissions, absolute uncertainty, and relative uncertainty for NO_x, HC, CO_2, and CO and for four strata based upon odometer reading and engine displacement.

Table 7-16. Absolute and Relative Uncertainty Estimates for Mean Total Emissions of NO_x, HC, CO_2, and CO for Four Odometer Reading and Engine Displacement Tier 1 Vehicle Strata for the IM240 Cycle.

Odometer reading (mile)	Engine displacement (liters)	NO_x			HC			CO_2			CO		
		Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]
< 50,000	< 3.5	0.45	0.018	4.0	0.14	0.0079	5.6	660	5.3	0.79	3.3	0.35	11
< 50,000	> 3.5	0.35	0.042	12	0.24	0.061	25	841	14	1.6	7.9	1.9	24
> 50,000	< 3.5	0.68	0.030	4.3	0.33	0.018	5.5	728	6.8	0.93	4.6	0.35	7.7
> 50,000	> 3.5	1.3	0.15	11	0.32	0.083	26	962	12	1.3	11	2.7	25

[a] total emissions, grams
[b] absolute upper and lower limits, grams
[c] relative upper and lower limits, %

Table 7-17. Absolute and Relative Uncertainty Estimates for Mean Total Emissions of NO_x, HC, CO_2, and CO for Four Odometer Reading and Engine Displacement Tier 1 Vehicle Strata for the ART-EF Cycle.

Odometer reading (mile)	Engine displacement (liters)	NO_x			HC			CO_2			CO		
		Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]
< 50,000	< 3.5	0.53	0.021	3.9	0.24	0.015	6.3	969	8.2	0.85	4.0	0.41	10
< 50,000	> 3.5	0.34	0.040	12	0.18	0.040	23	1176	19	1.7	8.8	2.3	26
> 50,000	< 3.5	0.77	0.032	4.2	0.54	0.037	6.9	1025	11	1.0	5.8	0.44	7.7
> 50,000	> 3.5	1.3	0.13	9.8	0.37	0.12	31	1318	21	1.6	11	3.1	30

[a] total emissions, grams
[b] absolute upper and lower limits, grams
[c] relative upper and lower limits, %

Table 7-18. Absolute and Relative Uncertainty Estimates for Mean Total Emissions of NO_x, HC, CO_2, and CO for Four Odometer Reading and Engine Displacement Tier 1 Vehicle Strata for the FTP (Bags 2 and 3) Cycle.

Odometer reading (mile)	Engine displacement (liters)	NO_x			HC			CO_2			CO		
		Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]
< 50,000	< 3.5	1.7	0.069	4.0	0.67	0.038	5.7	2997	25	0.84	13	1.4	11
< 50,000	> 3.5	1.1	0.13	11	0.73	0.17	23	3640	55	1.5	27	6.5	24
> 50,000	< 3.5	2.5	0.11	4.3	1.5	0.097	6.2	3209	33	1.0	18	1.5	8.0
> 50,000	> 3.5	4.6	0.46	9.9	1.1	0.30	27	4123	56	1.4	33	7.8	24

[a] total emissions, grams
[b] absolute upper and lower limits, grams
[c] relative upper and lower limits, %

Table 7-19. Absolute and Relative Uncertainty Estimates for Mean Total Emissions of NO_x, HC, CO_2, and CO for Four Odometer Reading and Engine Displacement Tier 1 Vehicle Strata for the US06 Cycle.

Odometer reading (mile)	Engine displacement (liters)	NO_x			HC			CO_2			CO		
		Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]	Total Emis.[a]	Abs. Lmt.[b]	Rel. Lmt.[c]
< 50,000	< 3.5	2.3	0.15	6.5	0.72	0.094	13	2334	27	1.2	35	5.6	16
< 50,000	> 3.5	2.4	0.63	27	0.93	0.22	24	3395	60	1.8	72	20	28
> 50,000	< 3.5	3.2	0.16	5.1	1.3	0.076	5.9	2512	26	1.0	35	5.3	15
> 50,000	> 3.5	7.3	1.3	17	2.1	0.54	26	3827	51	1.3	117	30	26

[a] total emissions, grams
[b] absolute upper and lower limits, grams
[c] relative upper and lower limits, %

The relative range of uncertainty, on a percentage basis in comparison to the mean total emissions, is similar for the four cycles for a given pollutant and strata in most cases. For example, for vehicles with odometer reading less than 50,000 miles and engine displacement less than 3.5 liters, the relative uncertainty range is approximately 4 to 7 percent for NO_x, 6 to 13 percent for HC, one percent for CO_2 and 10 to 16 percent for CO when comparing all four driving cycles. Within these ranges, the US06 cycle tends to have larger relative uncertainty compared to the other three cycles. For example, for the same vehicle strata, the uncertainty in NO_x emissions for the US06 cycle is plus or minus 7 percent compared to only plus or minus 4 percent for the IM240, ART-EF, and FTP cycles. The uncertainty estimates for the US06 cycle are larger than for the other three cycles for NOx for all strata and for CO for strata 11 (<50,000 miles, < 3.5 liters) and 21 (>50,000 miles, <3.5 liters).

Setting aside the differences between the US06 and the other cycles, the typical ranges of uncertainty also vary by strata, with smaller ranges of uncertainty for those strata for which there are more data. These include the strata for engine displacement less than 3.5 liters for both odometer reading ranges. For these two strata, a typical range of uncertainty is plus or minus 4 percent for NO_x, plus or minus 6 percent for HC, plus or minus 1 percent for CO_2, and plus or minus 10 percent for CO. For the larger engine displacement strata for both odometer reading ranges, the typical ranges of uncertainty are plus or minus 10 percent for NO_x, plus or minus 25 percent for HC, plus or minus 2 percent for CO_2, and plus or minus 25 percent for CO. The uncertainty ranges are typically narrowest for CO_2.

The relative uncertainty ranges in NO_x emissions are typically larger than that for CO_2 but less than that for HC and CO. The relative uncertainty ranges for HC and CO are comparable to each other in most cases. Thus, the key insights are that: (1) the amount of uncertainty appears to increase as the average VSP or range of VSP of a cycle increases; (2) the amount of uncertainty is a function of sample size; and (3) the relative amount of uncertainty is smallest for CO_2, largest for both HC and CO, and in between for NO_x. Furthermore, the relative range of uncertainty for these particular cycles is as small as only one or two percent for CO_2 and as large as 30 percent or more for HC and CO. Thus, in some cases, the range of uncertainty in total emissions is substantial.

The uncertainty estimates presented in this section represent uncertainty in total emissions for a single vehicle of a given odometer reading and engine displacement. In order to estimate uncertainty in total emissions for a fleet of vehicles, these estimates can be multiplied by the total number of vehicles operated on each activity pattern for each strata. For example, suppose that 100 vehicles of odometer reading less than 50,000 miles and engine displacement less than 3.5 liters were operated on an activity pattern similar to the US06 cycle. The total emissions and the relative range of uncertainty would be 230 g ± 6.5% for NO_x, 72 g ± 13% for HC, 233,400 g ±1.2% for CO_2, and 3,500 g ± 16% for CO. Suppose in addition that there were 100 vehicles in each of the other three odometer reading and engine displacement strata. In this case, the results would be be 1,520 g ± 9.6% for NO_x, 505 g ± 12% for HC, 1,207,000 g ±0.7% for CO_2, and 25,900 g ± 14% for CO. Of course, the method for estimating uncertainty in total emissions can be expanded to account for the sum of total emissions and uncertainty in total emissions when different vehicles are operating on different activity patterns.

7.5.3 Estimation of Uncertainty in Total Emissions for Different Numbers of Vehicles

The purpose of this section is to illustrate that the relative range of uncertainty in total emissions for a particular activity pattern is not a function of the number of vehicles operating on that pattern for a given strata. As a case study, the mean total emissions and the uncertainty in the mean total emissions was estimated for 13 vehicles operating on the ART-EF cycle. In this case study, the inter-vehicle variability in the speed traces for each test is taken into account. The allocation of the second-by-second emission data from the driving cycle tests into VSP modes is summarized in Table 7-20. Although on average the distribution of modes among the 13 vehicles is similar to the distribution of modes for the standard ART-EF cycle as shown in Table Table 7-15, there is variability in the amount of time spent in each mode from one test to another. For example, for 12 of the tests the amount of time spent in Mode 3 varied from 191 seconds to 211 seconds, while for another test the amount of time spent in this mode was 253 seconds. For comparison, the standard ART-EF speed trace has 196 seconds in Mode 3. Thus, it is the case that individual tests do not exactly reproduce the standard speed trace.

As an example, the uncertainty in total NOx emissions were quantified for the 13 vehicles taking into account inter-vehicle variability in the speed traces and uncertainty in the emission rate for each individual mode. The average estimate of mean total NO_x emission from the 13 vehicles, based upon Monte Carlo simulation with 10,000 replications, is 7.11 grams. The quantified absolute 95% confidence interval is from 6.84 gram to 7.38 gram, corresponding to a relative range of minus 3.8 percent to plus 3.8 percent. The CDF of the quantified uncertainty in the mean total emissions is shown in Figure 7-21.

The relative range of uncertainty of plus or minus 3.8 percent is influenced in part by the variability in the distribution of the modes among the 13 vehicles because of the variability in the speed traces for each test. From the previous section, the uncertainty estimated based upon the standard speed trace for the same strata of vehicles was plus or minus 3.9 percent. The difference in the relative range of uncertainty of 0.1 percent is most likely attributable to the role of inter-vehicle variability in the speed traces. Therefore, these results illustrate that the relative range of uncertainty in mean total emissions is relatively insensitive to the number of vehicles tested or for which predictions are being made, even though there may be some inter-vehicle variability in the speed traces.

7.6 Summary and Recommendations

This chapter has demonstrated several key issues pertaining to quantification of variability and uncertainty in vehicle emissions estimates. With regard to characterization of variability, the key points addressed in this work include the following:

- Single component distributions are often useful and reasonably accurate for estimating inter-vehicle variability in emissions for most modes and vehicle strata, but they do not work well for all modes and vehicle strata;
- Single component distributions whose parameters are estimated using Maximum Likelihoood Estimation (MLE) can have means and standard deviations that are substantially different from that of the data;

Table 7-20. Allocation of the Actual ART-EF Driving Cycle Speed Traces Into VSP Modes With Respect to Time Spent in Each Mode for 13 Different Vehicles

VSP bin[a]	Vehicle ID												
	#7	#10	#11	#15	#18	#21	#22	#26	#27	#39	#42	#48	#50
1101	74	64	74	75	68	71	73	71	67	54	72	73	61
1102	54	67	55	45	51	53	59	57	62	50	56	56	69
1103	206	198	200	202	211	206	202	200	202	253	202	199	191
1104	42	66	51	62	56	52	50	56	60	55	56	54	99
1105	43	33	41	50	38	47	34	45	36	40	42	39	47
1106	42	35	38	31	36	34	42	29	32	24	38	40	16
1107	19	17	20	16	18	19	24	19	22	4	15	22	10
1108	8	10	12	8	10	8	7	12	9	11	9	8	5
1109	8	6	7	7	9	5	7	8	6	2	6	4	2
1110	6	4	3	6	5	7	4	5	4	2	6	6	2
1111		2	1						2	4		1	
1112										2			
1113										2			
1114													

[a] First two digit of VSP Bins: 11: odometer reading < 50,000 miles and engine displacement < 3.5 liters

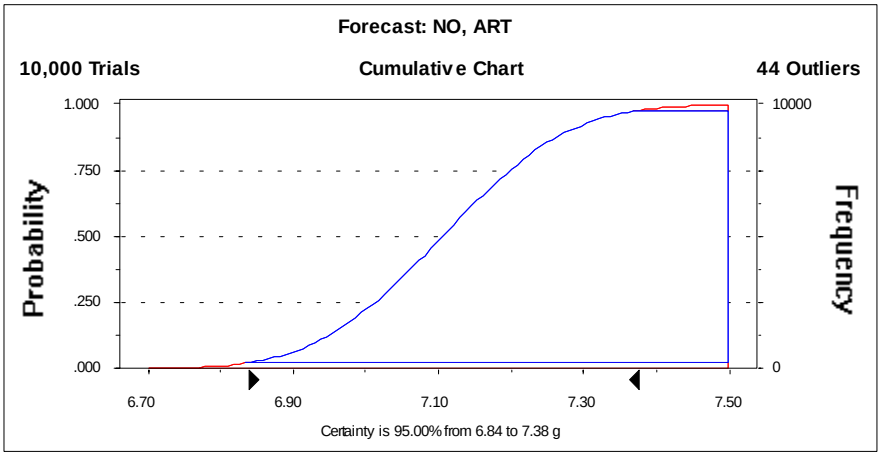

Figure 7-21. Quantification of Uncertainty Based upon Monte Carlo Simulation for Total NO_x Emission from 13 Vehicles Tested on the ART-EF Cycle.

- The mean and standard deviations of fitted distribution can be forced to match those of the data if the Method of Matching Moments (MoMM) is used instead of MLE;
- In specific examples evaluated here, distributions fitted using MoMM appeared to better represent the upper tail of the distribution of emissions for a given mode than did distributions fitted using MLE;
- The distribution of emissions within any given mode is typically positively skewed and for most modes either a lognormal or a Weibull distribution could provide an adequate fit to the data;
- There were a few modes out of 56 for which single component distributions (e.g., lognormal, Weibull) could not provide a good fit to the data;
- Case studies were developed illustrating that two component mixtures of lognormal distributions could be fit to data sets for which a single component distribution was a poor fit, and that the mixture distribution provided an excellent fit to the data.
- For mixture distributions, MLE is a more readily available and easily applied parameter estimation method than MoMM; however, the differences between these two techniques become less important when the fit of the distribution to the data is very good.
- The use of parametric distributions, whether single component or mixtures, was shown to be a feasible approach for characterizing variability.

With regarding to the characterization of uncertainty in mean emissions for specific modes, the main findings of this work are as follows:

- The sample sizes are sufficiently large and/or the relative standard error of the means are sufficiently small, in most cases, so that a normality assumption can be applied for most modes when estimating uncertainty in the mean emission rates;
- The estimation of uncertainty in the mean emission rates can be based directly upon the data and need not be based upon the distributions fitted to the data to represent variability; therefore, any discrepancies between the fitted distributions for variability and the data need not influence the uncertainty analysis;
- For situations in which the sample size is less than 40 or the relative standard error of the mean is greater than 0.2, a more detailed assessment is necessary regarding whether a normality assumption is appropriate for estimating uncertainty in mean modal emission rates;
- The numerical method of bootstrap simulation can be used to estimate the sampling distribution of the mean for situations in which a normality assumptions is suspected to be inaccurate;
- The results of bootstrap simulation may sometimes confirm that a normality assumption is appropriate, or may provide a strong indication that a normality assumption is not appropriate;
- Parametric distributions, such as beta, Weibull, gamma, and lognormal, can be fit well to the distributions of bootstrap replications of the mean in order to compactly represent uncertainty in mean modal emissions even for cases in which a normality assumption is not valid;
- The range of uncertainty in mean modal emission rates is a function of averaging time; therefore, it was necessary to develop an averaging time correction factor in order to

adjust uncertainty estimates developed based upon one second averages to uncertainty estimates applicable for other averaging times;

- When comparing a 10 second average to a 1 second average, the range of uncertainty increases by a factor of approximately 2.5;
- A method was demonstrated for estimating averaging time correction factors; the results of analysis of data from the modeling database suggest that the rate of increase of the correction factor becomes small for an averaging time of 10 seconds; therefore, the correction factor values estimated for the 10 second averaging time are suggested for use for averaging times longer than 10 seconds.
- The averaging time correction factor has some sensitivity to average VSP within a mode; therefore, a "bin adjustment factor" was developed in order to produce a mode-specific refined estimate of the correction factor.

With respect to the estimation of uncertainty in total emissions, the key findings of this work are as follows:

- Monte Carlo simulation is a flexible method for accounting for uncertainty in not just the modal emission rates but also in activity data, such as the percentage of time spent in each mode;
- The computational burden of Monte Carlo simulation depends on the selected sample size for the numerical simulation of uncertainty; the choice of sample size can be made taking into account trade-offs between the precision of the estimate of uncertainty in the model output versus computational time. Furthermore, techniques such as Latin Hypercube Sampling can be used to reduce the sample size for a given level of precision in the estimated distribution for a model output;
- For simple models involving linear combinations of normal distributions, an analytical approach will give an exact solution with relatively little computational burden; however, in order to include uncertainty from activity data in addition to uncertainty in modal emission rates, the analytical approach must be modified to an approximate approach;
- The results obtained from Monte Carlo simulation and from the analytical solution for linear models based upon normality were shown to be equivalent for a case study of estimating uncertainty in total emissions for a standard driving cycle;
- Based upon case studies for four driving cycles, four pollutants, and four vehicle strata, the key insights are that: (1) the amount of uncertainty appears to increase as the average VSP or range of VSP of a cycle increases; (2) the amount of uncertainty is a function of sample size; and (3) the relative amount of uncertainty is smallest for CO_2, largest for both HC and CO, and in between for NO_x. For the specific case studies, the uncertainty range was as narrow as plus or minus 1 percent for CO_2 and as large as plus or minus 30 percent for HC and CO;
- Uncertainty estimates for total emissions of individual vehicles can be aggregated to make estimates of uncertainty in total emissions for a fleet of vehicles;
- Inter-vehicle variability in speed traces for a standardized driving cycle had little influence on the uncertainty estimates for multiple vehicles for the case study of the ART-EF cycle;

- The relative range of uncertainty in total emissions for multiple vehicles is relatively insensitive to the number of vehicles even when there is inter-vehicle variability with respect to a standard speed trace, for the example of the ART-EF cycle.

The recommendations based upon this work include the following with respect to quantification of variability:

- It is feasible to use parametric distributions to represent variability in emissions for specific modes and the use of parametric distributions is preferred over empirical distributions because they represent a more compact method of summarizing variability.
- The Method of Matching Moments appears to be a preferred method for fitting distributions to data because the mean and standard deviation of the fitted distribution will be the same as that of the data and because distributions fitted using MoMM appear to provide a better fit to the upper tail of the distribution, compared to MLE. Therefore, the use of MoMM is recommended for additional evaluation and application.
- Single component distributions such as lognormal and Weibull distributions will typically be able to adequately describe variability for most modes.
- In cases where single component distributions fail to provide an adequate fit, a two component lognormal mixture distribution is recommended as a strong candidate for substantially improving the fit.
- It is not necessary for the uncertainty analysis to be conditioned on the distributions fitted to represent variability within modes; therefore, if there are discrepancies between the fitted distributions and the data, such discrepancies need not introduce any error into the uncertainty analysis.

With respect to quantification of uncertainty in mean modal emission rates, the recommendations based upon this work include the following:

- The development of uncertainty estimates for mean emissions should be based directly upon the data if there are problems in fitting distributions for variability to the data; however, if the fits of the distributions for variability are good, then the uncertainty analysis can be based either upon the data or upon the fitted distributions for variability;
- A normality assumption will typically be adequate for most modal emission rates as long as there are sufficient data;
- For modes for which the sample size is less than 40 and/or the relative standard error of the mean is greater than 0.2, the assumption of normality should be tested by developing a sampling distribution of uncertainty in the mean based upon bootstrap simulation;
- For cases in which a normality assumption is not valid, bootstrap simulation can be used to estimate a distribution of bootstrap replications of the mean, and a parametric distribution such as beta, Weibull, gamma, or lognormal can be fit to the distribution of the means;
- The range of uncertainty in modal emission rates must be adjusted for different averaging times using an approach such as the correction factor and bin adjustment factor approach demonstrated here.

With respect to the quantification of uncertainty in total emissions, the recommendations based upon this work include the following:

- A simple analytical approach for estimating uncertainty in total emissions is adequate as long as the uncertainty in modal emission estimates are normal or approximately normal for most or all of the modes and as long as there is no need to include uncertainty in vehicle activity in the estimate;
- An analytical calculation method based upon normality can be included for comparison purposes even if a Monte Carlo method is also used; for example, results from the analytical method could be used as a quality assurance check on the Monte Carlo simulation results;
- A Monte Carlo simulation-based methods, including variants based upon Latin Hypercube Sampling, is recommended if the objective is to include uncertainty in activity as an input to the estimation of uncertainty in total emissions;
- In situations for which the sample sizes are small and/or the variability in data is large, normality assumptions will not be valid. For such situations, a Monte Carlo-based method is preferable.
- The range of uncertainty is sufficiently large in many cases that a quantitative uncertainty analysis is well-justified.

8 FEASIBILITY OF ESTIMATING MODAL EMISSIONS FROM AGGREGATE BAG DATA

The objective of this task is to evaluate a methodology for deriving modal emission rates from data in which only aggregate emission results are available, in order to answer the key question: How should aggregate bag data be analyzed to derive estimates of modal emission rates? The first section provides background and theory, upon which the analyses in the later sections are based.

8.1 Methodological Overview

In order to estimate modal emission rates, the fraction of time spent in each mode for a driving cycle is estimated based upon the second-by-second speed trace used for the bag measurements (preferably the actual speed trace for the test, as opposed to the nominal speed trace), and any other available information regarding simulation of loads with the dynamometer. A system of equations for the unknown modal emissions, the fraction of time in each mode, and the total (agrgretage) emissions is developed since the average emission rate for each trip can be represented by the fraction of time spent in each mode multiplied by modal emission rate. For example for four different modes for running exhaust emissions, as was the case for the shootout project that was conducted by NCSU, the following equation was specified (Frey, Unal, and Chen, 2002):

$$ER_{cs} \times ft_{cs} + ER_{idle} \times ft_{idle} + ER_{accel} \times ft_{accel} + ER_{decel} \times ft_{decel} + ER_{cruise} \times ft_{cruise} = ER_{ave} \qquad (8\text{-}1)$$

where,

ER_i = emission rate for mode i (g/sec)

ft_i = fraction of time spent in mode i

Subscripts

- cs = cold start mode
- idle = idle mode
- accel = acceleration mode
- decel = deceleration mode
- cruise = cruise mode
- ave = average of all modes

From the bag data, the average emission rate for the entire bag (or trip) can be estimated. From the speed trace, the fraction of time in each mode can be estimated. Therefore, the unknowns are the modal emission rates.

In order to solve systems of equations such as the one given in Equation (8-1), there are different methods. A system where the number of equations used is the same as the number of unknowns is identified as a “square” system, and has unique solutions (Kress, 1998). For “square” systems, an exact solution is sought by using methods such as Gaussian Elimination.

Systems which have a number of equations less than the number of unknowns are identified as “underdetermined” systems, and the solutions of these systems of equations are not unique.

Such systems can be converted to "square" systems by adding additional equations, such as an assumption regarding the ratio of the g/sec emission rate for one mode with respect to another.

Conditions where there are more equations than unknowns are identified as “overdetermined” cases. In these cases, which are likely to be common with respect to the use of existing vehicle emissions bag data, least-squares methods can be used to find solutions (Kress, 1998).

According to Kress (1998), in order to be able to solve linear systems directly, the system should be “well-conditioned”, rather than “ill-conditioned”. “Ill-conditioned” systems occur when small errors in the data of a linear system cause large errors in the solution (Kress, 1998; Hildebrand, 1987). The minimum number of equations (i.e., one equation represents one measurement of bag data) that are desirable in order to have a well-conditioned system will depend on number of unknowns, which is the number of modal “bins” in this case. Techniques for solving well-conditioned over-determined systems include least-squares regression and constrained least-squares. In the latter method, constraints can be included. For example, if it is known that emissions in one mode should be less than that of other modes, this can be added as a constraint in the system. Further, a non-negativity constraint can be included. In this study, both Least-Squares and Constrained Least-Squares were investigated. From the previous study it was observed that Constrained Least-Squares produced good results.

The performance of the modal emission estimation approach based upon aggregate data was evaluated based upon application of the method to second-by-second data. Specifically, the second-by-second data were used to estimate the fraction of time spent in each mode and the total (or trip average) emission rate. The calculation procedure described above was applied to estimate the modal emission rates. The estimated modal emission rates were compared to the actual modal emission rates. Uncertainty in the predictions of the solution technique were characterized by evaluating the distribution of the differences between the predicted modal emission rates and the actual modal emission rates. Ideally, if the solution method is unbiased, the average difference between the predicted and actual modal emission rates will be zero. If the average difference is not zero, then there is a bias. The magnitude of the bias was evaluated to determine whether it was significant. The uncertainty in the modal emission estimates obtained from the bag (aggregate) data must be considered in the uncertainty analysis of the emissions model if these modal emission estimates are used in the model.

8.2 Bag-Based Modal Emissions Estimation for Four Modes (Idle, Acceleration, Cruise, Deceleration) and for 14 VSP Modes

The objective of this portion of the work was to develop a methodology for deriving modal emission rates from data in which only aggregate emission results are available. The method was first applied to relatively simple modal emission models, including the four basic modes of idle, acceleration, cruise, and deceleration defined by NCSU in previous work and the 14 VSP modes defined in this project. The generic equation underlying the estimation process can be specified as:

$$ER_1 * ft_1 + \ldots + ER_i * ft_i + \ldots + ER_n * ft_n = ER_{avg} \qquad (8\text{-}2)$$

Where,

ER_i : emission rate for mode I (g/sec)
ft_i : fraction of time spent in mode i

Subscripts:

i: mode i
n: total number of modes
avg: average of all modes

From the bag data, the average emission rate for the entire bag (or trip) can be estimated. From the speed trace, the fraction of time in each mode can be estimated. Therefore, the unknowns are the modal emission rates.

Initially, tests of the method were done on two preliminary versions of modal definitions, including the four original NCSU based bins and the 14 VSP based bins developed in this project. The NCSU approach is comprised of four driving modes: idle, acceleration, deceleration, cruise, which are assigned mode numbers from 1 to 4 sequentially for purposes of this analysis.

Because the equation above corresponds to one trip and there are hundreds of trips in the data set, the equation is an "overdetermined" square system in which there are more equations than unknown variables. The techniques for solving such systems include least-squares and constrained least-squares as previously discussed. We used both of them and compared their applicability.

The basic assumption of the least squares method is to find a curve that has the minimal sum of the deviations squared (least square error) from a given set of data:

$$\text{Min} \quad y = f_1(x)* f_1(x) + \ldots + f_i(x)* f_i(x) + \ldots + f_m(x)* f_m(x) \qquad (8\text{-}3)$$

Where

$f_i(x) = ft_{i1}* x_1 + \ldots + ft_{ij}* x_j + \ldots + ft_{in}* x_n - ER_{avgi}$
$x_{j:}$ the emission rate of mode j
m: number of trips
n: number of modes
ER_{avgi} : aggregated emission rate for all modes in trip i(g/sec)
Ft_{ij} : fraction of time spent in mode j in trip i

For the constrained least square method, the approach is to solve the above least squares problem additionally with some constraints which may be linear or non-linear equations or inequalities. For example, it is known that emission rates in the acceleration mode should be larger than that in the idle modes, from which, we can assume: $x_{accel} > x_{idle}$. The constrained least squares problem is a special form of Nonlinear Programming, which is one of the classic topics in Operations Research. In the NLP terminology, the previous equation is an objective function which is nonlinear and quadratic.

At first, only simple constraints were used, but results with these were not promising, so strict constraints were created. Hence, there are 3 tests conducted respectively on each pollutant for each binning approach: unconstrained, basic constraints, and strict constraints. The basic

constraints just consider the order of emission rates of all the modes and their non-negative characteristic. For example, the following is the set of basic constraints set for the NCSU approach used in the test:

$$X_2 > X_4 > X_3 > X_1 > 0 \qquad (8\text{-}4)$$

Where $X_{2:}$ emission rate of acceleration mode
$X_{4:}$ emission rate of cruise mode
$X_{3:}$ emission rate of deceleration mode
$X_{2:}$ emission rate of idle mode

If the space of the control variables X is not sufficiently focused, it is possible that the estimated optimal value of X* might lie in an area that is infeasible, such as negative values. Thus, the more concentrated the effective space of X is, the more accurate the test results would typically be. Based on this, strict constraints were developed. To develop the strict constraints, the emission rates of each mode for each trip were calculated as ratios with respect to the smallest emission rate among all the modes, which is idle in the case of the NCSU approach, and then statistically summarized over the all the trips to get the means and confidence limits of those ratios. These ratios were used to develop the strict constraints.. The strict constraints also include either explicitly or implicitly the basic constraints set. Since the form of the latter was shown above, here just the additional strict constraints are displayed:

$$a * X_1 < X_i < b * X_1 \qquad (8\text{-}5)$$

where $X_{1:}$ the lowest emission rate among all the modes
a: the low bound of confidence limits for ratio X_i / X_1 (confidence=0.05)
b: the high bound of confidence limits of ratio X_i / X_1 (confidence=0.05)

Below is an example of complete strict constraints set for HC emissions based upon NCHRP data under the NCSU bin approach:

$$X_2 > X_4 > X_3 > X_1 > 0 \qquad (8\text{-}6)$$
$$56.5 * X_1 < X_2 < 73.4 * X_1$$
$$1.8 * X_1 < X_3 < 7.1 * X_1$$
$$3.6 * X_1 < X_3 < 13.3 * X_1$$

Where $X_{2:}$ emission rate of acceleration mode
$X_{4:}$ emission rate of cruise mode
$X_{3:}$ emission rate of deceleration mode
$X_{2:}$ emission rate of idle mode

The SAS mathematical programming software was used to solve the above NLP problem. The test was done based upon the NCHRP data set, which has more than one hundred trips and 92,000 observations. The results are shown in Tables 8-1 through 8-4 for NO_x, HC, CO, and CO_2, respectively. The results are summarized graphically in Figures 8-1 through 8-4 for the same four respective pollutants. The results indicate that for the analysis of only four modes, the accuracy of estimating the average modal emission rates is less than desirable. For example, the

Table 8-1. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for Four NCSU Driving Modes for NO_x: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

Mode	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
Er1	2.84	-12.3	-5.35	0	-1	0.78	-0.72
Er2	65.5	-285	-5.35	28.44	-0.57	34.05	-0.48
Er3	3.18	972.02	304.94	28.44	7.95	3.49	0.1
Er4	22.76	-148.98	-7.54	28.44	0.25	31.81	0.4
Avg. Error			131.4		2.44		0.43

Table 8-2. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for Four NCSU Driving Modes for HC: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

Mode	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
Er1	1.18	28.69	-23.36	0	1	0.49	0.59
Er2	19.7	-207.09	11.51	8.38	0.57	27.54	-0.4
Er3	2.8	295.24	-104.39	8.38	-1.99	3.46	-0.23
Er4	6.58	-12.31	2.87	8.38	-0.27	4.05	0.38
Avg. Error			35.53		0.96		0.4

Table 8-3. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for Four NCSU Driving Modes for CO: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

Mode	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
Er1	20.04	-3561.8	178.74	0	1	1.02	0.95
Er2	2013.96	-3957.6	2.97	688.62	0.66	1345.18	0.33
Er3	77.15	31522	-407.57	688.62	-7.93	152.54	-0.98
Er4	447.11	-6407.3	15.33	688.62	-0.54	636.76	-0.42
Avg. Error			151.15		2.53		0.67

Table 8-4. Results of Estimation of Modal Emission Rates (g/sec) from Aggregate Data for Four NCSU Driving Modes for CO_2: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

Mode	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
Er1	0.89	1.67	0.87	0	-1	0.96	0.07
Er2	5.76	-45.07	-8.82	3.4	-0.41	4.61	-0.2
Er3	0.98	84.78	85.14	3.4	2.46	1.01	0.02
Er4	3.29	-5.87	-2.78	3.4	0.03	3.65	0.11
Avg. Error			24.4		0.97		0.1

Notes for Tables 8-1 through 8-4:

[a] NC: No Constraint

[b] C: Constraint

[c] SC: Strict Constraint

[d] Error: (Predicted-Actual)/Actual

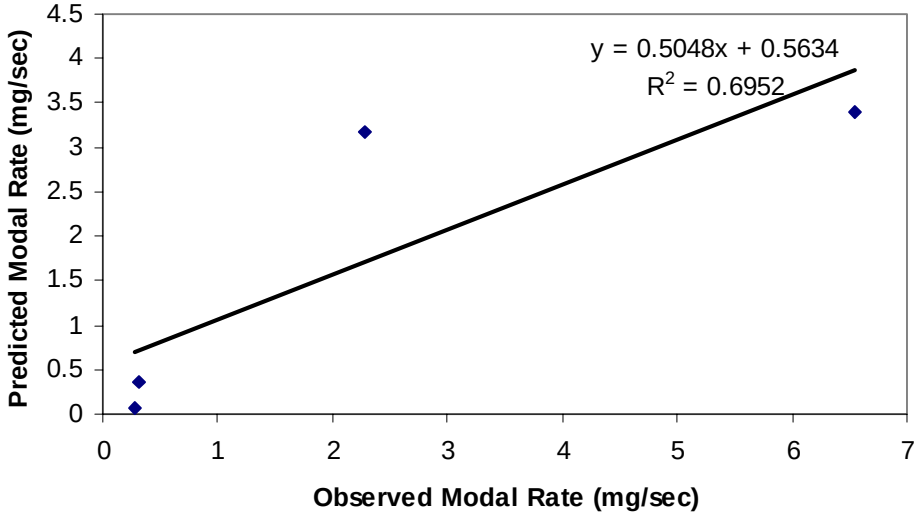

Figure 8-1. Predicted versus Observed NO_x NCSU Modal Emission Rates Estimated From NCHRP Data Using the Strict Constraints Approach.

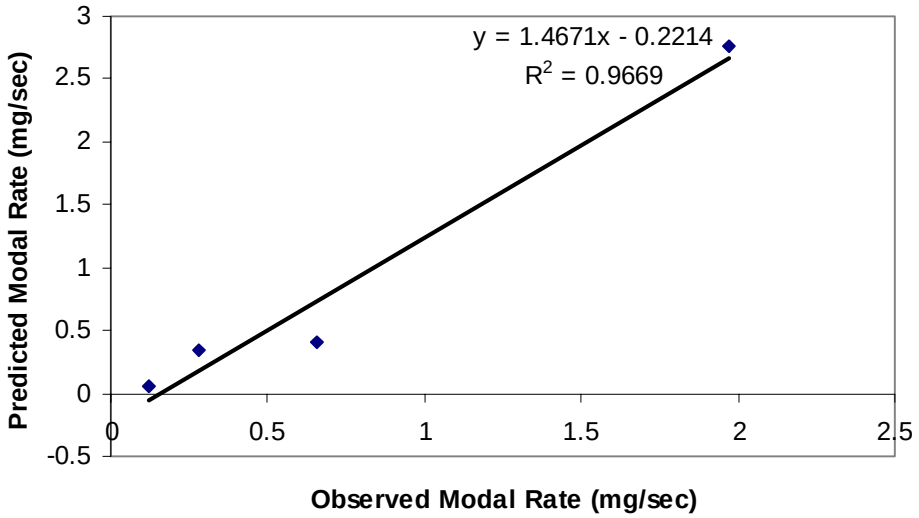

Figure 8-2. Predicted versus Observed HC NCSU Modal Emission Rates Estimated From NCHRP Data Using the Strict Constraints Approach.

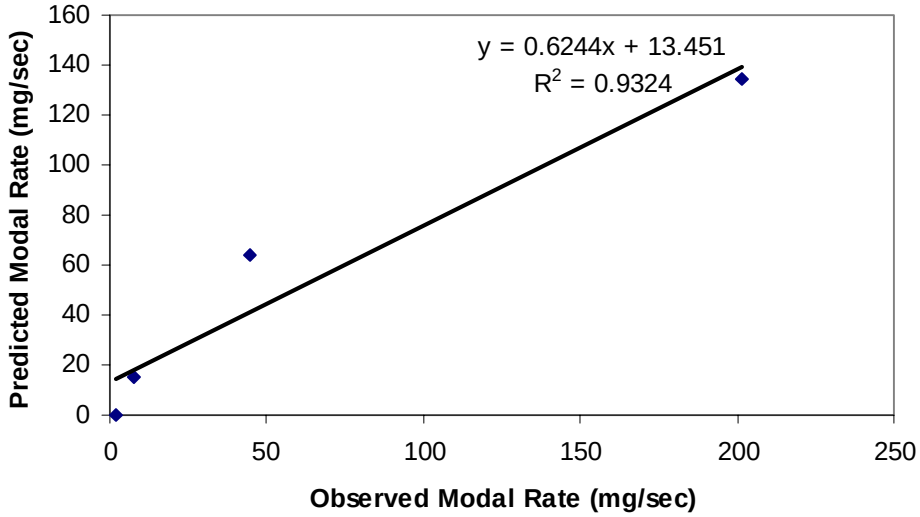

Figure 8-3. Predicted versus Observed CO NCSU Modal Emission Rates Estimated From NCHRP Data Using the Strict Constraints Approach.

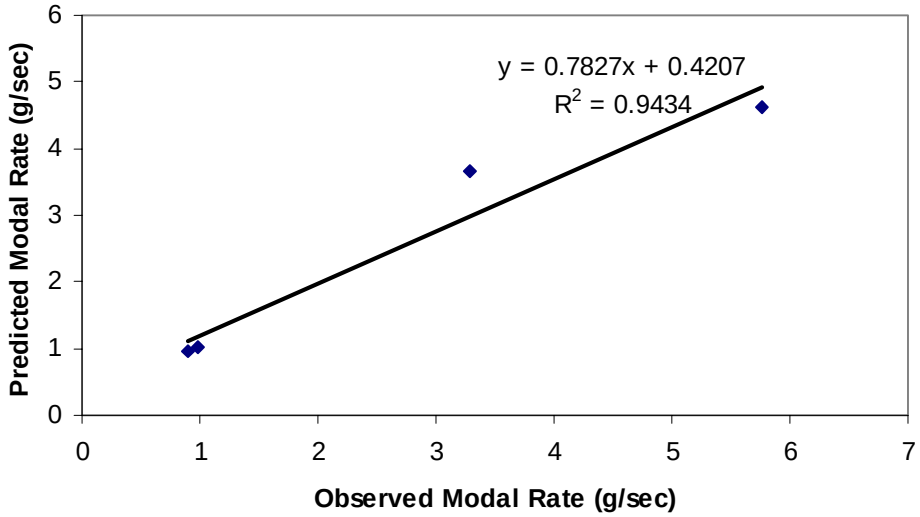

Figure 8-4. Predicted versus Observed CO_2 NCSU Modal Emission Rates Estimated From NCHRP Data Using the Strict Constraints Approach.

slopes of the best fit lines in the parity plots deviate substantially from an ideal value of 1 for all four pollutants. However, the strict constraints do produce modal estimates that qualitatively preserve the relative ordering among modes and that yield an acceleration mode with an emission rate substantially higher than for the other modes.

The results based upon application to the 14 VSP-based modes are shown in Tables 8-5 through 8-8 and Figures 8-5 through 8-8 for NO_x, HC, CO, and CO_2, respectively. These results are generally more promising, with the slope of the best fit line in the parity plots closer to one than was the case for the analysis based upon only four modes, and with coefficients of determination for the parity plots in excess of 0.80. The results are especially promising for CO_2.

As exspected, among three types of test, the test based on strict constraints gave the best performance, which confirms that the focus on the effective area of the control variables X will improve the predication accuracy.

Comparing the differences among the four pollutants, only the results for CO_2 are satisfying, with a predication error of approximately 10% or less. A possible reason for the superior results with CO_2 but not for the other pollutants is that is CO_2 has small inter-trip and inter-vehicle variance of the modal emission rates. Too much variability in modal emission rates from one vehicle to another may be the source of difficulties in estimation of modal rates for the other pollutants.

Table 8-5. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for 14 VSP Modes for NO_x: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

NO_x	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
ER1	4.54	357.88	77.82	11.23	1.47	2.53	-0.44
ER2	4.66	109.4	22.48	0	-1	2.47	-0.47
ER3	4.27	154.63	35.18	11.23	1.63	1.24	-0.71
ER4	13.71	-83.57	-7.09	11.23	-0.18	8.12	-0.41
ER5	20.26	-10.52	-1.52	11.23	-0.45	11.52	-0.43
ER6	25.97	-583.9	-23.48	11.23	-0.57	12.14	-0.53
ER7	34.1	-423.49	-13.42	11.23	-0.67	12.14	-0.64
ER8	48.69	-533.89	-11.97	11.23	-0.77	29.89	-0.39
ER9	61.91	260.33	3.21	11.23	-0.82	48.79	-0.21
ER10	86.39	515.21	4.96	95.29	0.1	66.9	-0.23
ER11	123.44	576.05	3.67	95.29	-0.23	80.16	-0.35
ER12	173.84	295.88	0.7	95.29	-0.45	93.48	-0.46
ER13	176.49	908.56	4.15	381.74	1.16	118.5	-0.33
ER14	201.72	849.94	3.21	1283.26	5.36	211.03	0.05
Avg. Error			15.2		1.06		0.4

[a] NC: No Constraint
[b] C: Constraint
[c] SC: Strict Constraint
[d] Error: (Predicted-Actual)/Actual

Table 8-6. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for 14 VSP Modes for HC: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

HC	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
ER1	3.69	130.98	34.51	0	-1	2.25	-0.39
ER2	2.27	0.84	56.12	0	-1.63	1.41	-0.63
ER3	1.92	23.35	66.48	5.52	-1.93	1.16	-0.75
ER4	4.02	2.09	31.65	0	-0.92	3.01	-0.36
ER5	5.97	-61.98	21.34	5.52	-0.62	4.04	-0.24
ER6	6.07	-177.83	20.96	5.52	-0.61	4.96	-0.24
ER7	7.57	49.79	16.82	5.52	-0.49	8.87	-0.19
ER8	11.15	-16.64	11.41	5.52	-0.33	8.87	-0.13
ER9	13.71	215.81	9.28	35.33	-0.27	22.33	-0.1
ER10	17.22	-169.45	7.39	35.33	-0.21	22.33	-0.08
ER11	28.09	110.83	4.53	35.33	-0.13	39.42	-0.05
ER12	50.43	-98.42	2.52	35.33	-0.07	39.42	-0.03
ER13	73.6	-180.59	1.73	35.33	-0.05	50.35	-0.02
ER14	98.75	146.08	1.29	211.99	-0.04	248.96	-0.01
AvgError			20.43		0.59		0.23

[a] NC: No Constraint
[b] C: Constraint
[c] SC: Strict Constraint
[d] Error: (Predicted-Actual)/Actual

Table 8-7. Results of Estimation of Modal Emission Rates (mg/sec) from Aggregate Data for 14 VSP Modes for CO: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

CO	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
ER1	149.59	23220	154.22	0	-1	121.22	-0.19
ER2	124.14	-2308	-19.6	0	-1	0	-1
ER3	83.59	-2028	-25.27	0	-1	36.62	-0.56
ER4	273.76	-2467	-10.01	0	-1	179.45	-0.34
ER5	338.76	-13068	-39.58	0	-1	179.45	-0.47
ER6	307.11	-2760	-9.99	0	-1	310.19	0.01
ER7	393.27	-1282	-4.26	1716	3.36	595.48	0.51
ER8	608.03	7636	11.56	1716	1.82	1114.42	0.83
ER9	755.63	17311	21.91	3403.35	3.5	1722.36	1.28
ER10	1015.26	-21646	-22.32	3403.35	2.35	1722.36	0.7
ER11	2063.31	-7639	-4.7	3403.35	0.65	4262.86	1.07
ER12	5530.73	-17753	-4.21	3403.35	-0.39	7571.34	0.37
ER13	10336.3	-31840	-4.08	3403.35	-0.67	7571.34	-0.27
ER14	16338.64	-39599	-3.42	3403.35	-0.79	13287	-0.19
AvgError			23.94		1.4		0.56

[a] NC: No Constraint
[b] C: Constraint
[c] SC: Strict Constraint
[d] Error: (Predicted-Actual)/Actual

Table 8-8. Results of Estimation of Modal Emission Rates (g/sec) from Aggregate Data for 14 VSP Modes for CO_2: Comparison of No Constraint, Basic Constraint, and Strict Constraint Solutions.

CO_2	Actual	NC[a]	ERROR[d]	C[b]	ERROR[d]	SC[c]	ERROR[d]
ER1	1.09	14.78	12.52	1.28	0.17	1.04	-0.05
ER2	1.26	4.43	2.5	1.28	0.01	1.19	-0.06
ER3	1.26	3.83	2.05	1.15	-0.08	1.23	-0.02
ER4	2.46	-4.37	-2.78	1.28	-0.48	2.32	-0.06
ER5	3.2	-9.19	-3.87	1.28	-0.6	3.07	-0.04
ER6	3.95	9.73	1.46	6.18	0.56	3.81	-0.04
ER7	4.69	-2.04	-1.44	6.18	0.32	4.95	0.05
ER8	5.52	-3.63	-1.66	6.18	0.12	5.81	0.05
ER9	6.41	9.47	0.48	6.18	-0.04	6.77	0.06
ER10	7.42	-8.69	-2.17	6.18	-0.17	7.82	0.05
ER11	8.89	17.11	0.93	7.04	-0.21	9.27	0.04
ER12	10.61	6.73	-0.37	7.04	-0.34	10.49	-0.01
ER13	11.87	9.74	-0.18	7.39	-0.38	11.75	-0.01
ER14	13.34	33.77	1.53	43.5	2.26	13.03	-0.02
AvgError			2.42		0.08		0.04

[a] NC: No Constraint
[b] C: Constraint
[c] SC: Strict Constraint
[d] Error: (Predicted-Actual)/Actual

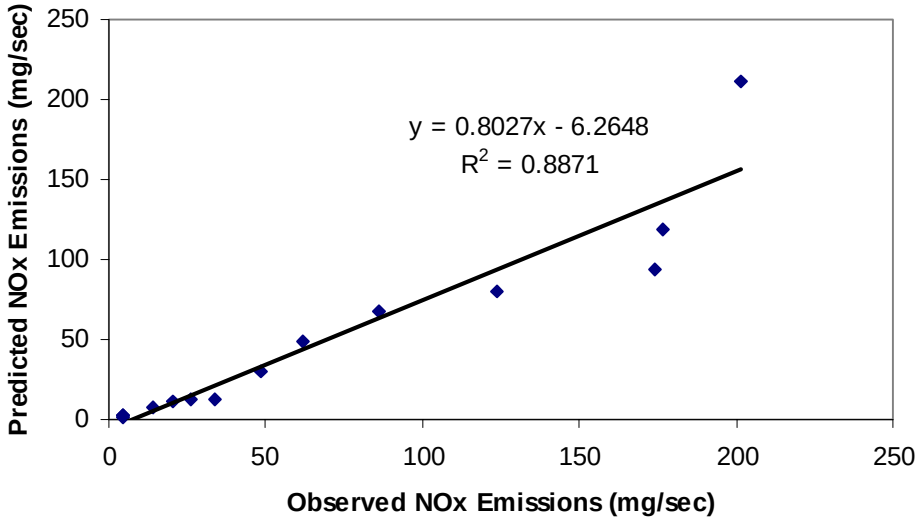

Figure 8-5. Predicted versus Observed NO_x Modal Emission Rates Based upon the 14 Mode VSP Approach Estimated From NCHRP Data Using the Strict Constraints Approach.

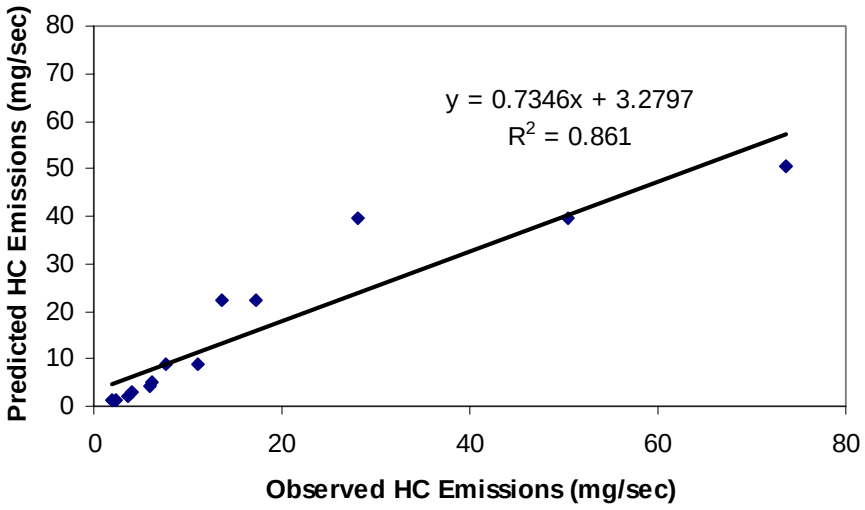

Figure 8-6. Predicted versus Observed HC Modal Emission Rates Based upon the 14 Mode VSP Approach Estimated From NCHRP Data Using the Strict Constraints Approach.

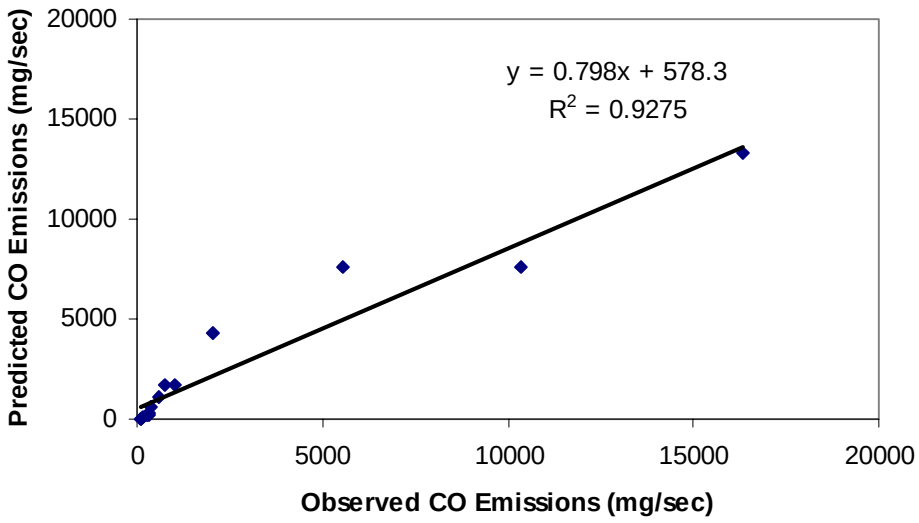

Figure 8-7. Predicted versus Observed CO Modal Emission Rates Based upon the 14 Mode VSP Approach Estimated From NCHRP Data Using the Strict Constraints Approach.

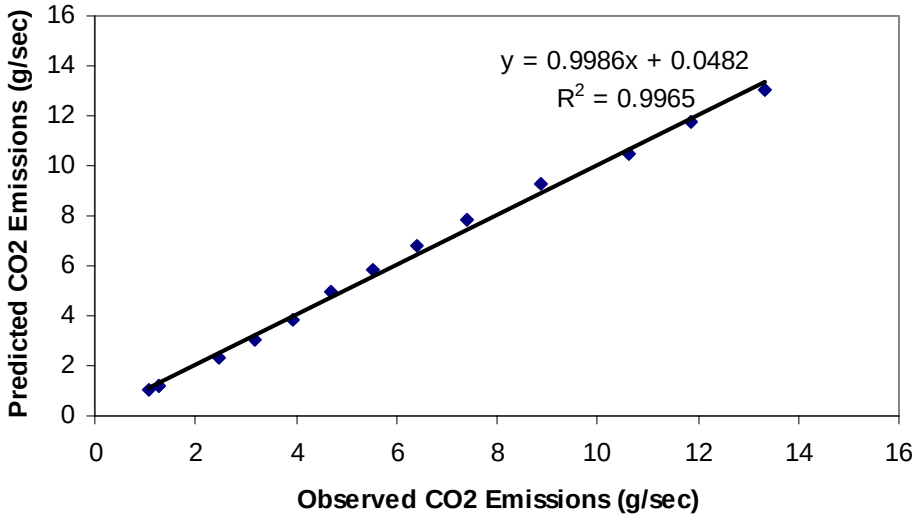

Figure 8-8. Predicted versus Observed CO_2 Modal Emission Rates Based upon the 14 Mode VSP Approach Estimated From NCHRP Data Using the Strict Constraints Approach.

8.3 Bag-Based Modal Emissions Estimation for the "56-bin" VSP-based Approach

In this section, evaluation of the modal estimation method for bag data was applied to the stratified bin approach. The original NCHRP data set was divided into 4 subsets of data in terms of odometer reading and engine displacement, based upon cut points of 50K miles and 3.5 liters, respectively. For each of the four subsets, the 14 VSP modes were applied. From the previous section, a key conclusion was that the strict-constraint method is more effective than the unconstrained and basic-constraint methods. Thus, the focus in this section was upon the strict constraint method. In the previous section, the strict constraints were developed based upon analysis of the NCHRP data set. In this section, the ranges for the strict constraints were developed based upon the NCHRP data set and, alternatively, based upon the modeling data set.

The results of the predicted modal emission rates estimated from the aggregate data, and the observed values, are shown in Tables 8-9 through 8-24. There are four tables for each pollutant, with each of the four tables representing a different vehicle strata with respect to odometer reading and engine displacement. All of the results for CO_2 based upon the strict constraints cases are shown in Figures 8-9 through 8-16. Selected results for the modal emissions estimated for HC are shown in Figures 8-17 through 8-22.

The results for CO_2 were generally very good, especially for the case in which the range of values for the constraints were estimated from data in the NCHRP database. For all four vehicle strata, the average relative error in the predicted versus observed modal emission rates was less than 10 percent, except for the first strata (odometer reading < 50,000 miles, engine displacement < 3.5 liters) when constraints were developed based upon the modeling database. These results imply that when the constraints are more representative of the data from which the modes are being estimated, the results will tend to be better. Figure 8-11 and 8-12 illustrate that the modal emission rates for CO2 estimated using the constraints estimated from the NCHRP data are better than those estimated using the constraints based upon the modeling database. In particular, the slope of the trend line for the predicted versus observed modes is closer to one, indicating a more accurate result. A similar comparison can be observed for Figures 8-13 and 8-14.

The results for HC were generally not as good as those for CO_2. The average relative errors for the modal estimates, as indicated in Tables 8-13 through 8-16, were typically 0.37 to 0.64 for the six cases in which results could be obtained. In two cases, it was not possible to get a solution. The predicted modal emissions tend to be low for the higher VSP modes, as illustrated in Figures 8-17 through 8-19, although there are examples in Figures 8-20 through 8-22 in which the predictions for the higher VSP modes are relatively more accurate.

For both NO_x and CO, the estimation method failed for most cases. For NO_x, it was possible to get results in only three of eight cases, and the errors in these cases ranged from 0.24 to 0.55. For CO, it was possible to get results in only two of eight cases, with errors of 0.48 and 0.94.

Overall, the key findings of the attempts to estimate modal emission rates for the 56-bin approach based upon NCHRP data were: (1) the method worked well only for CO_2; the method worked for HC for most cases but the accuracy of the predictions was less than desirable; and (3)

Table 8-9. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO_2 Emissions (g/sec) for Engine Displacement < 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	0.94	1.58	0.68	0.91	-0.03
ER2	1.06	1.51	0.42	0.95	-0.10
ER3	1.2	1.26	0.05	1.08	-0.10
ER4	2.21	2.16	-0.022	2	-0.10
ER5	2.86	2.62	-0.084	2.63	-0.08
ER6	3.53	3.03	-0.14	3.25	-0.08
ER7	4.19	4.25	0.014	4.51	0.08
ER8	4.92	4.82	-0.02	5.31	0.08
ER9	5.74	5.51	-0.04	6.18	0.08
ER10	6.67	6.18	-0.07	7.13	0.07
ER11	7.82	7.34	-0.06	8.65	0.11
ER12	9.49	9.2	-0.03	9.9	0.04
ER13	10.89	11.61	0.066	11.48	0.05
ER14	12.08	12.29	0.017	12.18	0.01
Avg. Error			0.122		0.072

[a] Error: (Predicted-Actual)/Actual

Table 8-10. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO_2 Emissions (g/sec) for Engine Displacement > 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	1.03	1.24	-0.20	1.01	0.019
ER2	1.31	1.4	-0.07	1.18	0.099
ER3	1.07	1.08	-0.01	1	0.065
ER4	2.4	2.29	0.05	2.17	0.096
ER5	3.15	2.85	0.10	2.9	0.079
ER6	3.84	3.46	0.10	3.58	0.068
ER7	4.55	5.07	-0.11	4.86	-0.068
ER8	5.32	5.81	-0.09	5.68	-0.068
ER9	6.16	6.56	-0.06	6.6	-0.071
ER10	7	7.55	-0.08	7.54	-0.077
ER11	8.43	8.66	-0.03	9.07	-0.076
ER12	9.91	8.66	0.13	10.54	-0.064
ER13	10.54	9.15	0.13	11.27	-0.069
ER14	11.92	9.9	0.17	11.27	0.055
Avg. Error			0.09		0.070

[a] Error: (Predicted-Actual)/Actual

Table 8-11. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO_2 Emissions (g/sec) for Engine Displacement < 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	1.5	1.56	-0.04	1.55	-0.033
ER2	1.53	1.66	-0.08	1.41	0.078
ER3	1.66	1.33	0.20	1.52	0.084
ER4	2.93	2.36	0.19	2.63	0.102
ER5	3.88	2.93	0.24	3.7	0.046
ER6	4.94	5.46	-0.11	4.75	0.038
ER7	5.95	6.55	-0.10	6.67	-0.121
ER8	7.05	7.95	-0.13	7.9	-0.121
ER9	8.23	7.95	0.03	9.28	-0.128
ER10	9.64	7.95	0.18	9.28	0.037
ER11	11.13	12.94	-0.16	12.25	-0.101
ER12	14.24	18.87	-0.33	15.19	-0.067
ER13	15.84	18.87	-0.19	15.25	0.037
ER14	17.47	18.87	-0.08	15.25	0.127
Avg. Error			0.15		0.080

[a] Error: (Predicted-Actual)/Actual

Table 8-12. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO_2 Emissions (g/sec) for Engine Displacement > 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	1.67	1.64	0.018	1.64	0.02
ER2	1.97	2.15	-0.091	2.15	-0.09
ER3	1.69	1.54	0.089	1.54	0.09
ER4	3.5	3	0.143	3	0.14
ER5	4.48	4.07	0.092	4.07	0.09
ER6	5.46	5.1	0.066	5.1	0.07
ER7	6.48	6.74	-0.040	6.74	-0.04
ER8	7.64	6.97	0.088	6.97	0.09
ER9	8.83	9.42	-0.067	9.42	-0.07
ER10	10.3	11.36	-0.103	11.36	-0.10
ER11	12.54	13.41	-0.069	13.41	-0.07
ER12	14.75	13.41	0.091	13.41	0.09
ER13	16.96	20.25	-0.194	20.25	-0.19
ER14	18.76	21.42	-0.142	21.42	-0.14
Avg. Error			0.092		0.09

[a] Error: (Predicted-Actual)/Actual

Table 8-13. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: HC Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	2.18	0		3.26	-0.50
ER2	1.67	0		0.93	0.44
ER3	1.82	0		1.16	0.36
ER4	4.11	0		2.75	0.33
ER5	4.16	0		3.26	0.22
ER6	5.37	0		7.09	-0.32
ER7	6.56	0		7.79	-0.19
ER8	8.82	0		7.79	0.12
ER9	10.52	0		7.91	0.25
ER10	13.25	0		26.16	-0.97
ER11	24.06	0		27.79	-0.16
ER12	31.79	0		27.79	0.13
ER13	59.91	0		27.79	0.54
ER14	70.41	0		27.79	0.61
Avg. Error					0.37

[a] Error: (Predicted-Actual)/Actual

Table 8-14. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: HC Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	4.98	2.52	0.494	2.37	0.52
ER2	2.06	1.73	0.160	1.27	0.38
ER3	0.95	1.33	-0.400	0.91	0.04
ER4	3.11	2.79	0.103	2.18	0.30
ER5	5.15	3.19	0.381	2.73	0.47
ER6	5.17	4.38	0.153	3.73	0.28
ER7	6.17	11.42	-0.851	11.65	-0.89
ER8	7.67	13.01	-0.696	11.65	-0.52
ER9	13.26	13.01	0.019	11.65	0.12
ER10	15.18	27.09	-0.785	28.75	-0.89
ER11	24.58	42.49	-0.729	46.4	-0.89
ER12	44.64	42.49	0.048	46.4	-0.04
ER13	70.17	42.49	0.394	46.4	0.34
ER14	116.55	42.49	0.635	46.4	0.60
Avg. Error			0.418		0.45

[a] Error: (Predicted-Actual)/Actual

Table 8-15. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: HC Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	1.58	0		0.94	0.41
ER2	1.45	0		0.75	0.48
ER3	1.84	0		2.48	-0.35
ER4	2.39	0		2.01	0.16
ER5	9.17	0		4.4	0.52
ER6	4.72	0		5.42	-0.15
ER7	5.48	0		5.42	0.01
ER8	11.3	0		27.42	-1.43
ER9	12.66	0		27.42	-1.17
ER10	20.14	0		27.42	-0.36
ER11	20.14	0		42.75	-1.12
ER12	71.33	0		91.07	-0.28
ER13	70.54	0		91.07	-0.29
ER14	77.97	0		91.07	-0.17
Avg. Error					0.49

[a] Error: (Predicted-Actual)/Actual

Table 8-16. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: HC Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	10.75	1.59	0.852	1.59	0.85
ER2	7.39	1.78	0.759	1.78	0.76
ER3	5.71	3.8	0.335	3.8	0.33
ER4	8.51	0	1.000	0	1.00
ER5	15	7.29	0.514	7.29	0.51
ER6	14.76	8.35	0.434	8.35	0.43
ER7	20.53	9.15	0.554	9.15	0.55
ER8	35.71	44.64	-0.250	44.64	-0.25
ER9	34.84	86.61	-1.486	86.61	-1.49
ER10	43.06	86.61	-1.011	86.61	-1.01
ER11	64.77	122.99	-0.899	122.99	-0.90
ER12	137.02	122.99	0.102	122.99	0.10
ER13	161.42	122.99	0.238	122.99	0.24
ER14	209.61	315.45	-0.505	315.45	-0.50
Avg. Error			0.639		0.64

[a] Error: (Predicted-Actual)/Actual

Table 8-17. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	144.4	0		116.78	0.19
ER2	86.18	0		35.4	0.59
ER3	82.35	0		45.98	0.44
ER4	284.3	0		179.31	0.37
ER5	283.62	0		210.11	0.26
ER6	300.11	0		279.07	0.07
ER7	393.08	0		479.53	-0.22
ER8	625.93	0		479.53	0.23
ER9	749.09	0		2438.1	-2.25
ER10	1033.99	0		2684.08	-1.60
ER11	2576.85	0		2684.08	-0.04
ER12	3944.7	0		3204.4	0.19
ER13	8785.4	0		8891.55	-0.01
ER14	12567.67	0		8891.55	0.29
Avg. Error					0.48

[a] Error: (Predicted-Actual)/Actual

Table 8-18. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	150.28	0		63.17	0.58
ER2	130	0		0	1.00
ER3	48.96	0		30.66	0.37
ER4	221.4	0		111.62	0.50
ER5	285.13	0		111.62	0.61
ER6	241.95	0		252.67	-0.04
ER7	277.95	0		340.68	-0.23
ER8	327.58	0		430.83	-0.32
ER9	519.72	0		2103.27	-3.05
ER10	651.3	0		2225.11	-2.42
ER11	1249.86	0		5239.32	-3.19
ER12	6740.72	0		5239.32	0.22
ER13	12956.1	0		5239.32	0.60
ER14	23713.22	0		22508	0.05
Avg. Error					0.94

[a] Error: (Predicted-Actual)/Actual

Table 8-19. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading >50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	80.7	0		0	
ER2	129.75	0		0	
ER3	130.09	0		0	
ER4	227.75	0		0	
ER5	637.64	0		0	
ER6	280.52	0		0	
ER7	416.31	0		0	
ER8	696.73	0		0	
ER9	1094.9	0		0	
ER10	1253.14	0		0	
ER11	2031.25	0		0	
ER12	8029.59	0		0	
ER13	8933.28	0		0	
ER14	12979.73	0		0	
Avg. Error					

[a] Error: (Predicted-Actual)/Actual

Table 8-20. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: CO Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	263.35	0		0	
ER2	316.27	0		0	
ER3	145.17	0		0	
ER4	440.86	0		0	
ER5	456.54	0		0	
ER6	592.43	0		0	
ER7	740.36	0		0	
ER8	1305.73	0		0	
ER9	1135.74	0		0	
ER10	1793.1	0		0	
ER11	2394.7	0		0	
ER12	8240.6	0		0	
ER13	13064.57	0		0	
ER14	19173.19	0		0	
Avg. Error					

[a] Error: (Predicted-Actual)/Actual

Table 8-21. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: NO_x Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	4.4	6.61	-0.502	0	
ER2	3.85	5.82	-0.512	0	
ER3	4.41	3.77	0.145	0	
ER4	11.8	9.85	0.165	0	
ER5	15.52	9.85	0.365	0	
ER6	18.17	18.71	-0.030	0	
ER7	22.95	18.71	0.185	0	
ER8	33.86	45.54	-0.345	0	
ER9	47.21	45.54	0.035	0	
ER10	65.22	89.59	-0.374	0	
ER11	78.39	89.59	-0.143	0	
ER12	137.34	121.26	0.117	0	
ER13	141.33	121.26	0.142	0	
ER14	183.97	121.26	0.341	0	
Avg. Error			0.243		

[a] Error: (Predicted-Actual)/Actual

Table 8-22. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: NO_x Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading < 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	2.66	0		0	
ER2	1.39	0		0	
ER3	1.75	0		0	
ER4	7.56	0		0	
ER5	11.67	0		0	
ER6	18.45	0		0	
ER7	26.75	0		0	
ER8	37.46	0		0	
ER9	53.37	0		0	
ER10	68.14	0		0	
ER11	65.56	0		0	
ER12	125.35	0		0	
ER13	141.54	0		0	
ER14	120.47	0		0	
Avg. Error					

[a] Error: (Predicted-Actual)/Actual

Table 8-23. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: NO_x Emissions (mg/sec) for Engine Displacement < 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	1.58	0		0	
ER2	1.45	0		0	
ER3	1.84	0		0	
ER4	2.39	0		0	
ER5	9.17	0		0	
ER6	4.72	0		0	
ER7	5.48	0		0	
ER8	11.3	0		0	
ER9	12.66	0		0	
ER10	20.14	0		0	
ER11	20.14	0		0	
ER12	71.33	0		0	
ER13	70.54	0		0	
ER14	77.97	0		0	
Avg. Error					

[a] Error: (Predicted-Actual)/Actual

Table 8-24. Comparison of Modal Emission Rates Estimated Based Upon the Strict Constraints Approach for Two Different Constraints Versus Actual Rates: NO_x Emissions (mg/sec) for Engine Displacement > 3.5 Liters and Odometer Reading > 50,000 Miles.

Mode	Actual	CONSTRAINT_ALLDATA	Error [a]	CONSTRAINT_NCHRP	Error [a]
ER1	8.2	19.68	-1.400	19.68	-1.40
ER2	9.36	13.18	-0.408	13.18	-0.41
ER3	8.1	8.46	-0.044	8.46	-0.04
ER4	32.86	41.91	-0.275	41.91	-0.28
ER5	57.24	47.23	0.175	47.23	0.17
ER6	82.87	78.71	0.050	78.71	0.05
ER7	109.92	86.39	0.214	86.39	0.21
ER8	155.13	137.75	0.112	137.75	0.11
ER9	173.28	177.1	-0.022	177.1	-0.02
ER10	229.28	177.1	0.228	177.1	0.23
ER11	362.89	177.1	0.512	177.1	0.51
ER12	490.97	177.1	0.639	177.1	0.64
ER13	485	214.1	0.559	214.1	0.56
ER14	543.47	2172.47	-2.997	2172.47	-3.00
Avg. Error			0.545		0.55

[a] Error: (Predicted-Actual)/Actual

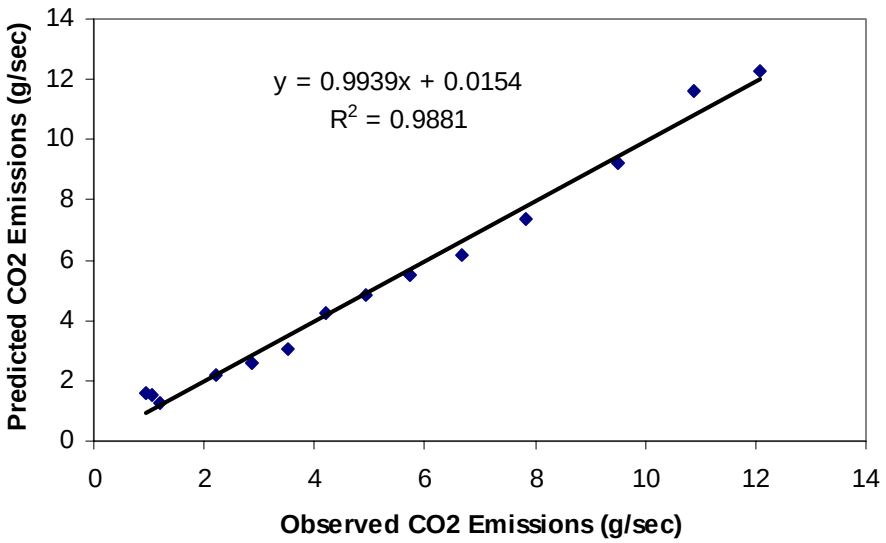

Figure 8-9. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement < 3.5 liter and Odometer Reading < 50,000 Miles.

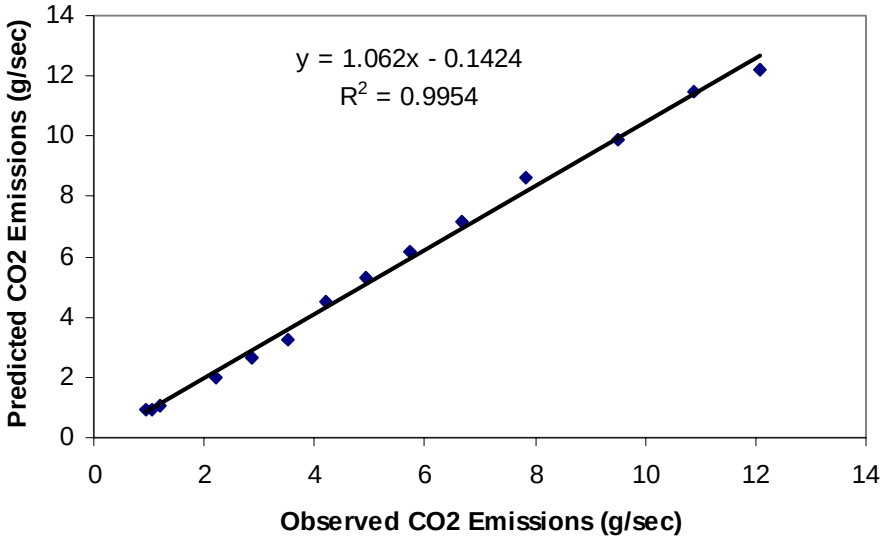

Figure 8-10. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement < 3.5 liter and Odometer Reading < 50,000 Miles.

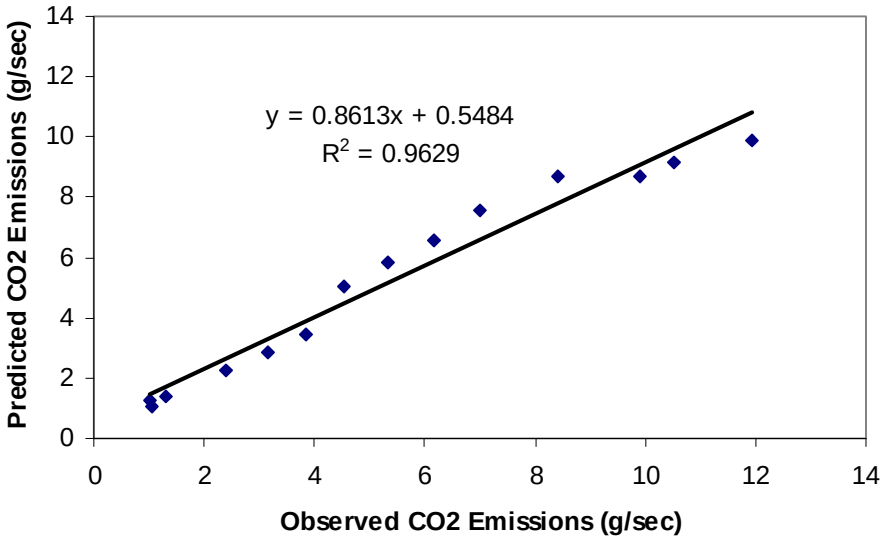

Figure 8-11. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement > 3.5 liter and Odometer Reading < 50,000 Miles.

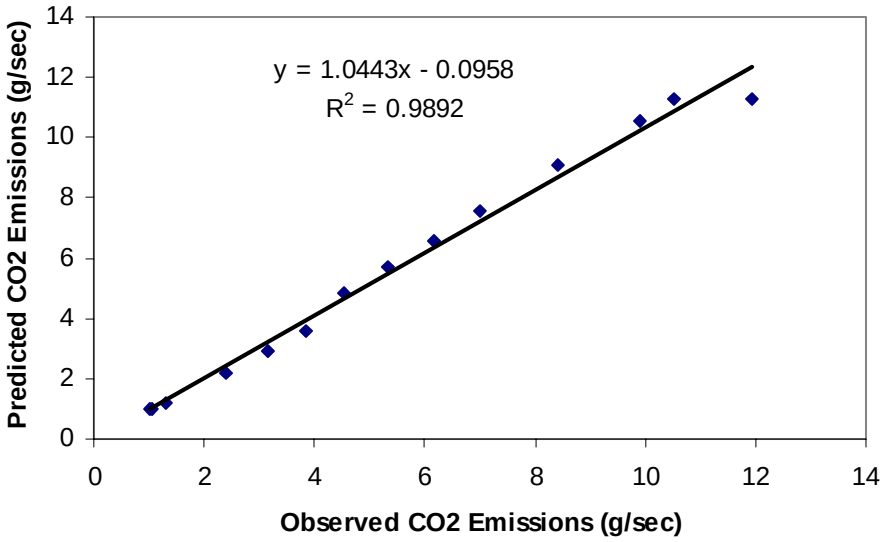

Figure 8-12. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement > 3.5 liter and Odometer Reading < 50,000 Miles.

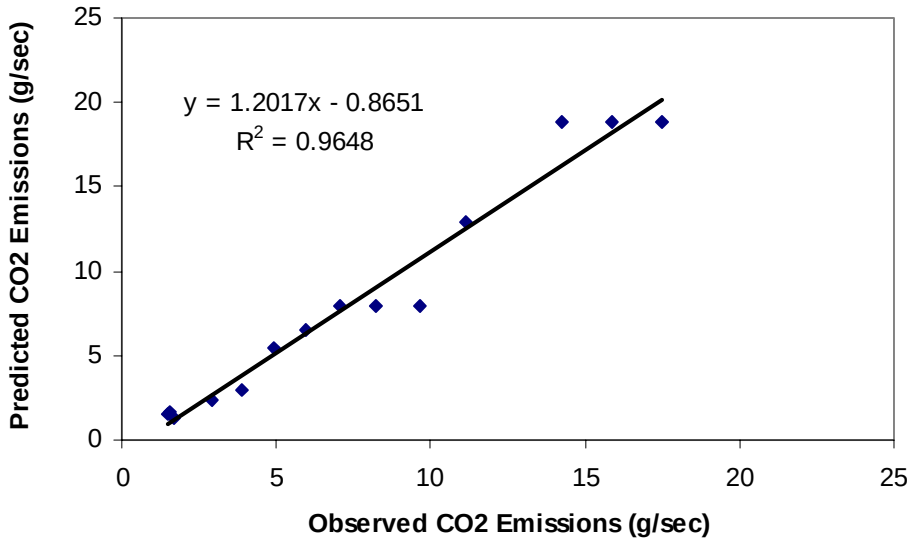

Figure 8-13. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement < 3.5 liter and Odometer Reading > 50,000 Miles.

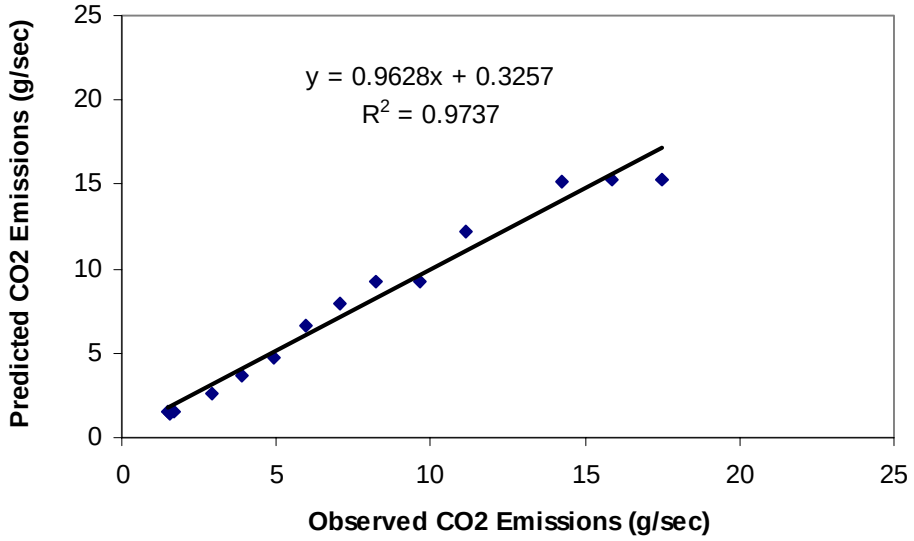

Figure 8-14. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement < 3.5 liter and Odometer Reading > 50,000 Miles.

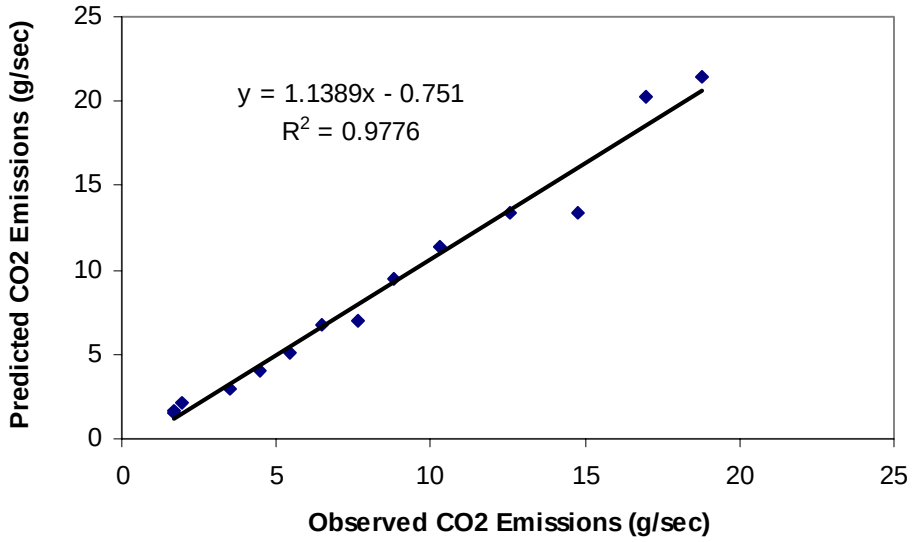

Figure 8-15. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement > 3.5 liter and Odometer Reading > 50,000 Miles.

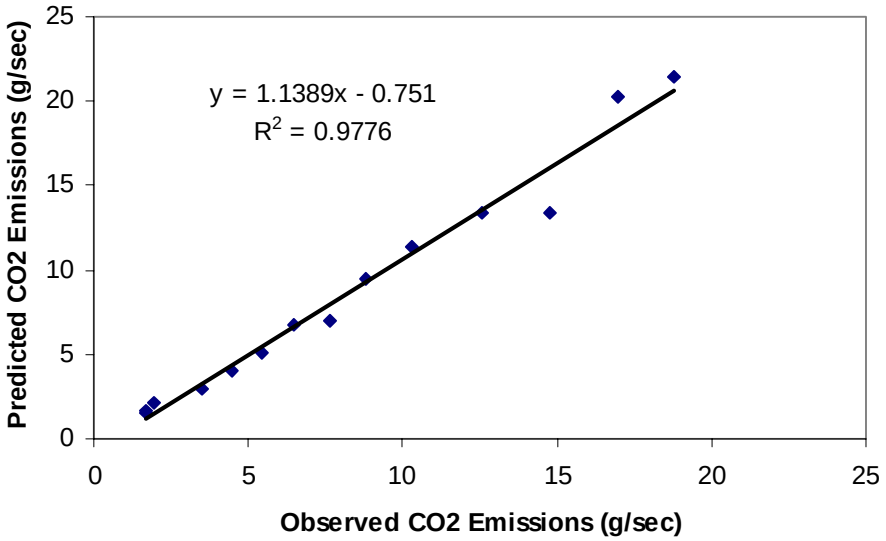

Figure 8-16. Predicted versus Observed CO_2 Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement > 3.5 liter and Odometer Reading > 50,000 Miles.

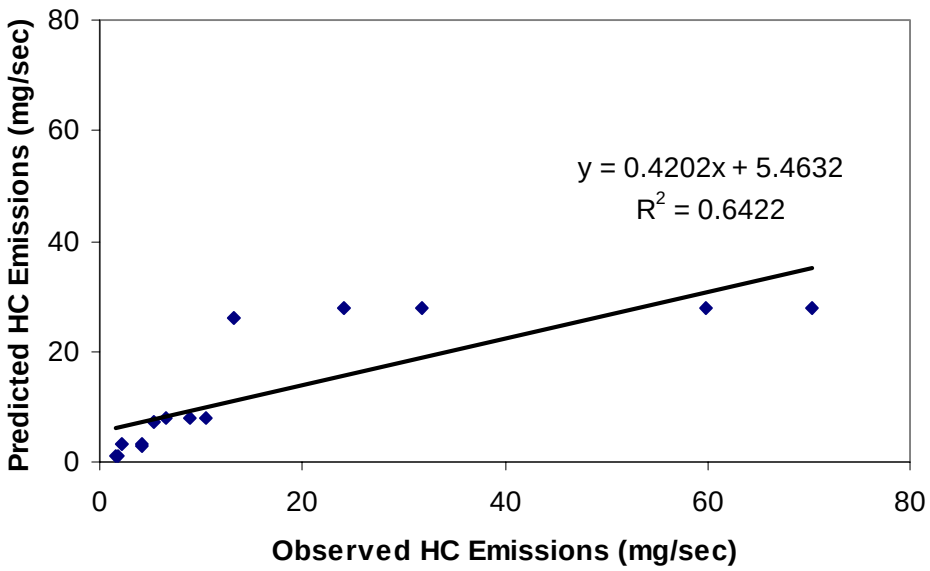

Figure 8-17. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement < 3.5 liter and Odometer Reading < 50,000 Miles.

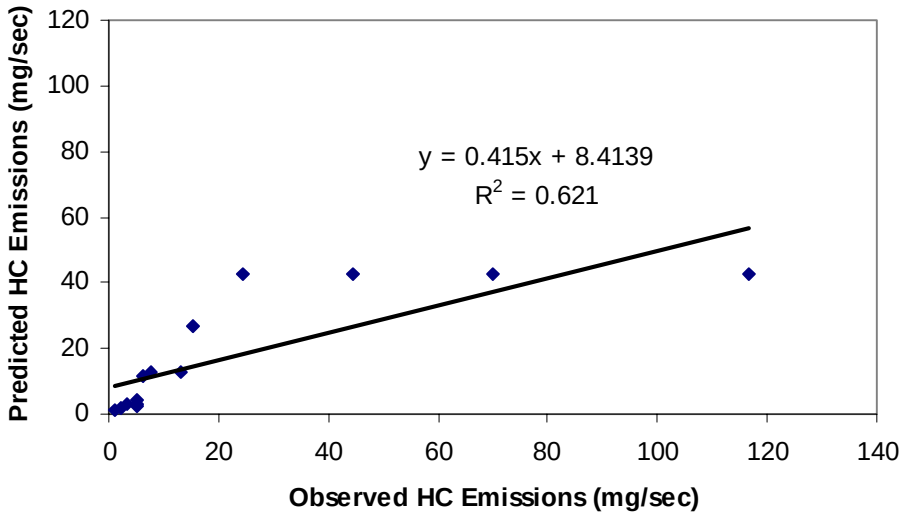

Figure 8-18. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement > 3.5 liter and Odometer Reading < 50,000 Miles.

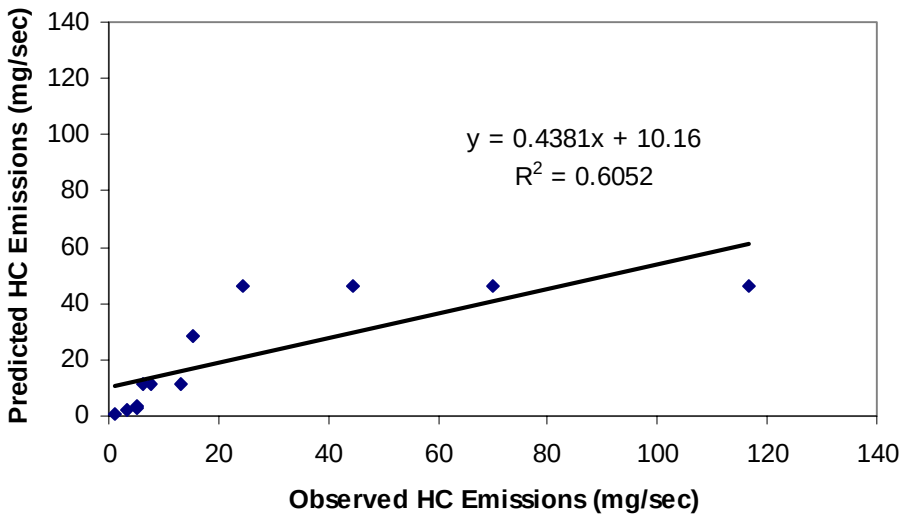

Figure 8-19. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement > 3.5 liter and Odometer Reading < 50,000 Miles.

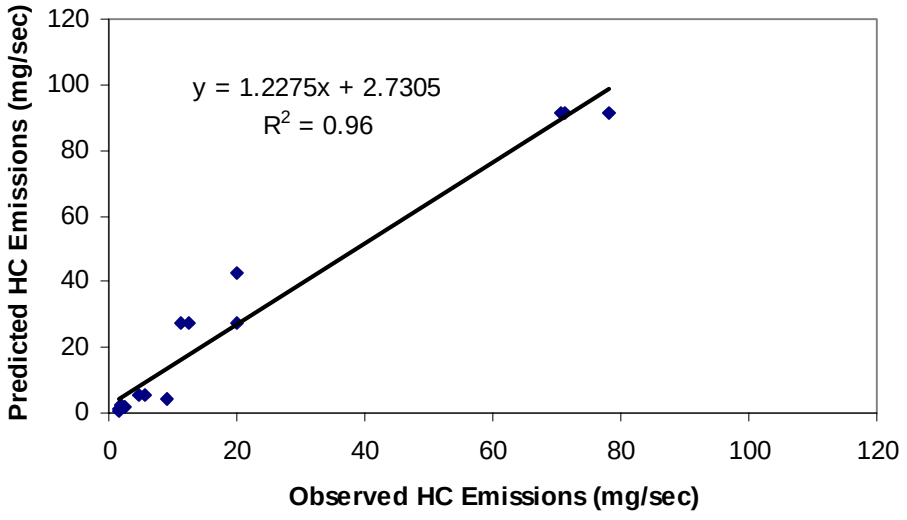

Figure 8-20. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement < 3.5 liter and Odometer Reading > 50,000 Miles.

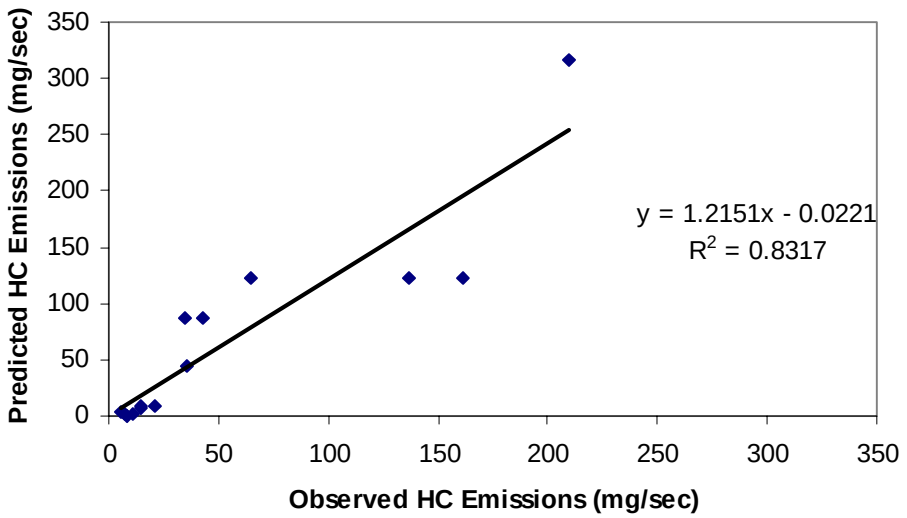

Figure 8-21. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the Modeling Database: Engine Displacement > 3.5 liter and Odometer Reading > 50,000 Miles.

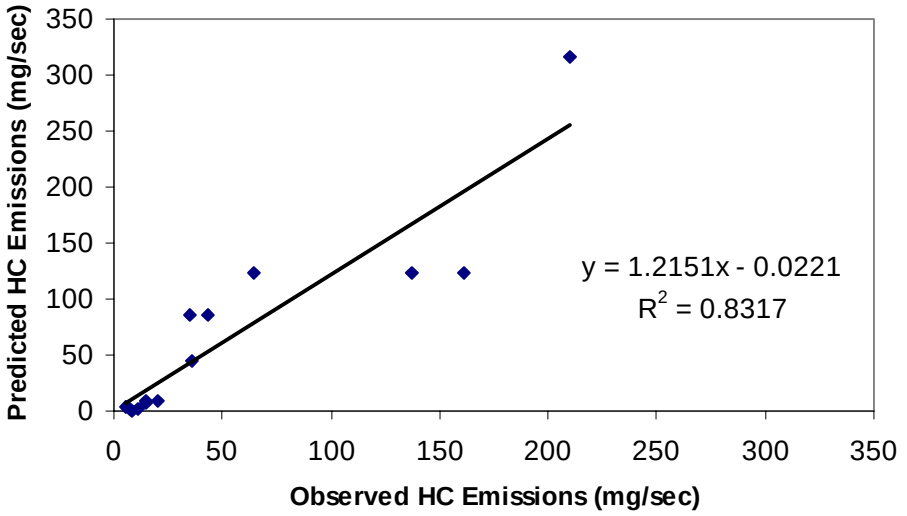

Figure 8-22. Predicted versus Observed HC Modal Emission Rates for 14 VSP Modes Estimated From NCHRP Data Using Strict Constraints Estimated From the NCHRP Database: Engine Displacement > 3.5 liter and Odometer Reading > 50,000 Miles.

the method failed in most cases for NO_x and CO. A likely reason for the failure to obtain results in many cases for the 56-bin approach is that the sample sizes for the stratified data sets are smaller than for the case of the 14-mode approach in the previous section. An implication is that it may be necessary to have a sufficient large data set in order to estimate modal emission rates from aggregate data. It is also apparent that the strict constraint approach produces better results when the bounds of the constraints are derived from data similar to that being analyzed.

8.4 Characterization of Uncertainty in Predicted Modal Emissions

The objective of this part of work is to characterize the distribution of errors in the predicted modal emissions in order to identify whether biases in the modal estimates are statistically significant. Because the results from the 56 bin approach were not satisfying, this work was based upon the results obtained with the 14 VSP bin approach.

In order to characterize uncertainty in the predictions, the distribution of the error of each modal prediction, based upon the difference between the actual value for each vehicle minus the predicted value, was estimated. These distributions are summarized by presenting the mean, standard deviation, 95 percent confidence interval on the mean, and skewness. The results are presented for NO_x, HC, CO, and CO_2 in Tables 8-25 through 8-28, respectively. The predictions are based upon the strict constraint method. The average observed and predicted rates are given in Tables 8-5 through 8-8, respectively, for these same pollutants.

Table 8-25 summarizes the analysis of the distribution of prediction errors among all the vehicles and cycles in the database for predictions of modal emissions for NO_x emissions. The mean prediction error is given for each VSP mode along with the standard deviation, lower and upper limit for the 95 percent confidence interval on the mean, number of data points, and skewness estimate. The average prediction error for each mode is slightly different than zero, indicating the possibility that the modal predictions are biased. For example, for VSP mode 11, average prediction error is -0.0008. However, 95 percent confidence interval on the mean includes zero, which indicates that at a significance level of 0.05, the mean prediction error is not statistically significantly different from zero. Furthermore, the average prediction error is not statistically significantly different from zero for all VSP modes for NO_x as well as for all other pollutants. Thus, the results indicate that there are no statistically significant biases in the mean estimates of the prediction error.

However, the range of the prediction error is substantial in many cases. For example, for NO_x, the standard deviation of the prediction error is 5.1 mg/sec for Mode 1, compared to an observed emission rate of 4.5 mg/sec. Similarly, the standard deviation is 276 mg/sec versus an average observed emission rate of 202 mg/sec for Mode 14. For NO_x, HC, and CO, the standard deviation of the prediction error is comparable to the average emission rate for each mode. In contrast, the standard deviation of the prediction error for CO_2 is approximately one third of the mean observed emission rate for CO_2. When the standard deviation of the prediction error is large relative to the mean emission rate, the distribution of the prediction error tends to be positively skewed. For example, the range of skewness of the prediction errors among the 14 VSP modes is 2.7 to 4.4 for NO_x, 2.0 to 5.2 for HC, and 1.0 to 4.3 for CO. In contrast, the distributions of the prediction errors for CO_2 tend to have only slight skewness, ranging from a

Table 8-25. Summary of Analysis of Uncertainty in the Prediction Error for the NO_x Modal Emission Rates (mg/sec) Estimated from Aggregate Data For the 14 Mode VSP-Based Approach.

VSP bin	Mean	Std Dev	N	Lower Limit (95%)	Upper Limit (95%)	Skewness
1	0.0005	5.09	90	-1.05	1.05	2.77
2	-0.0017	5.71	90	-1.18	1.18	2.99
3	0.0043	4.73	90	-0.97	0.98	2.69
4	0.0027	18.64	90	-3.85	3.85	3.25
5	0.0013	28.68	90	-5.92	5.93	3.56
6	0.0019	37.30	90	-7.70	7.71	4.40
7	-0.0046	48.75	90	-10.08	10.07	4.38
8	-0.0017	65.79	90	-13.59	13.59	4.03
9	-0.0012	79.83	90	-16.49	16.49	3.76
10	-0.0018	104.07	90	-21.50	21.50	2.82
11	-0.0008	165.71	77	-37.01	37.01	2.66
12	0.0038	220.48	45	-64.42	64.42	2.72
13	-0.0054	215.91	41	-66.09	66.08	2.98
14	-0.0016	276.33	37	-89.04	89.04	2.74

Table 8-26. Summary of Analysis of Uncertainty in the Prediction Error for the HC Modal Emission Rates (mg/sec) Estimated from Aggregate Data For the 14 Mode VSP-Based Approach.

VSP bin	Mean	Std Dev	N	Lower Limit (95%)	Upper Limit (95%)	Skewness
1	-0.00188	8.41	90	-1.740	1.736	4.45
2	-0.00173	5.03	90	-1.041	1.038	4.38
3	-0.00532	4.07	90	-0.847	0.837	4.54
4	0.00137	6.75	90	-1.394	1.396	4.23
5	-0.00490	10.49	90	-2.171	2.162	3.48
6	0.00329	10.98	90	-2.265	2.271	5.15
7	-0.00247	14.32	90	-2.961	2.956	4.90
8	0.00304	20.38	90	-4.207	4.213	4.10
9	0.00077	21.18	90	-4.375	4.376	3.67
10	0.00335	26.06	90	-5.381	5.388	3.62
11	-0.00135	41.84	77	-9.348	9.345	3.00
12	-0.00331	64.50	45	-18.84	18.84	2.38
13	0.00126	85.35	41	-26.12	26.12	2.03
14	-0.00448	123.3	37	-39.73	39.72	2.49

Table 8-27. Summary of Analysis of Uncertainty in the Prediction Error for the CO Modal Emission Rates (mg/sec) Estimated from Aggregate Data For the 14 Mode VSP-Based Approach.

VSP bin	Mean	Std Dev	N	Lower Limit (95%)	Upper Limit (95%)	Skewness
1	0.0028	233	90	-48.04	48.04	2.3
2	-0.0055	241	90	-49.88	49.87	2.5
3	0.0024	186	90	-38.49	38.50	3.4
4	0.0021	428	90	-88.51	88.52	2.1
5	0.0025	686	90	-141.8	141.8	4.0
6	0.0044	529	90	-109.3	109.3	3.4
7	-0.0005	747	90	-154.3	154.3	4.2
8	0.0042	1250	90	-258.2	258.2	3.7
9	0.0008	1472	90	-304.1	304.1	4.3
10	0.0031	1818	90	-375.5	375.5	4.1
11	0.0036	3324	78	-737.6	737.6	2.8
12	0.0021	190	45	-3859	3859	1.6
13	-0.0001	8622	41	-2639	2639	1.3
14	-0.0044	12297	37	-3962	3962	1.0

Table 8-28. Summary of Analysis of Uncertainty in the Prediction Error for the CO_2 Modal Emission Rates (g/sec) Estimated from Aggregate Data For the 14 Mode VSP-Based Approach.

VSP bin	Mean	Std Dev	N	Lower Limit (95%)	Upper Limit (95%)	Skewness
1	0.00336	0.34	90	-0.068	0.075	0.37
2	0.00340	0.45	90	-0.089	0.096	0.53
3	-0.00466	0.39	90	-0.086	0.076	0.37
4	-0.00046	0.80	90	-0.165	0.164	0.49
5	0.00007	0.89	90	-0.184	0.184	0.28
6	-0.00262	1.02	90	-0.213	0.207	0.17
7	0.00366	1.20	90	-0.245	0.253	0.24
8	-0.00207	1.39	90	-0.289	0.285	0.15
9	0.00160	1.65	90	-0.340	0.343	0.10
10	-0.00313	1.94	90	-0.405	0.398	0.04
11	0.00202	2.49	77	-0.553	0.557	-0.11
12	-0.00189	2.67	45	-0.782	0.779	0.45
13	-0.00017	2.98	41	-0.911	0.911	0.56
14	0.00237	3.25	37	-1.044	1.049	0.46

magnitude of 0.04 to 0.56 among the 14 modes. These results illustrate that the predictions for CO_2 are generally substantially better than those for the other three pollutants.

The range of uncertainty in the mean prediction error is typically a factor of approximately five less than the standard deviation of the prediction error, because the 95 percent confidence interval of the uncertainty in the mean is estimated based upon a factor of 1.96 multiplied by the standard error of the mean, which in turn is estimated based upon the standard deviation of the data divided by the square root of sample size. For a sample size of 90, which is typical of many of the estimates, this amounts to a factor of 0.207 multiplier of the standard deviation to arrive at the upper and lower ranges of the 95 percent confidence interval. Thus, the range of uncertainty in the mean error is comparable in many cases to a range of approximately plus or minus 25 to 50 percent of the mean observed emission rate for NO_x, HC, and CO, and approximately plus or minus 7 percent of the mean observed emission rate for CO_2. These ranges of uncertainty are larger than the ranges of uncertainty estimated based upon the modeling database in Chapter 7. Thus, it would be the case that incorporation of emissions estimates obtained from aggregate data would entail additional uncertainty than estimates obtained from second-by-second data.

8.5 Summary and Conclusions

The key findings from this analysis include:

- The strict constraint method gave the best results.
- The least squares optimization method with strict constraints worked for all of the cases for the four driving cycle approach (idle, deceleration, acceleration, and cruise) and for the 14 mode VSP-based approach.
- The method worked for the VSP 56 mode approach for CO_2 for all four vehicle strata, but success was more limited with the other three pollutants.
- The failures to obtain solutions or to obtain sufficiently accurate solutions for HC, CO, and NO_x with the 56-bin approach may be attributable to small sample sizes.
- The analysis of uncertainty in modal predictions for the 14 Mode VSP-based approach clearly illustrates that the quality of the predictions are substantially better for CO_2 than for the other pollutants.
- The standard deviation of prediction errors for a given mode for NO_x, HC, and CO based upon the 14-mode VSP approach is typically of the same order of magnitude as the observed mean emission rate, implying that the distribution of prediction errors are positively skewed.
- The standard deviation of prediction errors for a given mode for CO_2 based upon the 14 mode VSP approach are approximately one third of the observed mean emission rate, implying that the distribution of prediction errors are relatively symmetric.
- The range of uncertainty in modal estimates obtained from aggregate bag data are substantially larger than those obtained from second-by-second data

The key recommendations from this work are that the constrained least squares optimization method can be effective at estimating modal emission rates from aggregate data as long as there is a sufficiently large sample size of data. The method worked well for the 14-mode VSP case compared to the 4-mode NCSU case. Thus, the method appears capable of handling a relatively large number of modes for a given data set. The predictions are generally much better for CO_2 than for the other pollutants. Thus, this technique works well for CO_2 even for cases in which solutions could not be obtained for other pollutants. For future work, it may be worth exploring other types of constraints than those addressed in this project. For example, the “strict

constraints" employed in this work allowed for considerable variability in the ratio of the emission rate for a particular mode with respect to another mode. An even stricter constraint would be to require that these ratios be defined for much narrower ranges or that some or all combinations of ratios be point estimates. Of course, the more that constraints are imposed upon the solution, the more critically dependent the solution becomes upon the accuracy of the constraints themselves. If modal emission estimates are used in a modeling framework such as moves, the uncertainty in those estimates must be incorporated as well, since the range of uncertainty in modal emissions rates estimated from aggregate data will typically be much larger than that when estimated from second-by-second data.

9 VALIDATION OF THE CONCEPTUAL MODEL

This report presents three validation studies in which a VSP-based binning approach was used to estimate hot stabilized tailpipe emissions of CO_2, CO, HC, and NO_x. The VSP-based approach is based upon 1 second data in mass per time emission factor units.

The first case study includes the data utilized for model development and is only a consistency check in response to comments received by EPA from the FACA committee. The second validation case study is based upon comparisons of the model with EPA dynamometer, EPA on-board, and NCHRP dynamometer data that were withheld from the modeling dataset. The third validation case study is based upon an independent dataset from the California Air Resources Board.

9.1 Validation Case Study 1

In this study, internal consistency of the modeling approach was evaluated by: (1) estimating average modal emission rates for individual driving cycles using data only from the vehicles that were tested on those cycles based upon data in the modeling database; and (2) making predictions of average cycle emissions based upon the estimated modal emission rates. The purpose of this comparison was to demonstrate that the modal emissions approach is internally consistent in disaggregating and re-aggregating the emission estimates for a driving cycle. For this purpose, three driving cycles and on-board data were selected for analysis. The three cycles were: ART-EF; FTP; and US06. These cycles were selected because there were ten or more vehicles tested on these cycles in the modeling database and these three cycles different ranges of speeds, VSP, and emissions.

In Table 9-1, number of vehicles, number of trips and number of seconds of data associated with each of the selected driving cycles are reported. Validation Dataset 1 includes more than 100 vehicles and 169,112 seconds of data. Key characteristics of the cycles utilized for Validation Dataset 1 are given in Table 9-2, including average speed, maximum speed, minimum speed, maximum acceleration, average VSP, and Maximum VSP. For the on-board data, for which there was not a standard cycle, these statistics were calculated based upon all of the available data for all vehicles and trips. The average speeds for the cycles vary between 12 mph and 47 mph, with the lowest average speed associated with the ART-EF cycle and the highest average speed associated with the US06 cycle. The average maximum acceleration among all the cycles is approximately 6 mph/sec. Except for the FTP, all of the cycles have a maximum acceleration greater than 6 mph/sec. Two cycles, ART-EF and FTP, have an average VSP less than 5 Kw/ton, and two cycles, ART-EF and FTP, have maximum VSP less than 50 Kw/ton.

The predicted vehicle average total emissions and the observed vehicle average total emissions for the three driving cycles and for the on-board measurements are shown graphically in Figure 9-1. The 95 percent confidence intervals for the means are also shown. Comparisons between predicted and observed average total vehicle emissions are given in Tables 9-3 through 9-6 for CO_2, CO, HC, and NO_x, respectively. These tables present average observed values for each cycle with 95 percent confidence intervals, average predicted values for each cycle with 95 percent confidence intervals.

Table 9-1. Summary of Validation Dataset I

Vehicle Characteristics	Cycle	Number of vehicles	Number of seconds
Engine Size < 3.5 liter Odometer < 50,000	ART-EF	12	6024
	FTP	24	32952
	US06	22	13251
	On-Board	7	36096
Engine Size ≥ 3.5 liter Odometer < 50,000	ART-EF	0	0
	FTP	6	8238
	US06	4	2436
	On-Board	6	35603
Engine Size < 3.5 liter Odometer ≥ 50,000	ART-EF	0	0
	FTP	15	20595
	US06	11	6010
	On-Board	0	0
Engine Size ≥ 3.5 liter Odometer ≥ 50,000	ART-EF	0	0
	FTP	4	5492
	US06	4	2425
	On-Board	0	0

Table 9-2. Key Characteristics of the Activity Pattern of the ART-EF, FTP75 and US06 Cycles and of the On-Board Measurements Used in Validation Dataset I.

Cycle Name	**Time (s)**	**Average Speed (mph)**	**Max Speed (mph)**	**Min Speed (mph)**	**Max Acceleration (mph/sec)**	**Mean VSP (Kw/ton)**	**Max VSP (Kw/ton)**
Art-EF	504	12	40	0	5.8	0.9	22.8
FTP75	1875	21	57	0	3.3	2.2	25.1
US06	622	47	81	0	7.4	8.3	54.5
On-Board	1525	33	83	0	7.4	4.6	78.3

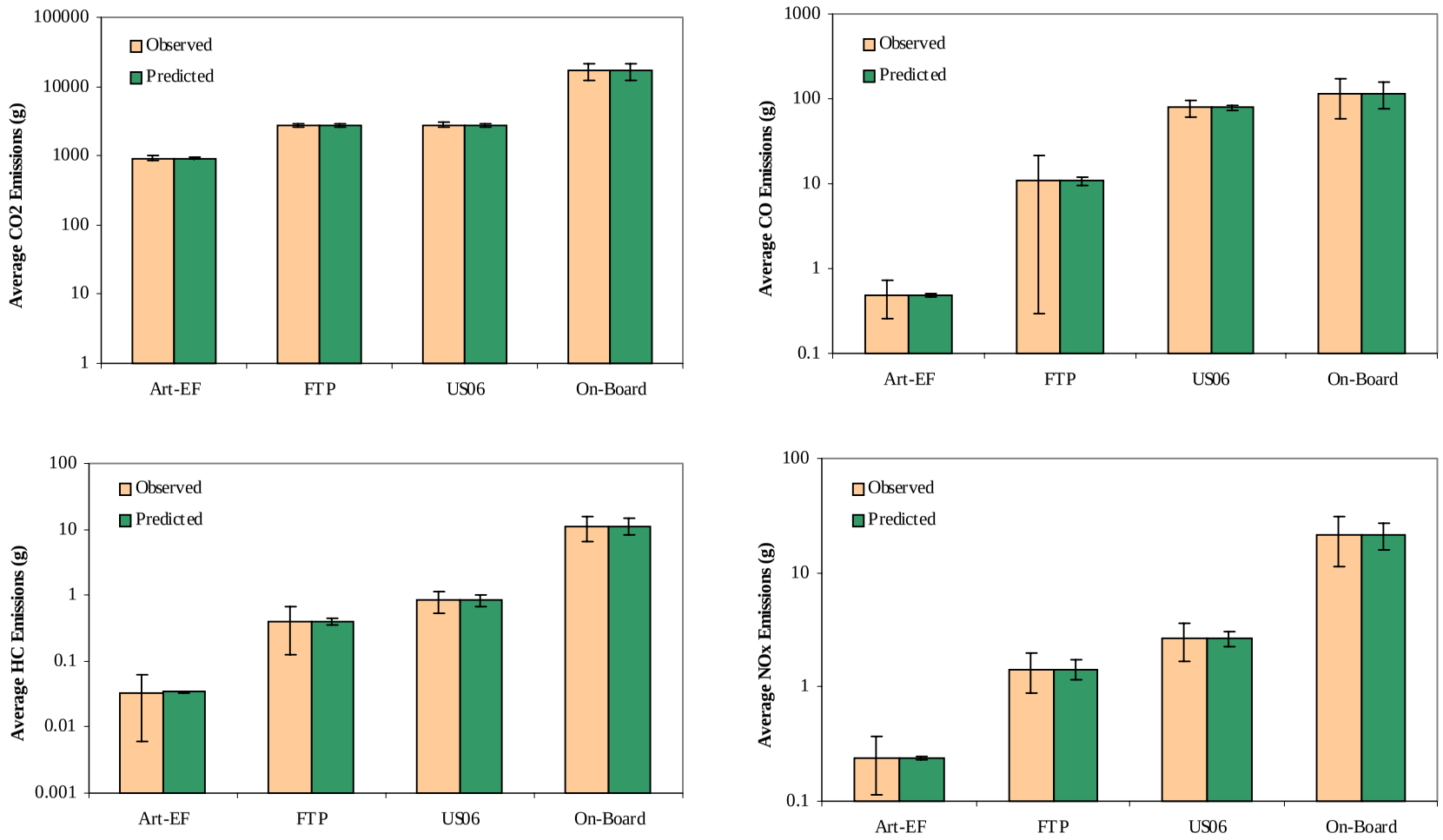

Figure 9-1. Comparison of Observed and Predicted Average Total Emissions of CO_2, CO, HC, and NO_x for Three Driving Cycles and for On-Board Data for Validation Dataset I.

Table 9-3. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset I for CO_2

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
ART-EF	926	800 - 1000	926	900 – 950	0	Y
FTP75	2740	2500 - 2900	2740	2600 – 2900	0	Y
US06	2790	2600 - 3000	2790	2600 - 2900	0	Y
On-Board	16800	11200 - 22000	16800	12000 - 21000	0	Y

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-4. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset I for CO

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
ART-EF	0.49	0.30 - 0.80	0.49	0.47 – 0.51	0	Y
FTP75	11	0.29 - 21	11	9.4 – 12	0	Y
US06	78	60 – 96	78	72 – 84	0	Y
On-Board	120	60 - 170	120	77 - 150	0	Y

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-5. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset I for HC

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
ART-EF	0.033	0.006 - 0.060	0.033	0.032 - 0.035	0	Y
FTP75	0.4	0.13 - 0.67	0.4	0.35 – 0.44	0	Y
US06	0.83	0.55 - 1.1	0.83	0.66 - 1.0	0	Y
On-Board	11	6.4 - 15	11	8.0 – 14	0	Y

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-6. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset I for NO_X

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
ART-EF	0.24	0.11 - 0.36	0.24	0.22 - 0.25	0	Y
FTP75	1.4	0.90 – 2.0	1.4	1.1 – 1.7	0	Y
US06	2.6	1.7 - 3.6	2.6	2.2 - 3.0	0	Y
On-Board	21	11 - 31	21	15 - 27	0	Y

[a] Diff: ((Predicted-Observed)/Observed)*100

The percentage difference in predicted and observed values is presented in Tables 9-3 through 9-6. An indication is given as to whether the confidence intervals for the predicted and observed means overlap.

The average total emissions predictions from the model are exactly the same as the observed values for all the cycles and for the on-board data: in all cases the percentage difference between the mean prediction and the mean observation is zero percent, and the confidence intervals for the predicted and observed means overlap. The three cycles and the on-board data differ substantially in terms of total average emissions. For example, the observed values for CO range between 0.5 grams to 115 grams when comparing the ART-EF cycle and the on-board data, respectively. Thus, the performance of the modeling approach is robust over a wide range of different emissions estimates.

The main findings from Validation Case Study 1 are:

- Percent difference in the predicted versus observed values are all zero
- There was excellent agreement between the predicted and observed CO_2, CO, HC, and NO_x emissions over a wide range of emissions
- The methodology for disaggregating driving cycle or trip emissions into driving modes, and re-aggregating the average modal emissions to make estimates of driving cycle or trip emissions, is demonstrated to be internally consistent, as is expected.

9.2 Validation Case Study 2

For Validation Case Study 2, model predictions were prepared based upon average modal emission rates calibrated to the modeling data set for all vehicles, all driving cycles, and all on-board data. Model predictions were made for an independent data set of emissions for vehicles that were not included in the modeling data set. The independent data set, referred to as Validation Data Set 2, is summarized in Table 9-7. This data set is comprised of 81,808 seconds of data from EPA dynamometer, EPA on-board measurement, and NCHRP dynamometer data. The number of vehicles, number of trips and number of seconds of data associated with each driving cycle are reported in the table. Validation Data Set 2 includes 78 vehicles, 83 trips, and 16 different cycles, including the on-board data as a lumped category. It should be noted that the number of vehicles tested on some cycles is very small. Specifically, except for the FTP75 and US06 cycles, three or fewer vehicles were tested. For validation purposes, comparisons were made only for FTP75, US06 cycles, and On-Board data for which many vehicles and/or many seconds of data were available. Key characteristics of the cycles utilized for the Validation Dataset II are given in Table 9-2. Key characteristics of vehicles in this dataset are shown in Appendix A.

The predicted and observed average total emissions for specific cycles, and the 95 percent confidence intervals on the averages, are shown in Figure 9-2 for total emissions of CO_2, CO, HC, and NO_x. The comparisons are summarized in Tables 9-8 through 9-11 for CO_2, CO, HC, and NO_x emissions, respectively.

Table 9-7. Summary of Driving Cycles, Number of Vehicles, Number of Trips, and Samples Size for Validation Dataset II

Data Source	Cycle	NO. of Vehicles	No. of Trips	Total Seconds
EPA Dynamometer	ART-AB	2	2	1471
EPA Dynamometer	ART-CD	2	2	1255
EPA Dynamometer	ART-EF	3	3	1507
EPA Dynamometer	FWY-AC	2	2	1029
EPA Dynamometer	FWY-D	2	2	809
EPA Dynamometer	FWY-E	2	2	909
EPA Dynamometer	FWY-F	3	3	1321
EPA Dynamometer	FWY-G	2	2	777
EPA Dynamometer	FWY-HI	3	3	1825
EPA Dynamometer	LOCAL	2	2	1047
EPA Dynamometer	NONFWY	2	2	2693
EPA Dynamometer	NYCC	3	3	1795
EPA Dynamometer	Ramp	2	2	529
NCHRP	FTP75	24	24	32950
NCHRP	US06	21	21	12648
On-Board Data	On-Board	3	18	19243

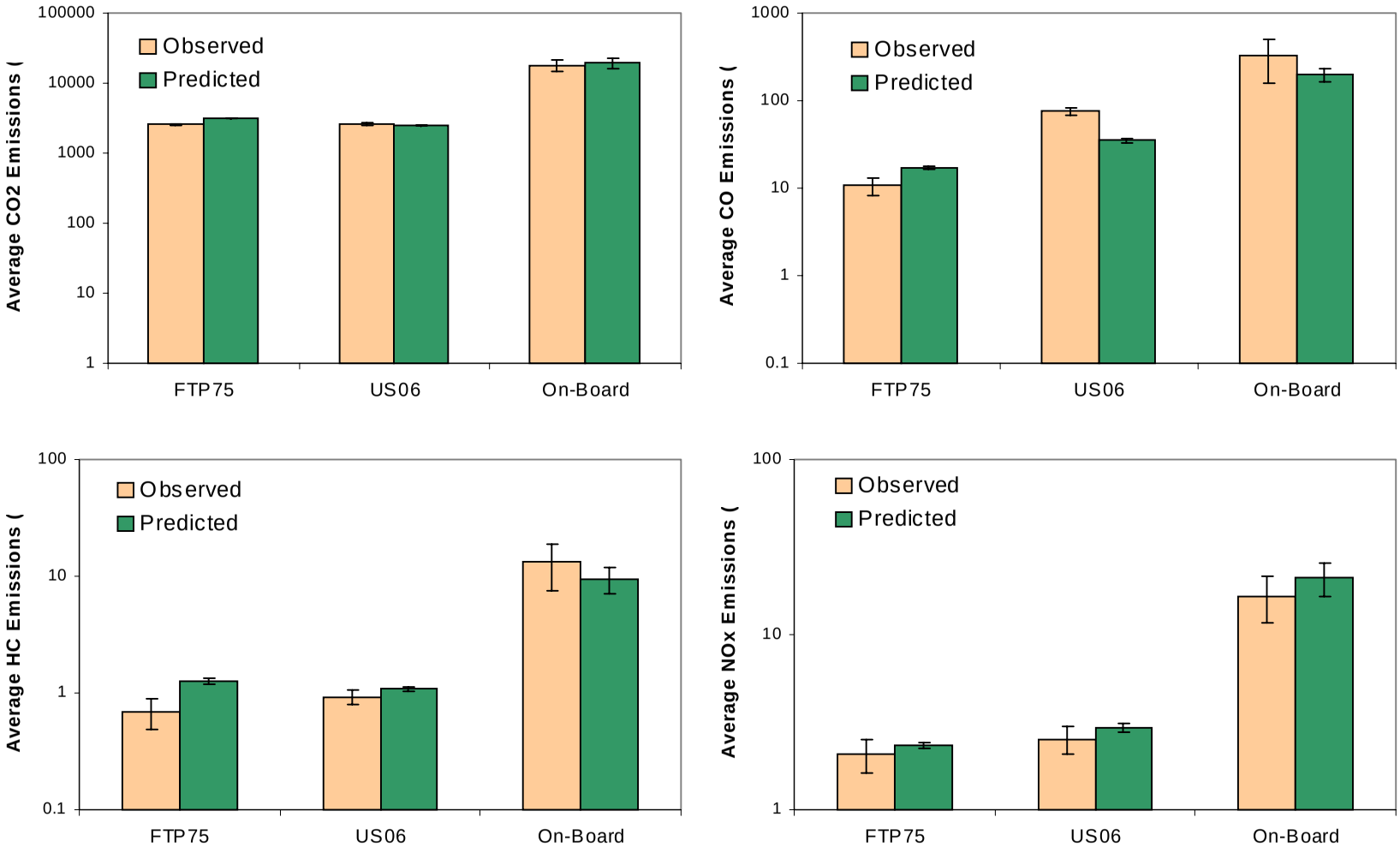

Figure 9-2. Comparison of Observed and Predicted Average Total Emissions of CO_2, CO, HC, and NO_x for the FTP75 and US06 Driving Cycles and for On-Board Measurements for Validation Dataset II.

Table 9-8. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset II for CO_2

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
FTP75	2563	2480 - 2645	3195	3164 - 3227	25	**N**
US06	2596	2505 - 2686	2491	2440 - 2542	-4	**Y**
On-Board	17775	14367 - 21184	19612	16083 - 23142	10	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-9. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset II for CO

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
FTP75	10.6	8.3 - 13.0	17.4	16.7 - 18.0	64	**N**
US06	75.1	67.7 - 82.5	34.9	32.2 - 37.5	-54	**N**
On-Board	328.4	161.0 - 495.8	199.8	162.7 - 236.9	-39	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-10. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset II for HC

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
FTP75	0.69	0.49 - 0.89	1.26	1.20 - 1.32	83	**N**
US06	0.93	0.80 - 1.06	1.08	1.02 - 1.13	16	**Y**
On-Board	13.17	7.49 - 18.85	9.40	7.02 - 11.78	-29	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-11. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset II for NO_X

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
FTP75	2.06	1.61 - 2.51	2.33	2.24 - 2.42	13	**Y**
US06	2.53	2.09 - 2.97	2.93	2.78 - 3.07	16	**Y**
On-Board	16.60	11.57 - 21.62	21.05	16.46 - 25.65	27	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

As observed in Figure 9-2, the predicted average total CO_2 emissions are close to the observed average total CO_2 emissions, especially for the US06 cycle and the on-board data. In these latter two cases, the confidence intervals of the predicted and observed means overlap. The predicted average CO_2 emissions are within 25 percent of the observed average values for the FTP75 cycle.

For CO, the qualitative trends of the model predictions are similar to that of the observed data, as illustrated in Figure 9-2. For example, the on-board data had the highest observed total emissions and also had the highest predicted total emissions. Both the observed and predicted emissions decreased when comparing the FTP75 driving cycle to the US06 driving cycle. Except for the FTP75 cycle, the model underpredicted the observed emissions. The underprediction is suggestive of a different vehicle mix in Validation Data Set 2 versus the modeling data set. Validation Data Set 2 contains a larger proportion of smaller engine sizes and higher mileage than does the modeling data set. Nonetheless, the model predictions were not statistically significantly different from the observed values for the on-board data, and were comparable in magnitude to the data from the two driving cycles.

Qualitatively, the model predictions perform well compared to the observations for HC emissions. Similar to the situation for CO emissions, the model appropriately predicts the highest emissions for the on-board data, which have the highest observed emissions. The US06 and FTP75 cycles are predicted to have moderate emissions, comparable in magnitude to the observed values. Furthermore, the predictions of the model were not statistically significantly different from the observed emissions for the US06 driving cycle and for the on-board data.

For NO_x, the model performed well for all three of the comparisons. In particular, the confidence intervals of the model predictions overlapped with the confidence interval of the observed emissions. Thus, the model predictions were not statistically significantly different than the observed values. Therefore, the average error in the model prediction ranging from 13 to 27 percent among the three comparisons are not considered significant and are within the random error of the data.

The overall findings of this case study are:

- There is good concordance in the model predictions versus the observations in terms of the ordinal ranking of which cycles have the highest and lowest emissions.
- The predictions for CO, HC, and NO_x tend to be better when the prediction for CO_2 is also reasonably close. For example, the predictions for all three pollutants were very good for the on-board data, and the predictions of two of the three pollutants were very good for the US06 cycle. The CO_2 predictions were generally very good for these three data sets. In contrast, somewhat surprisingly, the predictions were generally not as good as expected for the FTP75 cycle, for which the CO_2 average prediction was also different from the average observed value by 25 percent.
- A comparison of CO_2 predicted and observed values may be a good diagnostic tool for identifying systematic differences between data sets. It appears that the Validation Data Set 2 is more heavily weighted toward vehicles with smaller engines compared to the calibration data set.

- The systematic differences observed here for CO_2 suggest that additional refinement may be warranted for the engine displacement criteria when binning data. For example, rather than grouping all engine displacements of less than 3.5 liters into a bin for a given VSP, it may be appropriate to further subdivide this bin into two or more subcategories.

9.3 Validation Case Study 3

Validation Dataset III includes California Air Resources Board (CARB) data provided by the EPA. This dataset includes data from the following cycles: UCC17; UCC20; UCC25; UCC30; UCC35; UCC40; UCC45; OLD UCC50; UCC50; Modified Unified Cycle (MUC); and UCC60. The data provided by EPA did not include second-by-second speed profiles for each test. However, nominal speed profiles for these cycles were provided. The nominal speed profiles were used to determine the fraction of time that the vehicle was in each VSP mode. Table 9-12 summarizes Validation Dataset III. A total of 17 vehicles were tested, over 164 tests, on 11 different cycles. However, the number of vehicles tested on some cycles was small. For example, four or fewer vehicles were tested on the MUC, UCC50, and UCC60 cycles. For comparison purposes, only cycles for which 10 or more vehicles were tested were utilized in this study.

Key characteristics of the cycles utilized for Validation Dataset III are given in Table 9-13. Average speeds for the cycles ranges between 13 mph and 53 mph. The lowest average speed occurred for the UCC17 cycle and the highest average speed occurred for the UCC60 cycle. The lowest maximum speed of 37 mph occurred for the UCC17 cycle and the highest maximum speed of 81 mph occurred for the UCC60 cycle. Except for the Old UCC50 and UCC50 cycles, all cycles have a maximum acceleration of less than 7 mph/sec. Seven of the 11 cycles have an average VSP of less than 5 Kw/ton. The UCC35, Old UCC50, and UCC60 cycles have a maximum VSP greater than 50 Kw/ton.

Since engine displacement data were not available for Validation Data Set III, it was assumed that all vehicles in this dataset have engine displacement less than 3.5 liters based upon discussion with EPA.

The average predicted and observed emissions, along with 95 percent confidence intervals are shown in Figure 9-3 for all four pollutants. The comparisons are detailed in Tables 9-14 through 9-17 for CO_2, CO, HC, and NO_x emissions, respectively. The predictions were made using the average modal emission rates estimated from the modeling database.

For CO_2, the average model predictions are close to the average observed values as indicated by the fact that for six of the eight cycles for which comparisons were done, the means agreed to within 10 percent. Furthermore, for seven of the cycles, the confidence intervals of the predictions overlapped with the confidence intervals of the observations, and for all cycles the mean predictions were within 15 percent. These findings imply strong agreement between the model predictions and the observations. The model average predictions vary among the driving cycles by a factor of approximately 8 for the largest to the smallest prediction compared to a factor of approximately 10 for the average observations. The model appears to slightly overpredict for the lower emissions cycles.

Table 9-12. Summary of Driving Cycles, Number of Vehicles, Number of Tests, and Sample Size for Validation Dataset III

Data Source	Cycle	No. of Vehicles	No. of Tests	Total Seconds
ARB data	UCC17	17	17	7174
ARB data	UCC20	17	17	15048
ARB data	UCC25	17	17	15372
ARB data	UCC30	17	17	17712
ARB data	UCC35	17	17	24318
ARB data	UCC40	17	17	24012
ARB data	UCC45	17	17	23472
ARB data	OLD UCC50	15	15	34663
ARB data	MUC*	4	20	46760
ARB data	UCC50	2	4	8768
ARB data	UCC60	2	4	11240

* MUC: Modified Unified Cycle

Table 9-13. Key Characteristics of the Activity Patterns of the Driving Cycles in Validation Dataset III.

Cycle ID	**Time (s)**	**Average Speed (mph)**	**Max Speed (mph)**	**Min Speed (mph)**	**Max Acceleration (mph/sec)**	**Mean VSP (Kw/ton)**	**Max VSP (Kw/ton)**
UCC17	422	13	37	0	4.6	1.4	22.3
UCC20	836	18	44	0	5.7	1.9	25.6
UCC25	854	23	50	0	5.9	2.5	23.1
UCC30	984	27	59	0	5.5	3.1	35.8
UCC35	1351	32	69	0	5.6	4.1	68.2
UCC40	1334	36	72	0	5.5	5.1	48.9
UCC45	1304	45	71	0	5.7	6.5	43.3
OLD UCC50	2039	48	76	0	8.1	7.8	86.5
MUC*	2338	17	67	0	6.9	2.1	35.1
UCC50	2192	43	72	0	7.5	6.3	28.1
UCC60	2810	53	81	0	6.4	9.2	57.2

* MUC: Modified Unified Cycle

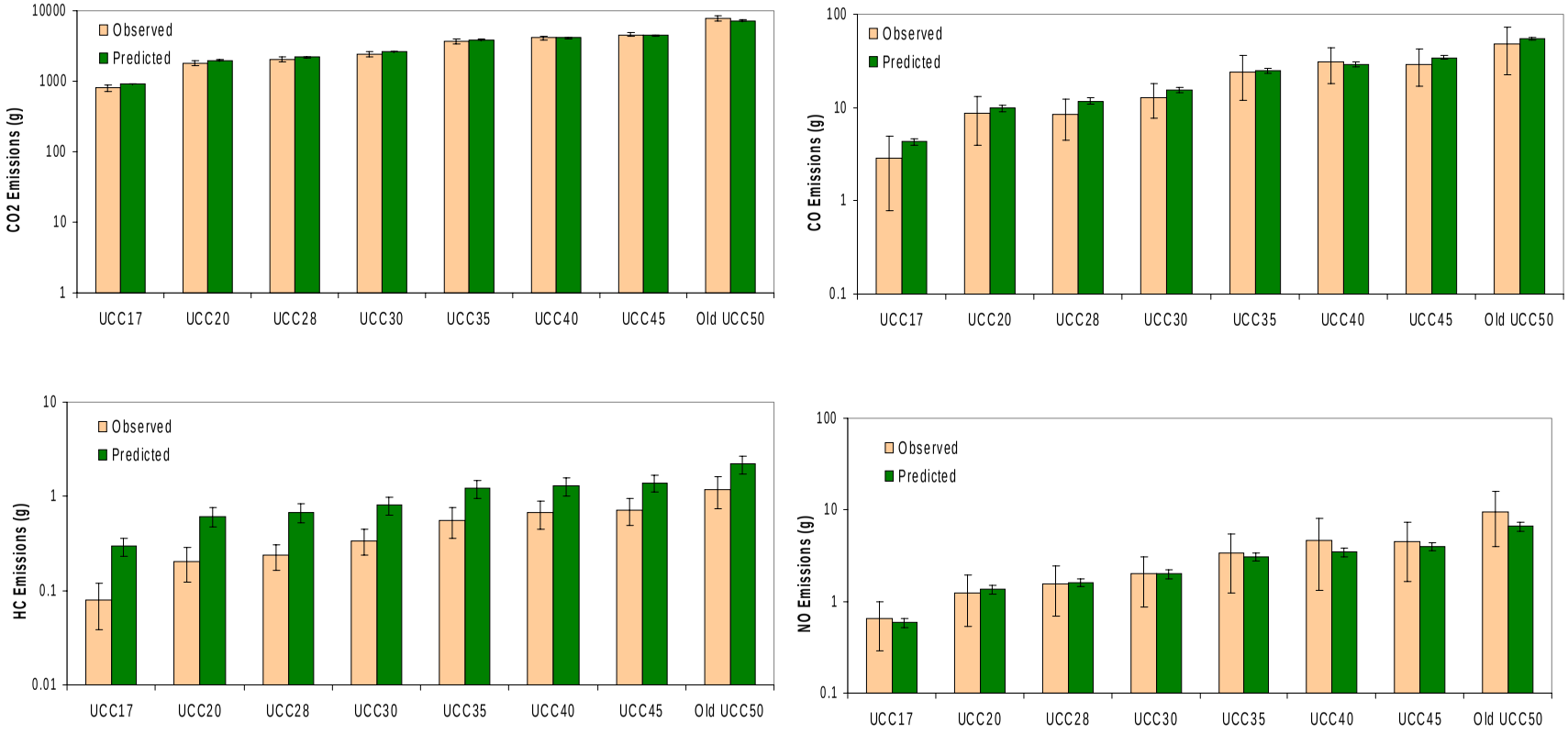

Figure 9-3. Comparison of Observed and Predicted Average Total Emissions of CO_2, CO, HC, and NO_x for Eight UCC Driving Cycles for Validation Dataset III.

Table 9-14. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset III for CO_2

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
UCC17	800	722 - 879	915	902 - 929	14	**N**
UCC20	1787	1632 - 1941	1975	1941 - 2008	11	**Y**
UCC25	2050	1888 - 2211	2196	2155 - 2237	7	**Y**
UCC30	2407	2220 - 2594	2617	2568 - 2666	9	**Y**
UCC35	3690	3416 - 3963	3849	3771 - 3926	4	**Y**
UCC40	4078	3799 - 4356	4084	3998 - 4171	0	**Y**
UCC45	4586	4257 - 4916	4439	4338 - 4540	-3	**Y**
OLD UCC50	7856	7235 - 8477	7252	7070 - 7435	-8	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-15. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset III for CO

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
UCC17	2.9	0.8 – 4.9	4.3	3.9 - 4.7	48	Y
UCC20	8.6	3.9 – 13.4	9.8	9.0 - 10.6	14	Y
UCC25	8.3	4.4 – 12.2	11.6	10.7 - 12.6	40	Y
UCC30	12.8	7.6 – 18.0	15.5	14.4 - 16.6	21	Y
UCC35	24.3	11.9 – 36.8	25.1	23.6 - 26.5	3	Y
UCC40	31.2	18.1 – 44.4	29.0	27.4 - 30.5	-7	Y
UCC45	29.5	16.9 – 42.1	34.4	32.9 - 35.9	17	Y
OLD UCC50	47.7	22.4 – 73.1	54.8	52.2 - 57.4	15	Y

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-16. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset III for HC

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
UCC17	0.08	0.04 - 0.12	0.29	0.23 - 0.36	263	**N**
UCC20	0.20	0.12 - 0.29	0.62	0.48 - 0.76	210	**N**
UCC25	0.24	0.16 - 0.31	0.68	0.53 - 0.83	183	**N**
UCC30	0.34	0.24 - 0.44	0.81	0.63 - 0.99	138	**N**
UCC35	0.56	0.36 - 0.76	1.20	0.94 - 1.46	114	**N**
UCC40	0.67	0.45 - 0.89	1.28	1.01 - 1.56	91	**N**
UCC45	0.71	0.49 - 0.93	1.40	1.10 - 1.69	97	**N**
OLD UCC50	1.19	0.74 - 1.63	2.21	1.71 - 2.71	86	**N**

[a] Diff: ((Predicted-Observed)/Observed)*100

Table 9-17. Summary of Comparisons of Predicted versus Observed Vehicle Average Total Emissions for Validation Dataset III for NO_X

Cycles	Mean Obs. (g)	95 % CI	Mean Pred. (g)	95 % CI	Diff. [a] (%)	CIs Overlap
UCC17	0.65	0.29 - 1.00	0.59	0.53 - 0.65	-9	**Y**
UCC20	1.25	0.54 - 1.96	1.36	1.22 - 1.50	9	**Y**
UCC25	1.57	0.70 - 2.44	1.62	1.45 - 1.79	3	**Y**
UCC30	1.98	0.86 - 3.11	2.00	1.79 - 2.21	1	**Y**
UCC35	3.34	1.22 - 5.46	3.09	2.76 - 3.42	-7	**Y**
UCC40	4.67	1.34 - 8.00	3.46	3.10 - 3.82	-26	**Y**
UCC45	4.47	1.64 - 7.30	3.99	3.56 - 4.42	-11	**Y**
OLD UCC50	9.41	6.7 - 16	6.54	5.79 - 7.29	-30	**Y**

[a] Diff: ((Predicted-Observed)/Observed)*100

For CO and NO_x, the confidence intervals overlap for all eight of the driving cycles when comparing predicted and observed averages. This suggests strong agreement between the model and the observations for all of the cycles evaluated. The CO predictions typically are larger than the observed values and the prediction errors are as large as approximately 40 percent for the lower emission cycles and not larger than approximately 20 percent for the higher emission cycles. The observed CO emissions vary by a factor of 16 from the smallest to the largest values, and the predicted CO emissions vary similarly by a factor of 13. For NO_x, the prediction errors were less than plus or minus 10 percent for five of the eight cycles, and were less than or equal to plus or minus 30 percent for all cycles. The observed NO_x emissions varied by a factor of 15 from the smallest to the highest values, while the predictions varied similarly by a factor of 11.

For HC, the predictions were typically a factor of two to three larger than the observed values. However, the qualitative trend of the predictions was similar to the observed values when comparing cycles in terms of rank ordering with respect to emissions. For example, the model predicted the lowest emission rate for the UCC17 cycle and the highest emission rate for the Old UCC50 cycle, which is consistent with the observations.

There is some uncertainty regarding the regulations to which some of the vehicles in the CARB data set are subject. It is possible that some of the vehicles may be TLEV, rather than Tier 1, vehicles, although specific information regarding this was not available with the data set. TLEV vehicles are subject to a more stringent HC emission standard but are otherwise the same as Tier 1 vehicles. The comparison suggests that the CARB vehicles have similar CO_2, CO, and NO_x emissions but lower HC emissions when compared to the predictions made based upon modal emissions rates estimated from the modeling data set. An analysis was done for two subsets of the CARB database: (1) vehicles believed to be subject to Tier 1 standards; and (2) vehicles believed to be subject to TLEV standards. It turned out that these two subgroups of vehicles did not have any statistically significant difference in emissions with each other taking into account all four pollutants and all eight driving cycles. Thus, to the extent that TLEV vehicles may be present in the CARB database, the specific sample of TLEVs would not appear to have different average emissions than the specific sample of Tier 1 vehicles. It is possible, therefore, that the predicted and observed HC emissions may differ for reasons other than emission standards, such as perhaps because of different fuels. There was also uncertainty as to whether the HC emissions reported in the CARB database were for total hydrocarbons or for non-methane hydrocarbons (NMHC). The data were used assuming that they represented total hydrocarbons. However, if the HC data were actually for NMHC, then it would be necessary to add the estimated methane emissions in order to calculate the total observed hydrocarbons, in which case the comparison would improve. Confirmation on this point could not be obtained during the time period of this study.

The main findings from Validation Case Study 3 are:

- There was excellent agreement between the predicted and observed CO_2, CO, and NO_x emissions.
- There appears to be excellent concordance between the predicted and observed HC emissions.

9.4 Preliminary Exploration of Refinements to the Modal Modeling Approach

Validation Case Study II indicated that there was some disagreement between the model predictions and the observed values particularly for the FTP75 cycle. It was observed that the validation data set tended to have vehicles with smaller engines than did the modeling dataset. Therefore, a refinement to the modal modeling approach was explored in which the modeling database was stratified into more engine displacement categories than was used in the "56-bin" approach developed in Chapter 3. In addition, a second type of refinement was explored in which an additional explanatory variable was sought for purposes of disaggregating each VSP bin. Based upon an analysis of the sensitivity of the average emissions in a VSP bin to acceleration and to average speed, as illustrated in Appendix A in Figure A-7, either of these two variables was identified as potentially useful in further disaggregating the modeling database to create additional bins. Speed was selected as the explanatory variable for further consideration because speed is directly measured and because speed and acceleration are inversely related to each other for most of the VSP bins, as illustrated by the scatter plots shown in Chapter 5 in Figures 5-10 and 5-11. Thus, there is little need to include both speed and acceleration as additional explanatory variables.

In the case of refinement of the modal modeling approach based upon additional engine displacement categories, three levels of engine displacement were used, rather than two as in the original VSP-approach. These levels are: engine displacement less than 2.0 liter; engine displacement greater than 2.0 liters and less than 3.5 liters; and engine displacement greater than 3.5 liter. In this approach, there are totally 84 bins, (2 odometer reading categories, 3 engine displacement categories, and 14 VSP modes). The average modal emission rates for this "84-bin" approach are given in Appendix A in Figures A-5 and A-6 for vehicle with odometer reading less than 50,000 miles and for vehicles with odometer reading greater than 50,000 miles, respectively. Using these average modal rates, predictions were made and compared to the observed values for Validation Dataset II. There was no significant improvement in the predictions based upon the disaggregating of engine displacement into three instead of two categories.

In the case of refinement of the modal modeling approach based upon speed, two levels of speed were defined for each VSP mode based upon a selected cut point of 32 mph. The average emission rates for each VSP mode for the low and high speed bins are shown in Appendix A in Figures A-8 through A-11 for vehicles with the following characteristics, respectively: (1) engine displacement less than 3.5 liters and odometer reading less than 50,000 miles; (2) engine displacement greater than 3.5 liters and odometer reading less than 50,000 miles; (3) engine displacement less than 3.5 liters and odometer reading greater than 50,000 miles; and (4) engine displacement greater than 3.5 liters and odometer reading greater than 50,000 miles. For the higher speed bins, the average emission rates tend to be higher in many cases, such as for CO_2 emissions for the lower VSP modes, for CO for most modes, for HC especially for the lowest VSP modes, and for NO_x for low to moderate VSP modes. The comparison of the average modal emission rates for the two speed bins for a given VSP mode suggests that there are opportunities to refine the estimation of emission rates by considering speed as an additional explanatory variable. A trade-off is that the sample size of each bin becomes smaller, leading to wider confidence intervals in some cases. When the speed disaggregated VSP modes were used to make predictions of cycle emissions for Validation Case Study 2, there was not a significant

improvement in the prediction of total emissions compared to the predictions from the "56-bin" approach. Thus, it may be the case that additional levels of detail at the micro scale may not lead to substantial improvements in predictions at the macro scale. However, it is likely that disaggregation of VSP bins by speed will lead to more accurate predictions at the micro- or mesoscale.

Of the two refinements to the modal modeling approach explored here, the refinement based upon speed appears to offer promise for improving the accuracy of microscale or mesoscale predictions, even though it may not help substantially in improving macroscale predictions, at least for the conditions evaluated in this study.

9.5 Summary and Recommendations

The main findings from all three verification and validation case studies are:

- The modal modeling approach is internally consistent, as demonstrated by Validation Case Study I. Specifically, it is possible to reproduce total trip emissions based upon proper estimating and combination of average emissions for individual modes.
- The model generally performs well for the higher emission cycles and for cycles or conditions that are represented by a large portion of the data in the modeling data set.
- The model is highly responsive, predicting a wide range of variability in average emissions.
- Although the model tends to ove-rpredict for low emissions cycles, such cycles may be less important from an inventory perspective than the high emissions cycles for which the model performs better.
- The model performance for the low emissions cycles could be improved by working with modeling datasets that have a larger representation of such cycles, or perhaps by refining the modal definitions to better represent such cycles.
- A promising approach for refining the modal modeling method is to consider speed as an additional explanatory variable.
- Comparisons of CO_2 emissions appear to be a good method for determine the comparability of two datasets: in the case of the ARB data sets, there was excellent agreement for CO_2 and this extended to the other pollutants. For Validation Data Set 2, there were systematic differences in CO_2 for one of the driving cycles for which comparisons were done that appeared to extend to at least some of the other pollutants (e.g., CO, HC).

Overall, the results of the case studies illustrate the flexibility and robustness of a modal-based approach for making predictions for a wide variety of driving cycles and for on-board data.

10 RECOMMENDATIONS FOR METHODOLOGY FOR MODAL MODEL DEVELOPMENT

This report has explored in detail a number of key issues pertaining to the methodology for developing a modal emissions model. The main focus of the case studies have been with respect to hot stabilized tailpipe emissions from Tier 1 vehicles. However, when taking in the context of recent previous work by NCSU to develop approaches for estimating cold start emissions for gasoline vehicles, as well as modal emission rates for heavy duty diesel vehicles, this report combined with the previous efforts clearly demonstrates the feasibility of a modal modeling approach.

The key questions that were addressed in this work were the following:

1. What dataset should be used for the final version of the conceptual model? (Task 1a, Chapter 2)

2. Which binning approach should be used? (Task 1b, Chapter 3)

3. How much detail should be included in the binning approach, in terms of how many explanatory variables and how many strata for each variable? (Task 1b, Chapter 3)

4. What averaging time is preferred as a basis for model development? (Task 1b, Chapter 4)

5. What emission factor units should be used? (Task 1b, Chapter 5)

6. What weighting approach should be used, when comparing time-weighted, vehicle weighted, and trip weighted? (Task 1b, Chapter 6)

7. How should variability and uncertainty be characterized? (Task 1c, Chapter 7)

8. How should aggregate bag data be analyzed to derive estimates of modal emission rates? (Task 1d, Chapter 8)

9. What is the potential role and feasibility of incorporating RSD data into the conceptual modeling approach? (Task 1e, Chapter 5)

10. How should the conceptual model be validated and what are the results of validation exercises? (Task 2, Chapter 9)

The answers to these questions are briefly summarized here, and are given in more detail in the respective chapters devoted to each topic.

The data set used for the conceptual model was comprised of EPA dynamometer data, EPA on-board data, and NCHRP dynamometer data. These data comprised the modeling database. The modeling database was compared to several other databases, including an IM240 database and an RSD database.

The binning approach selected was a 14 mode VSP-based approach. However, it was shown that an approach based upon driving modes of idle, acceleration, cruise, and deceleration produced comparable predictions for total emissions. Thus, the 14 mode VSP-based approach is not unique in its capability to predict emissions, but it is expected to facilitate design of a modeling system perhaps moreso than the other approach.

There is a trade-off between improving the explanatory power of a model and having a model that becomes complicated to code or use. Odometer reading and engine displacement were identified as key explanatory variables. Engine displacement is highly correlated with vehicle net weight and with the number of cylinders of the engine. Therefore, it is not necessary to include net vehicle weight or number of cylinders if engine displacement is selected as an explanatory variable. Odometer reading is weakly correlated with model year. This suggests that there might be a role for model year in future model development. Because this study focused upon Tier 1 vehicles, with much of the data spanning only a very limited range of model years, it is possible that the influence of model year is understated with respect to this analysis and that it may be more important for other types of vehicles. Ambient parameters such as humidity were accounted for in correcting NO_x emissions. Ambient temperature was not found to be a significant explanatory variable. On the other hand, as discussed in Chapter 9, there may be an opportunity to improve the explanatory power of the 14 mode VSP-based approach by including either speed or acceleration as a criteria for further disaggregating the bins.

The method for selecting the specific definitions of the 14 VSP bins took into account that each pollutant has a different sensitivity to VSP. Thus, a "supervised" technique was used in which the contribution of any individual mode to total emissions for a given pollutant was considered as a key criteria. This approach produced one set of modal definitions that worked well for all four pollutants.

An approach based upon "56 bins" for which the 14 VSP modes were stratified into two odometer reading categories and two engine displacement categories performed reasonably well when predictions were compared to observations for independent data sets, as reported in Chapter 9. The validation case studies thus emphasize that the modal emissions approach is feasible. A key benefit of the conceptual modeling approach is that it works for all four pollutants considered, and it is not necessary to develop a separate approach for each pollutant.

Three averaging times were compared with respect to ability to make predictions of trip emissions. No substantial difference was found. Thus, for simplicity, the one second averaging time was recommended for model development and was employed in this work. However, although the issue of averaging time may not have a significant effect on prediction of average emissions, there is a significant effect on the prediction of uncertainty in average emissions. As noted in Chapter 7, the range of uncertainty in the average modal emission rates is a function of averaging times, and the uncertainty estimates should be adjusted appropriately when making predictions of uncertainty.

Three weighting approaches were compared, including time, trip, and vehicle weighted approaches. It is clear that the average emission estimates will differ depending on which approach is used, because each approach gives a different amount of weight to different

subgroups of the data. For example, the time weighted approach gives equal weight to each data point. The trip weighted approach gives each trip (or driving cycle test) equal weight, even though trip lengths may differ and even though some vehicles may be represented by many trips and others may be represented by only one. The vehicle weighted approach gives each vehicle equal weight regardless of the total testing time or number of trips (or tests). When comparing time, trip, and vehicle weighted approaches, the standard deviation of the variability in emissions decreases in the same order because each successive approach involves more averaging. However, the averaging time is not standardized for the trip and vehicle weighted approaches. Because averaging time is important to accurate estimation of uncertainty, preference was given in this work to the time weighted approach.

With regard to emission factor units, there was no clear overall advantage for emission ratios versus mass per time emission factors for CO, HC, and NO_x. Although it is the case that there is less variability in the averages among many of the modes for CO and HC for emission ratios when compared to mass per time emission rates, for NO_x there is substantial variability across all modes regardless of the units used. For software design purposes, it is simpler to use the same approach for all pollutants. Thus, an emission ratio approach would require a similar number of modes as the mass per time approach. In this regard, there was no clear advantage. Additionally, it is necessary to estimate mass per time emissions of CO_2, or to estimate mass per time fuel consumption, in order to convert emission ratios for CO, HC, and NO_x to mass emission rates as would be required for an emission inventory model. Although an emission ratio approach offers some benefits of simplicity when applied to an areawide macroscale emission inventory based upon information such as fuel sales, an emission ratio approach nonetheless would require modal estimates of CO_2 emissions or fuel use when applied to mesoscale emission inventories. Thus, for consistency in the modeling approach, the preferred strategy was to use mass per time emission rates for all pollutants and to apply the same modal emissions approach for all pollutants.

Considerable attention was devoted in this work to methods for characterizing variability in emission rates for individual modes, uncertainty in average emissions for individual modes, and uncertainty in total emissions estimated based upon weighted combinations of modes. The recommendations regarding these issues are given in more detail in Chapter 7. In brief, the feasibility of representing variability in modal emission rates with parametric distributions was demonstrated. In some cases, single component parametric distributions cannot provide a good fit, but in such cases a two component mixture of lognormal distributions provided an excellent fit. The Method of Matching Moments is recommended as a preferred parameter estimation method if the objective is to have the mean and standard deviation of the fitted distributions match those of the data. For mixture distributions, MoMM is not considered a feasible parameter estimation method and Maximum Likelihood Estimation is recommended. However, the differences in results between MoMM and MLE become smaller as the goodness-of-fit improves. Thus, a well fitting mixture distribution will typically have a mean and standard deviation similar to that of the data.

The analysis of uncertainty need not be conditioned upon the assumptions made regarding the characterization of variability based upon parametric distributions. For example, uncertainty in the mean can be estimated directly based upon the data using analytical or numerical methods. It

is recommended that the sample size and the relative standard error of the mean of each bin quantified. If the sample size is less than 40 and/or if the relative standard error of the mean is greater than 0.2, then bootstrap simulation is recommended as a technique for quantifying the sampling distribution of the mean. In all other cases, a normality assumption will typically be more than adequate. Parametric distributions can be fit to sampling distributions obtained from bootstrap simulation. Thus, for all modes, it is possible to use parametric distributions to represent uncertainty in the mean, which will facilitate software design and model applications.

Both numerical and analytical methods for propagating uncertainty through a model were explored. Numerical methods such as Monte Carlo simulation or Latin Hypercube Sampling offer the advantage of increased flexibility to accommodate many kinds of distributions and models, including situations in which uncertainty is quantified not only for modal emission rates but also for vehicle activity (e.g., percentage of time spent in different modes and trip duration). In contrast, the analytical approach offers the advantage of less computational burden but is also less flexible. An exact solution can be obtained for linear combinations of normal distributions, such as when uncertainty in only modal emission rates is quantified and when all such uncertainties are assumed to be normally distributed. Approximate analytical solutions can be developed for other situations, such as when propagating uncertainty in both activity and emission rates. If this latter approach is to be further considered, the approach should be evaluated quantitatively in comparison to a Monte Carlo approach to make sure that it will produce sufficiently accurate results. If a Monte Carlo approach is adopted, consideration should be given to also including an analytical approach for use as a quality assurance tool.

The range of uncertainty in total emissions estimates was large enough in many cases to justify the importance of performing an uncertainty analysis. For example, for HC and CO emissions the range of uncertainty was as large as plus or minus 30 percent for selected vehicle groups and for four different driving cycles.

With respect to the issue of how to estimate modal emission rates from aggregate dynamometer data (for which no second-by-second data are available), the results were mixed. It is possible to develop good modal emission estimates especially for CO_2 as long as there is a sufficient sample size and as long as sufficient constraints are specified in the least squares optimization approach. However, the range of uncertainty in the predicted modal emission rates can be much larger than the uncertainty in modal emission rates obtained from second by second data. The results imply that it is important to develop good estimates of the constraints; however, when applied to vehicle groups for which there are no or few comparable second-by-second data, such as for older carbureted vehicles, it may be difficult to develop good estimates of what the constraints should be. An alternative approach is to arbitrarily specify more stringent constraints, such as defining ratios to be multiples of each other, in which case the estimation problem becomes simpler but the answers obtained will be highly conditional upon such constraints.

The most critical issue in the modal modeling approach is to have a representative data set. This issue cannot be sidestepped regardless of the modeling approach employed. A representative data set should have proportional representation of vehicle emission rates and activity patterns similar to that in the real world. The development of such a database is resource limited and requires considerable judgment. In this particular work, the modeling database used for

development and demonstration of the modal emissions concept was compared to other databases, including IM240 and remote sensing data. It appears to be the case that modeling database produces lower emissions estimates for some modes and comparable emissions estimates for others when compared to these other data sources. A possible reason for the differences could be because of a different representation of high emitting versus normal emitting vehicles. However, another reason that was explored is that the activity patterns of the modeling database are generally different than those of the IM240 and RSD data. Thus, a key question is not only whether the modeling database contains sufficient representation of high emitting vehicles, but also whether the IM240 and RSD data contain adequate or appropriate representation of real world activity patterns from which it is useful to make inferences regarding emissions. The modeling database contained some high emitting vehicles, and it was apparent that the upper range of emission rates for a given mode of the modeling database were typically comparable to the upper range of emission rates from these other databases. Thus, the question is not whether the modeling database represents high emitting vehicles and/or high emitting episodes. Clearly, it does. The question is whether it contains a sufficient proportional representation of such situations. The evidence to support an answer to this question is inconclusive given the different nature of the activity patterns for the IM240 and RSD databases compared to that of the modeling database, as well as the possibility of other potential confounding factors, such as fuel effects. From a methodological perspective, the main implication of these comparisons in terms of future model development is to make sure that the modeling database for future work is more comprehensive in terms of sample size and coverage of vehicles considered to be both normal and high emitters.

Three approaches were taking toward validation of the conceptual modeling approach. The first was to perform a consistency check, which demonstrated that the modal emission approach can be applied to a dataset to disaggregate emissions into modes, and that it is possible to reaggregate the model emissions and reproduce the total trip emissions. The second was to compare model predictions to observed values for a set of vehicles similar to but not identical to those used in the modeling data base. The comparison demonstrated that differences in vehicle mix between the modeling database and the validation database can lead to differences when comparing predicted and observed emissions. However, for cases in which the model and the observed values agreed well for CO_2 emissions, they also tended to agree well for emissions of the other three pollutants. In the future, it is worthwhile to perform similar validation studies by withholding data from the modeling database for some of the trips made by a subset of vehicles, rather than to withhold from the modeling database all data for a particular set of vehicles. Such an approach would improve the likelihood that the vehicles in the validation data set are similar to those in the modeling data set. The third validation case study involved prediction of emissions for an independent set of vehicles based upon data provided by CARB. The comparison of predicted and observed emissions was generally excellent for CO_2, NO_x, and CO for eight different driving cycles. The model overpredicted for HC in all cases; however, it is possible that CARB may have reported only nonmethane hydrocarbons instead of total hydrocarbons or that there was a fuel effect. A potential distinction between Tier 1 and TLEV vehicles in the CARB database was explored. However, no significant difference in emissions was found for vehicles that might be TLEVs versus those that were Tier 1; therefore, it was not useful to report results separately for these two possible categories.

A key criteria for comparison when performing validation studies is to evaluate the statistical significance of differences between predicted and observed emissions. Emissions for individual vehicles can vary by orders of magnitude even for the same driving cycle; therefore, comparisons based upon a small number of vehicles will typically have wide confidence intervals for the mean and will be less reliable than those based upon a larger set of vehicles. Since the objective of an emission inventory model is to make accurate predictions for a fleet of vehicles, it is important to have a quantitative understanding of the level of uncertainty associated with mean predictions of the model, as has been demonstrated in this work.

In conclusion, this work has demonstrated the feasibility of an empirically-based method for modal emissions model. The methods demonstrated in this work can and should be incorporated or adapted for use in the development of MOVES and other emission estimation systems.

11 REFERENCES

Bachman, W. H. (1999), A GIS-Based Modal Model of Automobile Exhaust Emissions Final Report; Prepared by Georgia Institute of Technology for U.S. Environmental Protection Agency; Atlanta, Georgia.

Cullen, A.C., and H.C. Frey (1999). *The Use of Probabilistic Techniques in Exposure Assessment: A Handbook for Dealing with Variability and Uncertainty in Models and Inputs*. Plenum: New York, 1999. 335 pages.

Frey, H.C., R. Bharvirkar, and J. Zheng (1999), *Quantitative Analysis of Variability and Uncertainty in Emissions Estimation*, Prepared by North Carolina State University for the U.S. Environmental Protection Agency, Research Triangle Park, NC. July 1999.

Frey, H.C., and S. Bammi (2002a), "Quantification of Variability and Uncertainty in Lawn and Garden Equipment NO_x and Total Hydrocarbon Emission Factors," *Journal of the Air & Waste Management Association*, 52(4):435-448..

Frey, H.C., and S. Bammi (2002b), "Probabilistic Nonroad Mobile Source Emission Factors," *ASCE Journal of Environmental Engineering*, accepted for publication.

Frey, H.C., and D.E. Burmaster (1999), "Methods for Characterizing Variability and Uncertainty: Comparison of Bootstrap Simulation and Likelihood-Based Approaches," *Risk Analysis*, 19(1):109-130 (February 1999).

Frey, H.C., and D.A. Eichenberger (1997a), "Quantification of Uncertainty in Remote Sensing-Based School Bus CO and Hydrocarbon Emission Factors," Paper No. 97-RP143.07, *Proceedings of the 90th Annual Meeting* (held June 18-13 in Toronto, Canada), Air and Waste Management Association, Pittsburgh, Pennsylvania, June 1997 (CD-ROM).

Frey, H.C., and D.A. Eichenberger (1997b), *Remote Sensing of Mobile Source Air Pollutant Emissions: Variability and Uncertainty in On-Road Emissions Estimates of Carbon Monoxide and Hydrocarbons for School and Transit Buses*, FHWY/NC/97-005, Prepared by North Carolina State University for North Carolina Department of Transportation, Raleigh, June 1997.

Frey, H.C., and D.S. Rhodes (1996), "Characterizing, Simulating, and Analyzing Variability and Uncertainty: An Illustration of Methods Using an Air Toxics Emissions Example," *Human and Ecological Risk Assessment: an International Journal*, 2(4):762-797 (December 1996).

Frey, H.C., and D.S. Rhodes (1998), "Characterization and Simulation of Uncertain Frequency Distributions: Effects of Distribution Choice, Variability, Uncertainty, and Parameter Dependence," *Human and Ecological Risk Assessment: an International Journal*, 4(2):423-468 (April 1998).

Frey, H.C., and D.S. Rhodes (1999), *Quantitative Analysis of Variability and Uncertainty in Environmental Data and Models: Volume 1. Theory and Methodology Based Upon Bootstrap Simulation*, Report No. DOE/ER/30250--Vol. 1, Prepared by North Carolina State University for the U.S. Department of Energy, Germantown, MD, April 1999.

Frey, H.C., N. Rouphail, A. Unal, and J. Colyar (2000), "Emissions and Traffic Control: An Empirical Approach," Presented at CRC On-Road Vehicle Emissions Workshop, San Diego, CA, March 27-29, 2000.

Frey, H.C., N.M. Rouphail, A. Unal, and J.D. Colyar (2001), Emissions Reduction Through Better Traffic Management: An Empirical Evaluation Based Upon On-Road Measurements, FHWY/NC/2002-001, Prepared by North Carolina State University for North Carolina Department of Transportation, December 2001. 323 pp.

Frey, H.C., A. Unal, and J. Chen (2002), Recommended Strategy for On-Board Emission Data Analysis and Collection for the New Generation Model, Prepared by North Carolina State University for the Office of Transportation and Air Quality, U.S. Environmental Protection Agency, Ann Arbor, MI. February 2002.

Frey, H.C., and J. Zheng (2000), User's Guide for Analysis of Uncertainty and Variability in Emissions Estimation (AUVEE), Prepared by North Carolina State University for Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, September 2000.

Frey, H.C., and J. Zheng (2001), Methods and Example Case Study for Analysis of Variability and Uncertainty in Emissions Estimation (AUVEE), Prepared by North Carolina State University for Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC, February 2001.

Frey, H.C., and J. Zheng (2002a), "Quantification of Variability and Uncertainty in Utility NO_x Emission Inventories," *J. of Air & Waste Manage. Assoc.*, in press for September 2002 issue.

Frey, H.C., and J. Zheng (2002b), "Probabilistic Analysis of Driving Cycle-Based Highway Vehicle Emission Factors," *Environmental Science and Technology*, undergoing revision for April 2002 resubmission.

Frey, H.C., J. Zheng, Y. Zhao, S. Li, and Y. Zhu (2002), Technical Documentation of the AuvTool Software for Analysis of Variability and Uncertainty, Prepared by North Carolina State University for the Office of Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC. February 2002.

Hildebrand, F. B. (1987), *Introduction to Numerical Analysis*, Dover: New York, 669 pages.

Kini, M.D., and H.C. Frey (1997), *Probabilistic Evaluation of Mobile Source Air Pollution: Volume 1, Probabilistic Modeling of Exhaust Emissions from Light Duty Gasoline Vehicles*, Prepared by North Carolina State University for Center for Transportation and the Environment, Raleigh, December 1997.

Kress, R. (1998), *Numerical Analysis*, Springer: New York, 326 pages.

Morgan, M.G., and M. Henrion (1990), *Uncertainty*, Cambridge University Press: New York. 1990.

Rouphail, N.M., H.C. Frey, A. Unal, and R. Dalton (2000), *ITS Integration of Real-Time Emissions and Traffic Management Systems*, IDEA Project No. ITS-44, Prepared by North Carolina State University for the IDEA Program, Transportation Research Board, National

Research Council, Washington, DC. May 2000. (available at www4.ncsu.edu/~frey/freytech.html).

Unal, A. (1999), "Measurement, Analysis, and Modeling of On-Road Vehicle Emissions Using Remote Sensing," M.S. Thesis, Department of Civil Engineering, North Carolina State University, Raleigh, NC.

Washington, S., J. Wolf, and R. Guensler (1997), "A Binary Recursive Partitioning Method for Modeling Hot-Stabilized Emissions from Motor Vehicles," Prepared by School of Civil and Environmental Engineering, Georgia Institute of Technology for the 76th Annual Meeting of the Transportation Research Board, Atlanta, Georgia.

Zheng, J. (2002), PhD Dissertation, Department of Civil Engineering, North Carolina State University, Raleigh, NC.

Zheng, J., and H.C. Frey (2002), AuvTool User's Guide, Prepared by North Carolina State University for the Office of Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC. February 2002.

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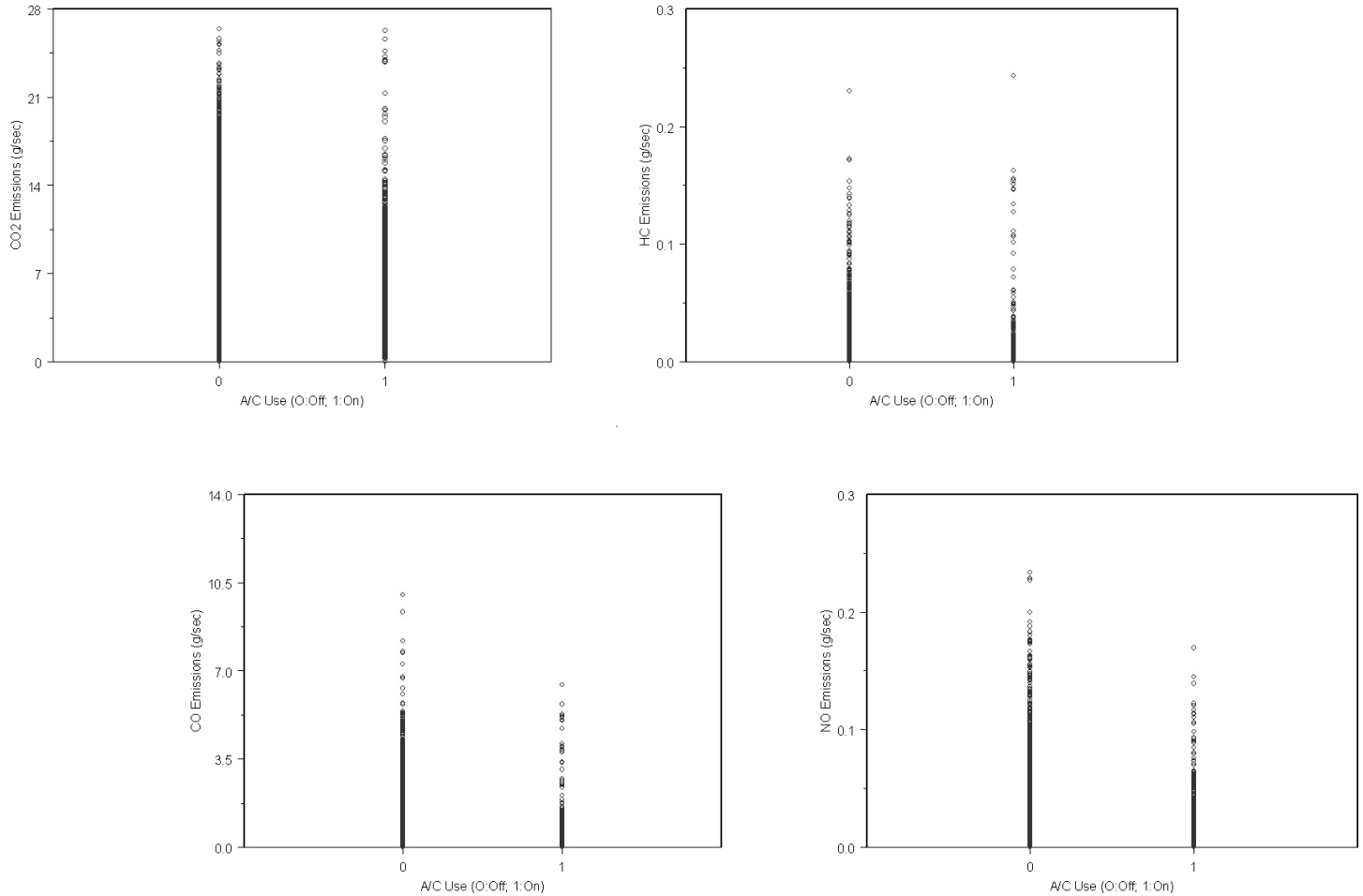

Figure A-1. Relationship between Air Condition Use and Emissions

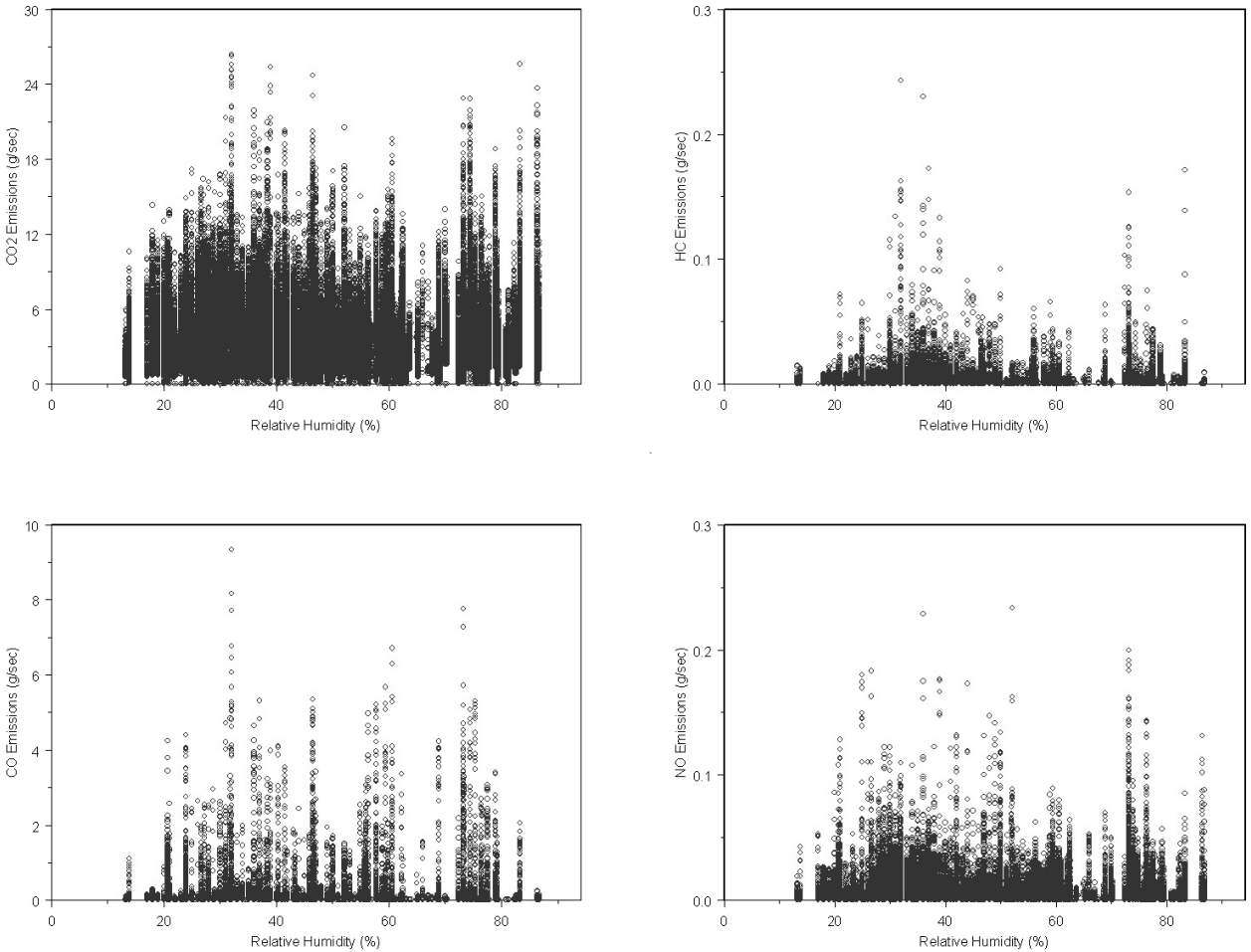

Figure A-2. Relationship between Relative Humidity and Emissions

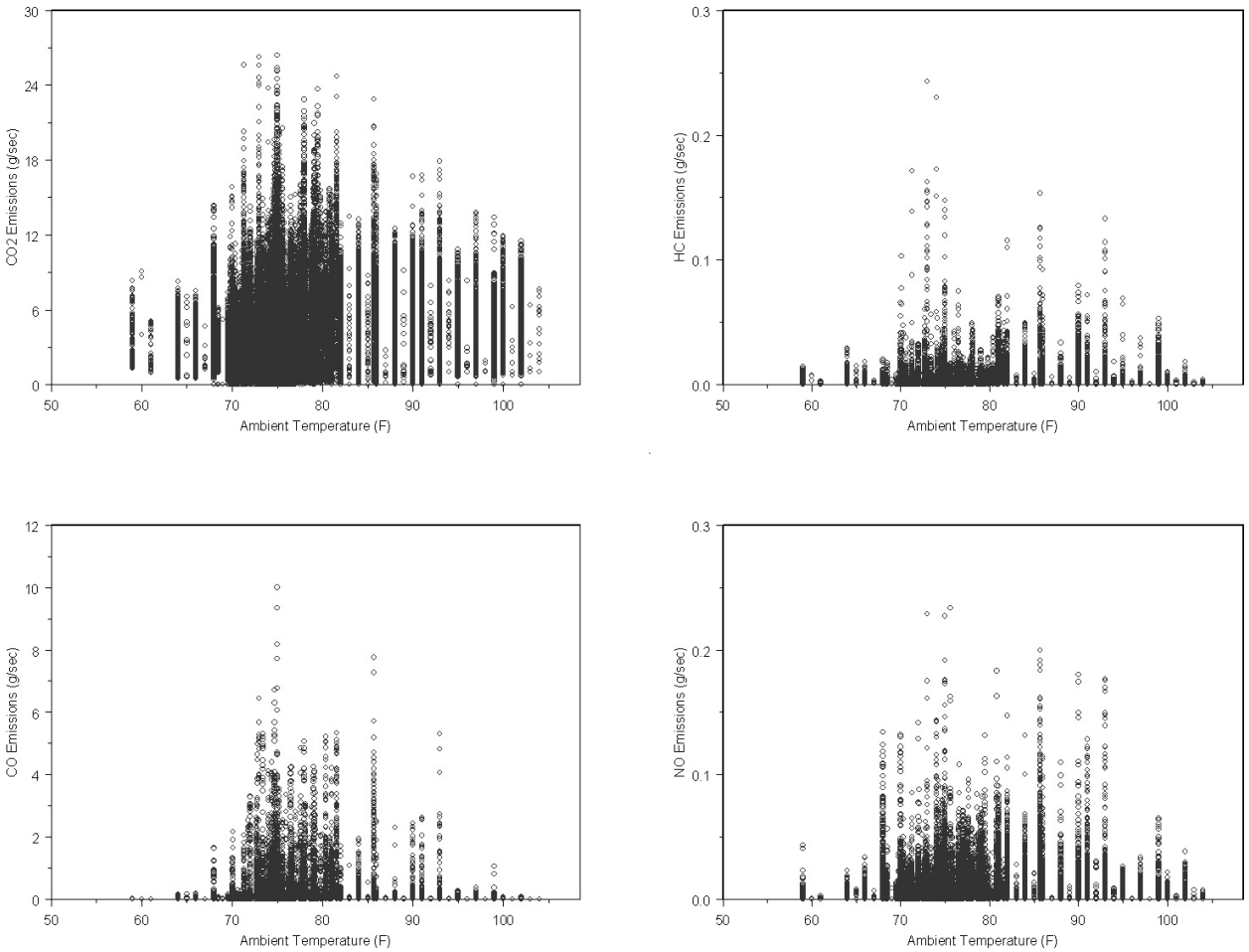

Figure A-3. Relationship between Ambient Temperature and Emissions

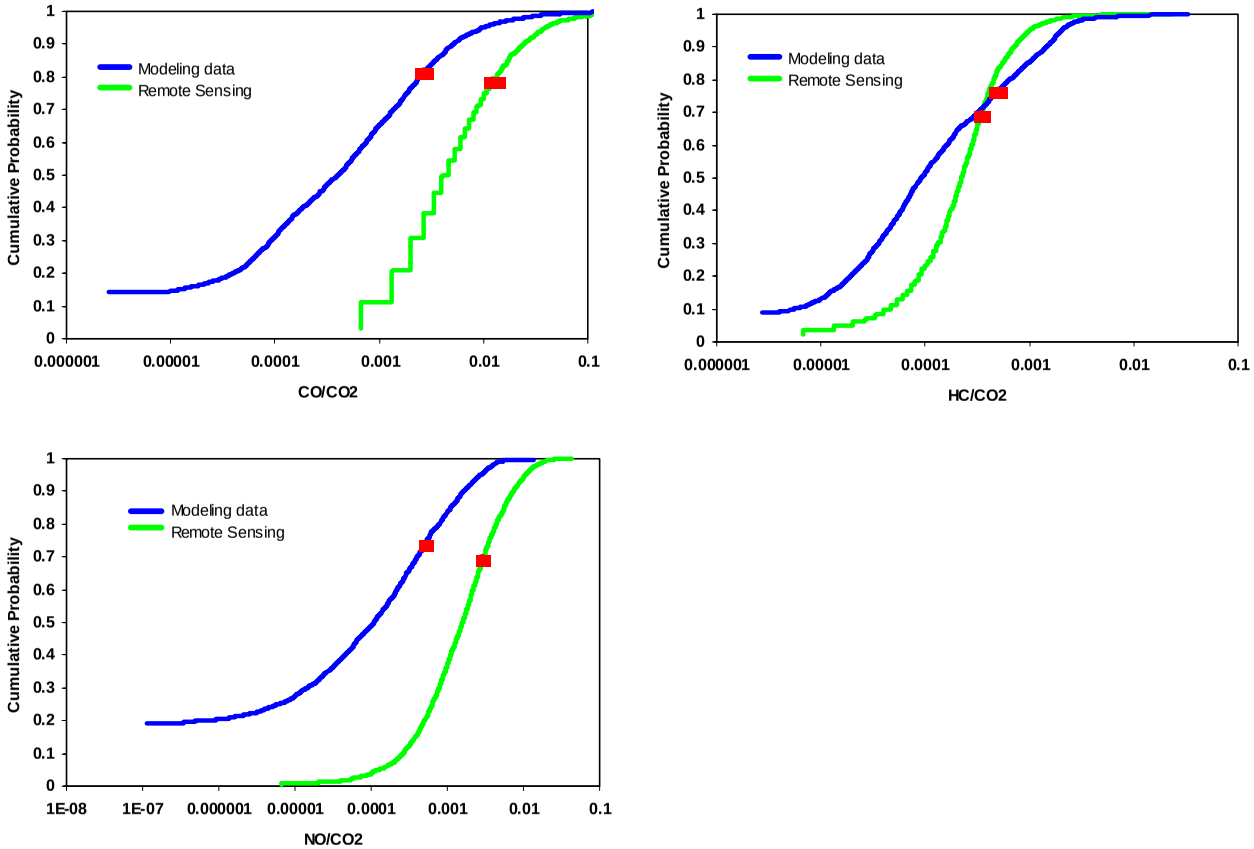

Figure A-4. Comparison of Variability for Modeling Data and Remote Sensing Data for VSP Mode 7 with Engine Size Less Than 3.5 Liters and Model Year at 1996.

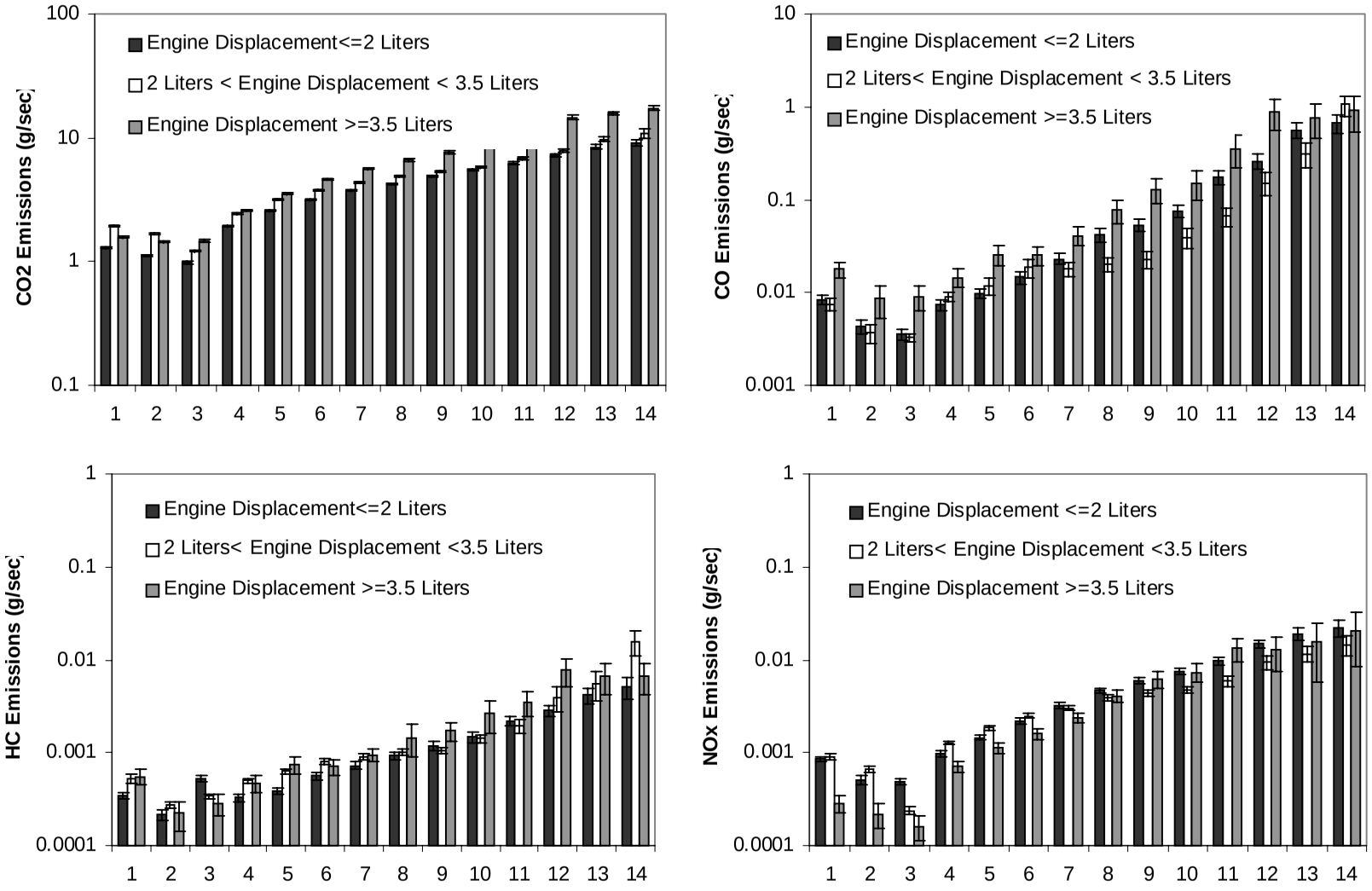

Figure A-5. Average Modal Emission Rates for Vehicles with Odometer Readings Less than 50,000 miles Based Upon VSP Bins

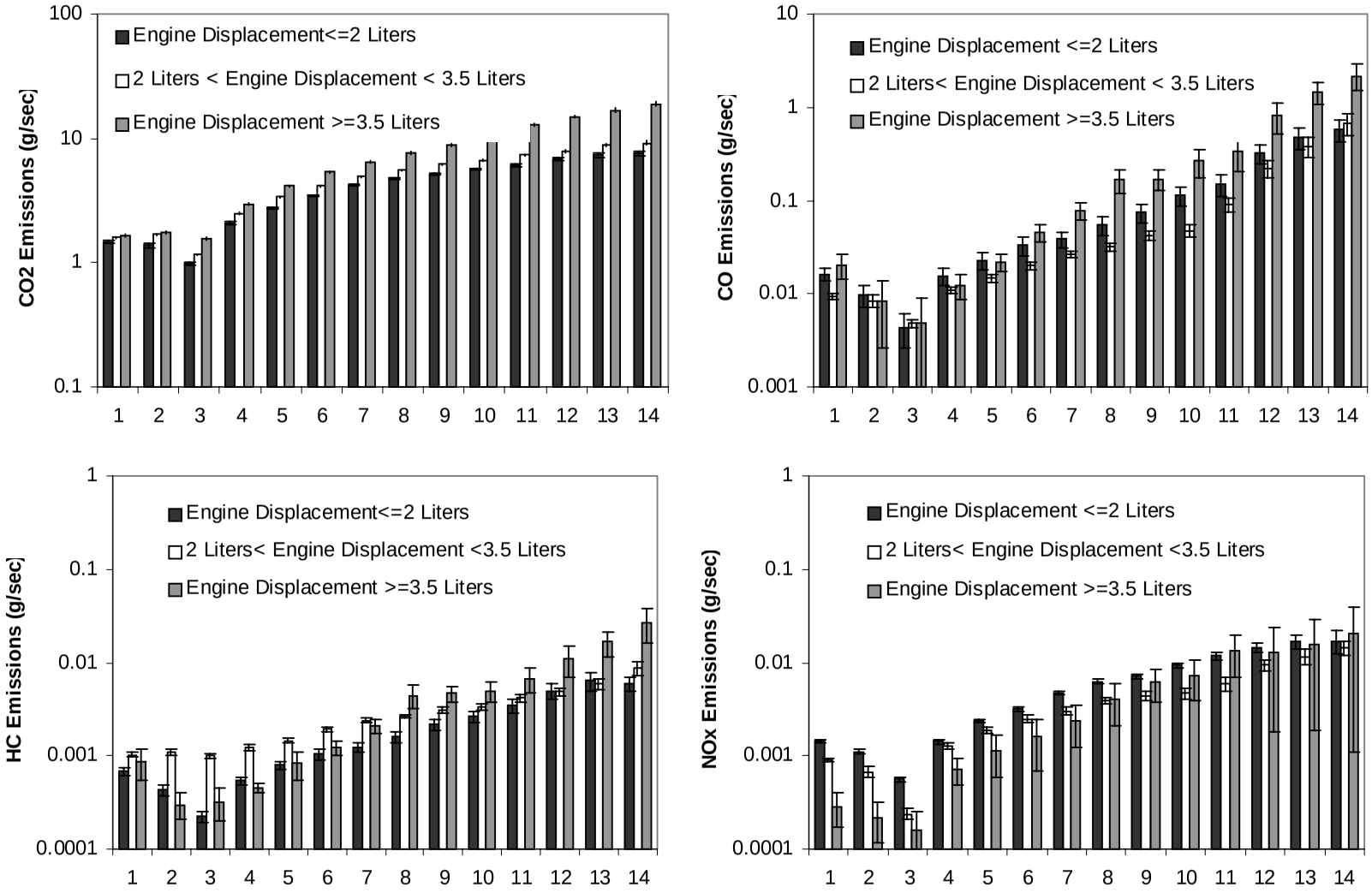

Figure A-6. Average Modal Emission Rates for Vehicles with Odometer Readings Greater than 50,000 miles Based Upon VSP Bins

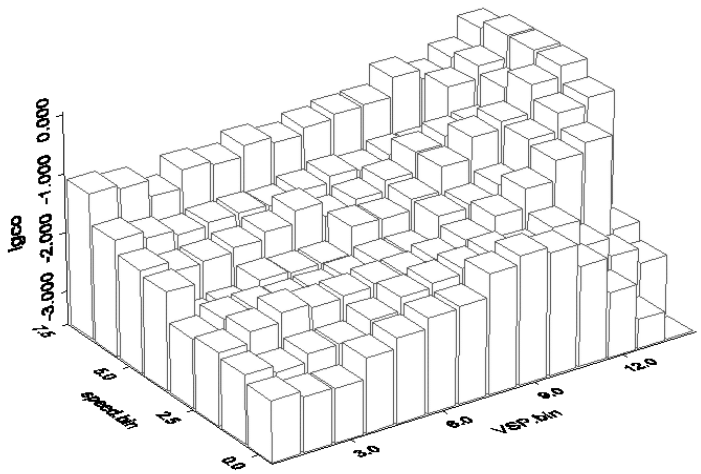

Figure A-7. Evaluation of Average CO Emission Rates for 14 VSP Bins with Respect to Acceleration (left panel) and Speed (right panel).

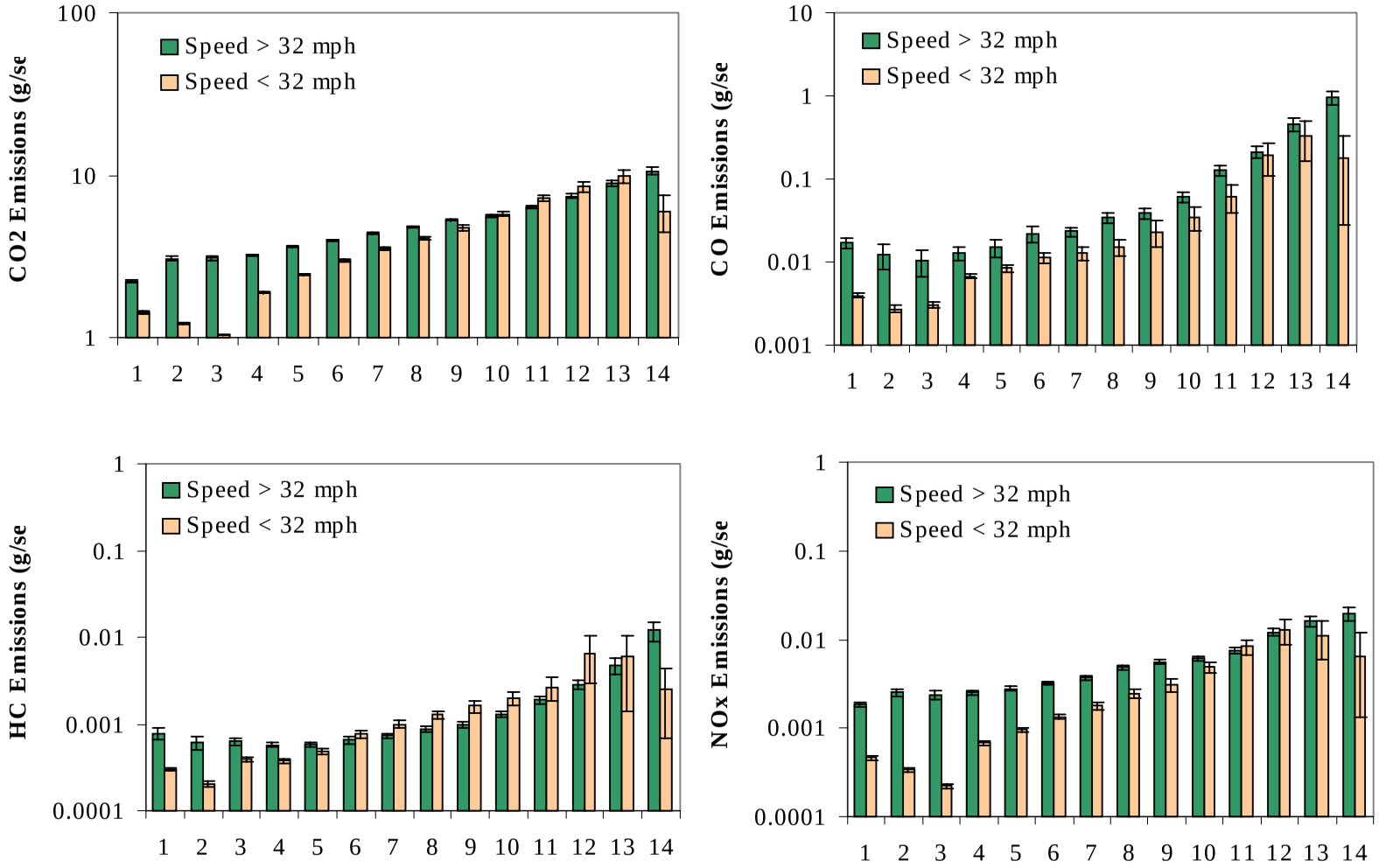

Figure A-8. Average Modal Emission Rates for VSP Bins for Engine Displacement < 3.5 liter and Odometer Reading < 50K miles for Two Different Speed Strata

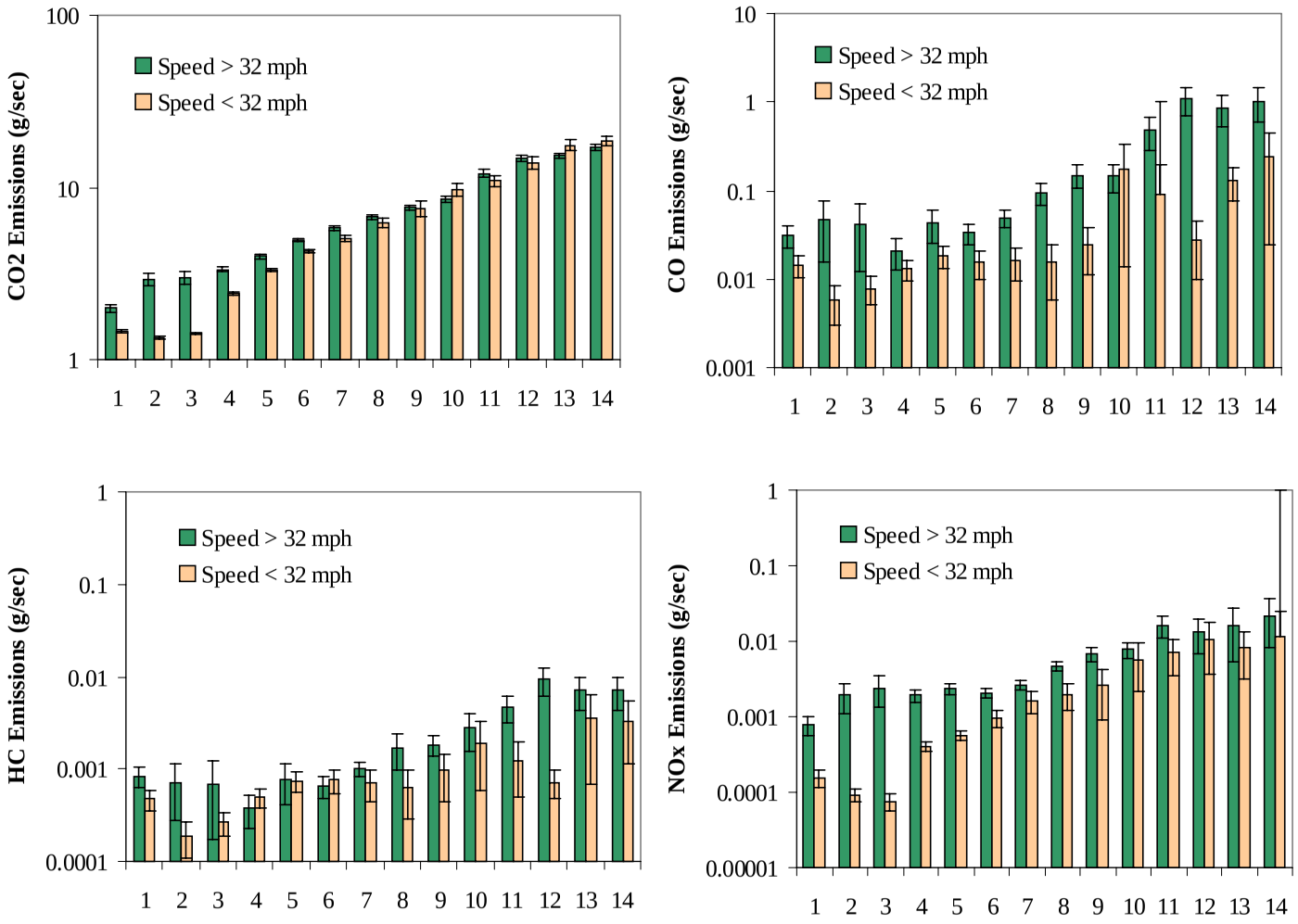

Figure A-9. Average Modal Emission Rates for VSP Bins for Engine Displacement > 3.5 liter and Odometer Reading < 50K miles for Two Different Speed Strata

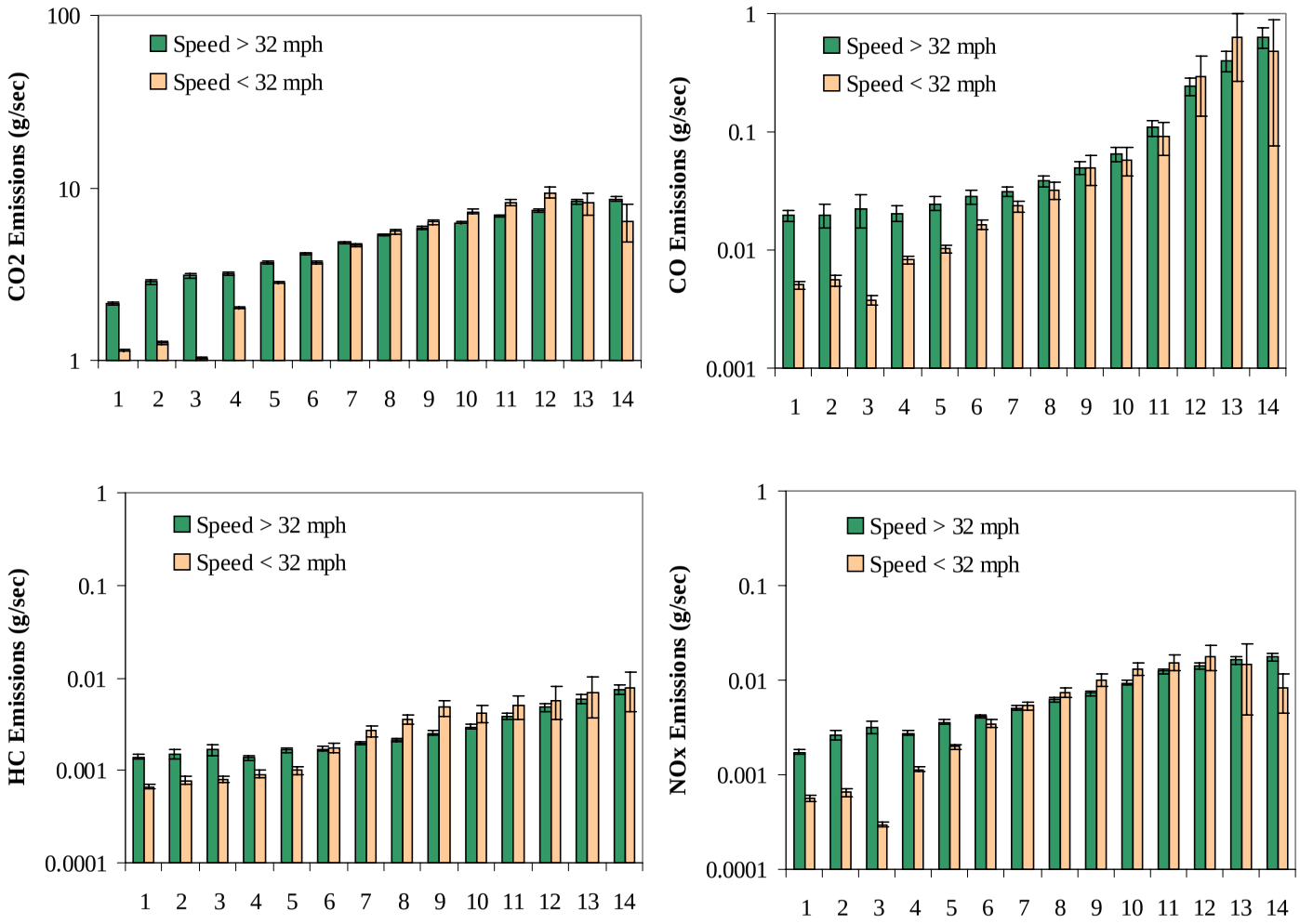

Figure A-10. Average Modal Emission Rates for VSP Bins for Engine Displacement < 3.5 liter and Odometer Reading > 50K miles for Two Different Speed Strata

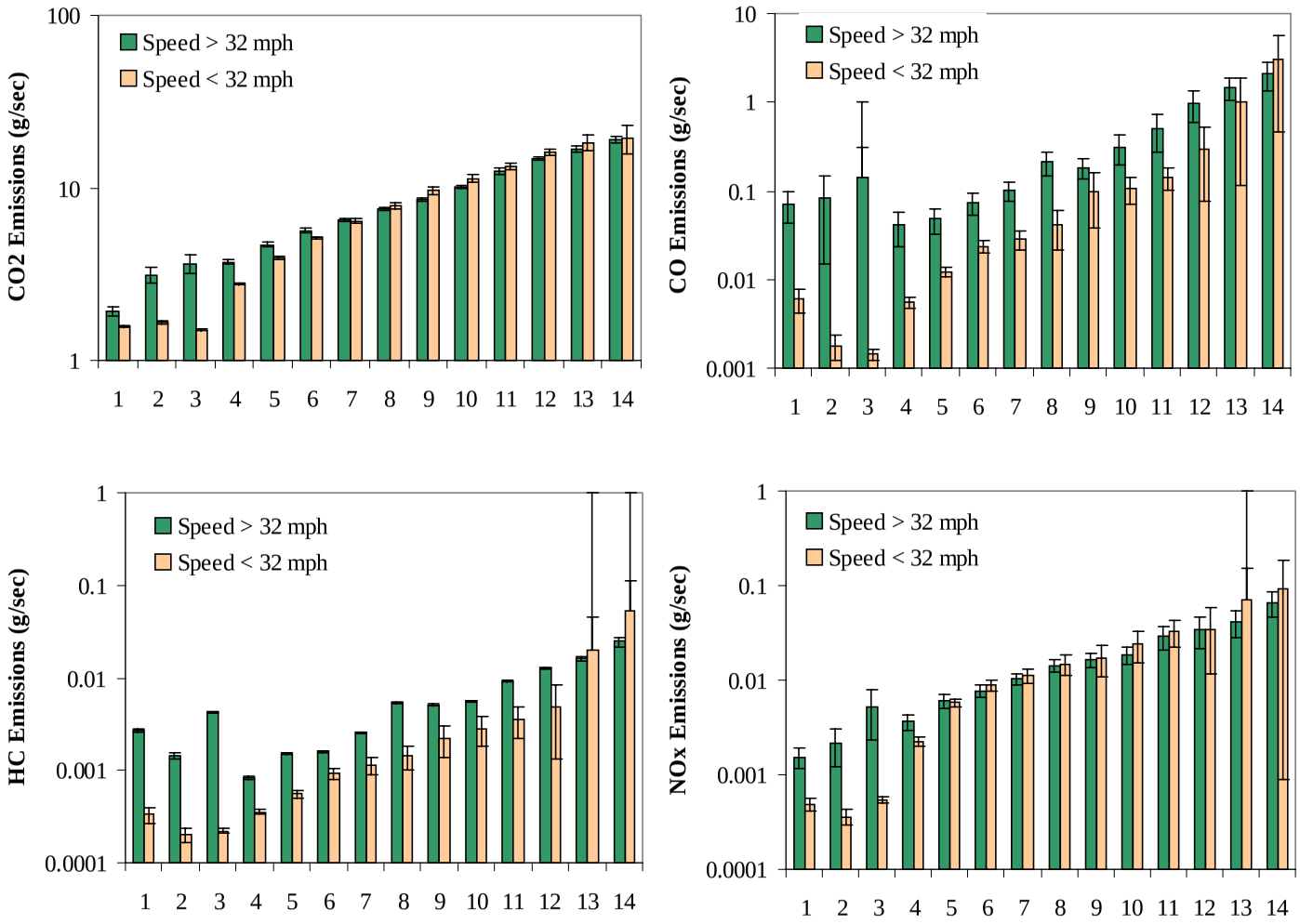

Figure A-11. Average Modal Emission Rates for VSP Bins for Engine Displacement > 3.5 liter and Odometer Reading > 50K miles for Two Different Speed Strata

Table A-1. Correlation Among Parameters

Parameter	Net Weight	Odometer	Number of Cylinders	Engine Displacement	Model Year
Net Weight	1	0.35	**0.76**	**0.78**	0.00
Odometer		1	0.18	0.10	0.47
Number of Cylinders			1	**0.93**	0.01
Engine Displacement				1	-0.02
Model Year					1

Table A-2. Summary of Vehicles in Validation Dataset •

Source	Vehicle	Year	Net Weight	Engine Size	Odometer
EPA	1	1997	2826	2	15806
EPA	2	1997	3553	3	58197
EPA	3	1996	3633	3	10102
EPA	4	1997	3650	3.1	22549
EPA	5	1996	2966	2.2	68768
EPA	6	1997	3223	2.5	17312
EPA	7	1996	3669	3.1	22000
EPA	8	1996	3279	3.1	23894
EPA	9	1996	3500	2.2	7573
EPA	10	1999	3538	3	19208
EPA	11	1996	3627	3.1	24798
EPA	12	1997	3699	3	12328
EPA	13	1996	2283	1.3	76931
EPA	14	1996	3625	3.1	17233
EPA	15	1997	3598	3.1	15248
EPA	16	1998	4216	4.6	19177
EPA	17	1998	4250	6.2	5098
EPA	18	1996	3625	3	18992
EPA	19	1998	3628	3.1	4983
EPA	20	1999	2827	1.6	10674
EPA	21	1999	2849	1.8	23800
EPA	22	1996	3338	N/A	30418
EPA	23	1997	2826	N/A	15768
EPA	24	1996	3633	N/A	9997
EPA	25	1997	3650	N/A	22093
EPA	26	1997	3223	N/A	17207
EPA	27	1996	3669	N/A	21951

(Continued on next page)

Table A-2. (Continued).

Source	Vehicle	Year	Net Weight	Engine Size	Odometer
EPA	28	1996	3279	N/A	23799
EPA	29	1996	3627	N/A	24708
EPA	30	1997	3699	N/A	1220
EPA	31	1997	3598	6	15182
EPA	32	1998	4250	8	5038
EPA	33	1998	3628	6	4829
NCHRP	1	1995	2250	1.5	23249
NCHRP	2	1996	4000	4.6	13287
NCHRP	3	1996	3500	3.8	22607
NCHRP	4	1995	3750	4	50541
NCHRP	5	1995	2250	1.6	49814
NCHRP	6	1995	2250	1.5	43708
NCHRP	7	1995	3000	2	21468
NCHRP	8	1996	3000	2	15096
NCHRP	9	1994	4250	4.3	43625
NCHRP	10	1994	2750	1.8	27339
NCHRP	11	1996	4000	4.6	16390
NCHRP	12	1996	2500	2	5312
NCHRP	13	1995	3500	3.8	28905
NCHRP	14	1996	2625	1.9	18000
NCHRP	15	1994	3000	3	49492
NCHRP	16	1995	2750	1.6	35291
NCHRP	17	1996	2625	1.9	7107
NCHRP	18	1996	2875	2.2	5690
NCHRP	19	1995	3500	2.2	29209
NCHRP	20	1996	3625	3.8	25877
NCHRP	21	1995	3375	3	22197
NCHRP	22	1995	3250	2.2	37194
NCHRP	23	1996	2875	1.9	13719
NCHRP	24	1996	3250	2.4	14212
NCHRP	25	1996	2875	1.8	4280
NCHRP	26	1995	2375	1.5	56213
NCHRP	27	1994	3500	2.2	56197
NCHRP	28	1993	2625	1.9	63125
NCHRP	29	1994	3000	2.5	56338
NCHRP	30	1996	2750	1.6	13845
NCHRP	31	1994	3250	2.2	57192
NCHRP	32	1997	2750	2	370
NCHRP	33	1994	4000	4.6	58923
NCHRP	34	1994	3875	3.8	54825
NCHRP	35	1996	2875	1.8	29480

(Continued on next page)

Table A-2. (Continued).

Source	Vehicle	Year	Net Weight	Engine Size	Odometer
NCHRP	36	1995	4000	3	51286
NCHRP	37	1995	2750	1.6	54843
NCHRP	38	1994	3125	2.5	56936
NCHRP	39	1993	2625	1.9	150139
NCHRP	40	1993	3250	2.2	72804
NCHRP	41	1995	3000	2.2	20606
NCHRP	42	1994	2875	2.5	72483
NCHRP	43	1994	4500	4.3	78060
NCHRP	44	1995	3625	3	63558
NCHRP	45	1994	2750	1.8	28630
NCHRP	46	1996	3250	2	105430
NCHRP	47	1998	2875	2.2	100250
NCHRP	48	1994	4000	3	100160
NCHRP	49	1998	3375	2.2	13247
On-Board	1	1998	3550	3.1	44362
On-Board	2	1997	3508	3	79984
On-Board	3	1996	3464	3	96099
On-Board	4	1996	3464	2.5	96099
On-Board	5	1998	2553	1.9	37278
On-Board	6	1999	3068	3.1	26288
On-Board	7	1999	2392	1.9	43242
On-Board	8	1999	2515	2	39429
On-Board	9	1997	3318	2	71446
On-Board	10	1998	2548	3	47439
On-Board	11	1998	2548	3	47439
On-Board	12	1996	2935	2.2	86999
On-Board	13	1996	3508	3	94321

Table A-3. Summary of Vehicles in Validation Dataset •

DATA	Vehicle	Year	GVWR	Engine Size	Odometer
EPA	1	1996	4036	2.4	30669
EPA	2	1996	N/A	3.1	21219
EPA	3	1996	N/A	1.6	9433
NCHRP	1	1996	3500	3.8	22651
NCHRP	2	1996	2625	1.6	20975
NCHRP	3	1997	3625	3	3415
NCHRP	4	1994	3625	3	22258
NCHRP	5	1995	2375	1.5	52111
NCHRP	6	1994	2625	1.5	78056
NCHRP	7	1994	2375	1.5	57742
NCHRP	8	1995	3625	3.3	62007
NCHRP	9	1994	3000	2.5	57407
NCHRP	10	1994	3875	3.8	72691
NCHRP	11	1993	2625	1.6	61032
NCHRP	12	1994	2625	1.9	64967
NCHRP	13	1996	2000	1	32034
NCHRP	14	1993	3500	2.2	97869
NCHRP	15	1994	3500	2.5	61040
NCHRP	16	1994	3250	3.1	80877
NCHRP	17	1993	2750	1.8	102240
NCHRP	18	1994	2625	1.5	91045
NCHRP	19	1997	2625	1.6	6172
NCHRP	20	1997	3375	3.1	3015
NCHRP	21	1997	3250	2	23099
NCHRP	22	1995	2625	1.9	104890
NCHRP	23	1996	2625	1.9	111203
NCHRP	24	1999	2875	3.1	100250
NCHRP	25	1995	2875	2.5	100250
On-Board	1	1998	4721	3	78187
On-Board	2	1998	N/A	2.2	56803
On-Board	3	1998	5166	2	41319

Table A-3. Summary of Vehicles in Validation Dataset •I

DATA	Vehicle	Year	Net weight	Odometer
ARB	2	1994	3500	65294
ARB	5	1997	3250	23503
ARB	24	1995	2750	12698
ARB	33	1996	3375	28454
ARB	36	1993	3250	52196
ARB	41	1995	2250	6181
ARB	49	1993	3500	40626
ARB	59	1993	3250	47368
ARB	77	1993	3125	37353
ARB	79	1994	2875	23730
ARB	84	1995	3125	3188
ARB	187	1994	4000	88592
ARB	216	1993	3375	90080
ARB	258	1995	2750	32015
ARB	315	1993	4000	66932
ARB	341	1995	3500	49437
ARB	342	1995	2750	14904

Table A-4. Comparison of Mean Emissions of VSP Bins, Time-Average vs. Trip-Average vs. Vehicle-Average

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
1101	0.000901	0.001097	22	0.000852	-6	0.00045	0.000391	-13	0.00034	-24	1.671078	2.092668	25	1.780418	7	0.007807	0.010418	33	0.009971	28
1102	0.000628	0.001017	62	0.000727	16	0.000257	0.000387	51	0.000337	31	1.457983	2.020811	39	1.70965	17	0.003908	0.007937	103	0.007968	104
1103	0.000346	0.000742	114	0.000411	19	0.000406	0.00035	-14	0.000274	-33	1.135362	1.667869	47	1.332954	17	0.003347	0.005155	54	0.004262	27
1104	0.001173	0.001389	18	0.001039	-11	0.000432	0.000528	22	0.000429	-1	2.233264	2.552053	14	2.338717	5	0.008335	0.01246	49	0.010144	22
1105	0.001706	0.001684	-1	0.00141	-17	0.00053	0.000572	8	0.000515	-3	2.91989	2.98235	2	2.931022	0	0.010959	0.013319	22	0.014101	29
1106	0.002368	0.002066	-13	0.00198	-16	0.000705	0.00065	-8	0.000666	-6	3.525303	3.327366	-6	3.502494	-1	0.017013	0.014941	-12	0.021879	29
1107	0.003103	0.002466	-21	0.002489	-20	0.000822	0.00077	-6	0.000804	-2	4.107483	3.739047	-9	4.054487	-1	0.020026	0.017961	-10	0.030889	54
1108	0.004234	0.003103	-27	0.003235	-24	0.000976	0.000813	-17	0.000946	-3	4.635048	4.121626	-11	4.52942	-2	0.029222	0.022877	-22	0.046249	58
1109	0.005069	0.004166	-18	0.004544	-10	0.001112	0.000871	-22	0.001097	-1	5.160731	4.606298	-11	5.152217	0	0.035531	0.027536	-23	0.059231	67
1110	0.005865	0.004178	-29	0.004414	-25	0.001443	0.001096	-24	0.00133	-8	5.632545	4.858016	-14	5.440037	-3	0.055068	0.03832	-30	0.086515	57
1111	0.007623	0.004979	-35	0.005441	-29	0.002061	0.001673	-19	0.0019	-8	6.53478	5.798515	-11	6.266617	-4	0.113824	0.08035	-29	0.175599	54
1112	0.012149	0.009459	-22	0.009449	-22	0.003373	0.003284	-3	0.002607	-23	7.585213	7.097114	-6	7.671417	1	0.207586	0.169395	-18	0.253183	22
1113	0.015456	0.010298	-33	0.010679	-31	0.004857	0.005374	11	0.004349	-10	9.024217	8.439456	-6	9.319705	3	0.441775	0.386715	-12	0.530003	20

Table A-4. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
1114	0.017863	0.015276	-14	0.018635	4	0.010948	0.005063	-54	0.005851	-47	10.08839	8.611693	-15	9.917922	-2	0.8823	0.574791	-35	0.820496	-7
1201	0.00029	0.000571	97	0.000767	165	0.000548	0.001243	127	0.000619	13	1.566819	1.742827	11	1.76866	13	0.017699	0.03866	118	0.019879	12
1202	0.000223	0.000526	136	0.000747	235	0.000222	0.001518	583	0.000704	217	1.443564	1.883233	30	1.812724	26	0.008608	0.055898	549	0.025235	193
1203	0.000174	0.000571	227	0.000899	415	0.000272	0.001165	329	0.000395	46	1.470553	1.778044	21	1.767513	20	0.008479	0.034922	312	0.011575	37
1204	0.000719	0.000938	30	0.001112	55	0.000472	0.001411	199	0.000649	38	2.611318	2.93208	12	2.769411	6	0.014548	0.04941	240	0.019972	37
1205	0.001136	0.001304	15	0.00152	34	0.000754	0.001704	126	0.000799	6	3.523681	3.620842	3	3.558054	1	0.025709	0.072916	184	0.026876	5
1206	0.001587	0.001657	4	0.001932	22	0.000702	0.001412	101	0.000809	15	4.650741	4.399458	-5	4.452864	-4	0.025212	0.047817	90	0.026926	7
1207	0.00237	0.002194	-7	0.002551	8	0.000944	0.001489	58	0.000939	0	5.635386	5.248342	-7	5.270724	-6	0.04113	0.059382	44	0.041535	1
1208	0.004098	0.002927	-29	0.00348	-15	0.001443	0.001799	25	0.001299	-10	6.599677	6.16888	-7	6.252616	-5	0.076601	0.070431	-8	0.060221	-21
1209	0.006124	0.004377	-29	0.005834	-5	0.001708	0.002151	26	0.001614	-5	7.647334	7.075418	-7	7.38033	-3	0.129248	0.103004	-20	0.103436	-20
1210	0.007313	0.00506	-31	0.006455	-12	0.002605	0.002985	15	0.002385	-8	8.808448	8.096559	-8	8.042326	-9	0.150578	0.122169	-19	0.123995	-18
1211	0.013178	0.00802	-39	0.011761	-11	0.003523	0.003469	-2	0.003386	-4	11.67061	9.372073	-20	9.594158	-18	0.355223	0.168599	-53	0.220936	-38
1212	0.012663	0.018412	45	0.018412	45	0.007653	0.005327	-30	0.005327	-30	14.52036	14.8929	3	14.8929	3	0.881642	0.546928	-38	0.546928	-38

Table A-4. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
1213	0.015387	0.020783	35	0.020783	35	0.006667	0.005828	-13	0.005828	-13	15.65327	15.30436	-2	15.30436	-2	0.755155	0.722783	-4	0.722783	-4
1214	0.020308	0.041798	106	0.041798	106	0.006574	0.006035	-8	0.006035	-8	17.36653	17.66742	2	17.66742	2	0.904851	0.909832	1	0.909832	1
2101	0.001014	0.001018	0	0.000965	-5	0.000901	0.000926	3	0.000607	-33	1.543686	1.395048	-10	1.330709	-14	0.01103	0.014076	28	0.011779	7
2102	0.001042	0.001243	19	0.001088	4	0.000901	0.000833	-8	0.000545	-40	1.604406	1.656132	3	1.547675	-4	0.008723	0.013194	51	0.009119	5
2103	0.000423	0.000793	87	0.000858	103	0.000835	0.000705	-16	0.000486	-42	1.130833	1.266896	12	1.270197	12	0.004682	0.007685	64	0.006283	34
2104	0.001613	0.002034	26	0.001561	-3	0.001027	0.001237	20	0.000757	-26	2.38626	2.640064	11	2.361957	-1	0.012154	0.021867	80	0.013167	8
2105	0.002638	0.002791	6	0.002287	-13	0.001253	0.001192	-5	0.000865	-31	3.210249	3.366473	5	3.10974	-3	0.016731	0.025063	50	0.016411	-2
2106	0.003793	0.003603	-5	0.003145	-17	0.001664	0.00134	-19	0.000994	-40	3.957732	3.973958	0	3.83721	-3	0.023269	0.024633	6	0.02069	-11
2107	0.005098	0.004579	-10	0.003967	-22	0.002089	0.001472	-30	0.001134	-46	4.752012	4.620807	-3	4.583745	-4	0.029322	0.027876	-5	0.027406	-7
2108	0.006373	0.005964	-6	0.005095	-20	0.002332	0.001585	-32	0.001232	-47	5.374221	5.332288	-1	5.321404	-1	0.036942	0.033271	-10	0.034868	-6
2109	0.007664	0.007039	-8	0.006184	-19	0.002818	0.002136	-24	0.001654	-41	5.940051	5.905244	-1	6.043941	2	0.049513	0.046846	-5	0.053282	8
2110	0.009913	0.01015	2	0.00841	-15	0.002985	0.002352	-21	0.001781	-40	6.427506	6.722447	5	6.755205	5	0.063759	0.060781	-5	0.071075	11
2111	0.012685	0.013099	3	0.012178	-4	0.003786	0.00317	-16	0.002651	-30	7.065985	7.632773	8	7.972946	13	0.10538	0.10403	-1	0.139503	32

Table A-4. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
2112	0.014384	0.014329	0	0.01417	-1	0.004573	0.005006	9	0.004808	5	7.617703	8.201694	8	8.694089	14	0.24781	0.367169	48	0.504717	104
2113	0.015967	0.01535	-4	0.015462	-3	0.0057	0.006377	12	0.006267	10	8.322442	8.290563	0	9.310727	12	0.413069	0.63355	53	0.884127	114
2114	0.016717	0.015747	-6	0.013914	-17	0.007164	0.009796	37	0.009379	31	8.475028	8.780078	4	9.856257	16	0.624663	1.067502	71	1.495996	139
2201	0.000725	0.00082	13	0.000717	-1	0.000863	0.001075	25	0.000857	-1	1.649427	1.666261	1	1.637489	-1	0.020282	0.026335	30	0.020063	-1
2202	0.000504	0.000937	86	0.000607	20	0.0003	0.000739	146	0.000388	29	1.762407	1.971398	12	1.729282	-2	0.008183	0.031627	286	0.009787	20
2203	0.000661	0.000812	23	0.000619	-6	0.000323	0.000571	77	0.000298	-8	1.557773	1.688165	8	1.594651	2	0.00483	0.014518	201	0.004375	-9
2204	0.002518	0.003287	31	0.00248	-1	0.000449	0.000851	90	0.000444	-1	2.946419	3.503549	19	2.950934	0	0.012308	0.044087	258	0.012215	-1
2205	0.005847	0.005724	-2	0.005791	-1	0.000818	0.0015	84	0.000816	0	4.127492	4.476632	8	4.105545	-1	0.022033	0.045654	107	0.021965	0
2206	0.008361	0.008287	-1	0.008562	2	0.001216	0.001476	21	0.001255	3	5.343656	5.461154	2	5.347669	0	0.045073	0.059244	31	0.046499	3
2207	0.010582	0.010992	4	0.010822	2	0.00211	0.002053	-3	0.002082	-1	6.507179	6.480357	0	6.513549	0	0.077496	0.074036	-4	0.077436	0
2208	0.014473	0.015513	7	0.014517	0	0.004394	0.003571	-19	0.004342	-1	7.602431	7.642446	1	7.693818	1	0.166593	0.130573	-22	0.165597	-1
2209	0.016372	0.017328	6	0.015037	-8	0.004635	0.003484	-25	0.004221	-9	8.773093	8.827697	1	8.848806	1	0.170018	0.113574	-33	0.158411	-7
2210	0.019758	0.022928	16	0.019472	-1	0.004961	0.004306	-13	0.005332	7	10.36591	10.29987	-1	10.33755	0	0.263544	0.17931	-32	0.271669	3

Table A-4. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.	mean	mean	diff.	mean	diff.
2211	0.030507	0.036289	19	0.03191	5	0.006631	0.006477	-2	0.006673	1	12.84939	12.53602	-2	12.83404	0	0.338962	0.23947	-29	0.341425	1
2212	0.034219	0.049097	43	0.037247	9	0.0109	0.013702	26	0.011512	6	15.0303	14.74582	-2	15.13418	1	0.824829	0.82406	0	0.877657	6
2213	0.043387	0.0485	12	0.0485	12	0.016573	0.016142	-3	0.016142	-3	16.86173	16.96438	1	16.96438	1	1.444311	1.306457	-10	1.306457	-10
2214	0.068988	0.054347	-21	0.054347	-21	0.027066	0.020961	-23	0.020961	-23	18.94712	18.76208	-1	18.76208	-1	2.175099	1.917319	-12	1.917319	-12

[a] First two digit of VSP Bins: 11: odometer < 50,000 miles and engine size < 3.5 liter; 12: odometer < 50,000 miles and engine size > 3.5 liter; 21: odometer > 50,000 miles and engine size < 3.5 liter; 22: odometer > 50,000 miles and engine size > 3.5 liter.
[b] Unit of mean: g/sec; Unit of diff.: %.

Table A-5. Comparison of Standard Deviations of Variability in Original Emission Data Sets of VSP Bins, Time-Average vs. Trip-Average vs. Vehicle-Average

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.
1101	0.002945	0.001611	-45	0.000963	-67	0.002831	0.000566	-80	0.0005	-82	1.385471	1.12253	-19	0.935668	-32	0.058918	0.021028	-64	0.014674	-75
1102	0.00256	0.001587	-38	0.000811	-68	0.001123	0.000774	-31	0.000587	-48	1.212863	1.132493	-7	0.866006	-29	0.036678	0.019927	-46	0.018202	-50
1103	0.001543	0.001962	27	0.000375	-76	0.001502	0.000801	-47	0.000534	-64	0.816426	1.130622	38	0.61943	-24	0.021594	0.012754	-41	0.010782	-50
1104	0.003433	0.001756	-49	0.000878	-74	0.001414	0.000919	-35	0.000777	-45	1.384324	0.955028	-31	0.767325	-45	0.051944	0.028064	-46	0.026506	-49
1105	0.004418	0.001999	-55	0.001167	-74	0.001599	0.001047	-35	0.000917	-43	1.529625	0.894469	-42	0.709841	-54	0.096842	0.03279	-66	0.031709	-67
1106	0.005674	0.00236	-58	0.001735	-69	0.00237	0.00116	-51	0.001224	-48	1.667104	0.902644	-46	0.775961	-53	0.154603	0.036387	-76	0.049995	-68
1107	0.006712	0.002811	-58	0.00242	-64	0.002401	0.001414	-41	0.001481	-38	1.77441	1.1272	-36	0.899522	-49	0.106224	0.048599	-54	0.073973	-30
1108	0.007942	0.003529	-56	0.003294	-59	0.002812	0.001523	-46	0.001687	-40	1.938311	1.323727	-32	1.138721	-41	0.15224	0.077492	-49	0.115758	-24
1109	0.010076	0.005296	-47	0.005013	-50	0.002673	0.001854	-31	0.001912	-28	2.088216	1.598809	-23	1.322392	-37	0.165469	0.09141	-45	0.150854	-9
1110	0.010991	0.005133	-53	0.004874	-56	0.003685	0.002444	-34	0.002394	-35	2.35424	2.112815	-10	1.874281	-20	0.251833	0.11994	-52	0.191922	-24
1111	0.014662	0.007957	-46	0.006742	-54	0.005445	0.004588	-16	0.00348	-36	2.720312	2.556017	-6	2.543511	-6	0.396332	0.232956	-41	0.335661	-15
1112	0.02007	0.012712	-37	0.011631	-42	0.010402	0.010036	-4	0.003884	-63	2.987478	2.795777	-6	2.773975	-7	0.570599	0.300565	-47	0.334399	-41
1113	0.024682	0.013143	-47	0.013583	-45	0.013267	0.015286	15	0.007115	-46	3.637198	3.125796	-14	2.715516	-25	0.906088	0.622866	-31	0.689833	-24
1114	0.027726	0.027707	0	0.032729	18	0.024933	0.008866	-64	0.008941	-64	5.372496	4.190774	-22	3.666952	-32	1.521667	0.830872	-45	0.891284	-41

Table A-5. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.
1201	0.001353	0.001435	6	0.001873	38	0.002465	0.003384	37	0.001711	-31	0.752061	0.664471	-12	0.774477	3	0.087575	0.099099	13	0.049412	-44
1202	0.001423	0.001521	7	0.002003	41	0.001773	0.004194	137	0.002062	16	0.729907	0.668691	-8	0.77674	6	0.076393	0.141591	85	0.068659	-10
1203	0.001253	0.001896	51	0.002485	98	0.001936	0.003079	59	0.000929	-52	0.783702	0.697239	-11	0.855793	9	0.069682	0.078986	13	0.023375	-66
1204	0.002278	0.001665	-27	0.002125	-7	0.002461	0.003694	50	0.001778	-28	1.080752	0.677613	-37	0.628547	-42	0.080298	0.104564	30	0.04997	-38
1205	0.003336	0.002119	-36	0.002614	-22	0.003597	0.003467	-4	0.001681	-53	1.206617	0.794739	-34	0.714965	-41	0.138754	0.147007	6	0.054372	-61
1206	0.0044	0.002279	-48	0.002609	-41	0.002765	0.003178	15	0.001488	-46	1.78582	1.112786	-38	0.921626	-48	0.113237	0.093205	-18	0.042388	-63
1207	0.005525	0.001954	-65	0.002196	-60	0.002781	0.003305	19	0.001768	-36	2.306199	1.366	-41	1.220852	-47	0.16598	0.113099	-32	0.061202	-63
1208	0.008133	0.002694	-67	0.002807	-65	0.00722	0.003196	-56	0.001831	-75	2.635432	1.781243	-32	1.570403	-40	0.286122	0.111506	-61	0.090063	-69
1209	0.014025	0.005225	-63	0.006173	-56	0.004432	0.003916	-12	0.001976	-55	2.505814	2.228266	-11	1.895366	-24	0.410763	0.197293	-52	0.188263	-54
1210	0.014451	0.006155	-57	0.007053	-51	0.009088	0.005182	-43	0.003244	-64	2.799147	2.633155	-6	2.432006	-13	0.474955	0.196622	-59	0.166781	-65
1211	0.024503	0.014531	-41	0.017887	-27	0.006989	0.006375	-9	0.005167	-26	3.381765	3.876705	15	3.990195	18	0.933668	0.326539	-65	0.370172	-60
1212	0.023031	0.014183	-38	0.014183	-38	0.011665	0.006219	-47	0.006219	-47	2.530211	1.692154	-33	1.692154	-33	1.445647	0.856243	-41	0.856243	-41
1213	0.035852	0.020699	-42	0.020699	-42	0.009166	0.005278	-42	0.005278	-42	1.94742	1.40999	-28	1.40999	-28	1.100803	0.76091	-31	0.76091	-31
1214	0.037826	0.066474	76	0.066474	76	0.007689	0.004986	-35	0.004986	-35	2.208716	1.110591	-50	1.110591	-50	1.17728	0.932473	-21	0.932473	-21

Table A-5. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.
2101	0.002291	0.001038	-55	0.001092	-52	0.002249	0.001355	-40	0.000609	-73	1.109149	0.522517	-53	0.492078	-56	0.04711	0.017075	-64	0.008651	-82
2102	0.00257	0.001248	-51	0.001228	-52	0.002282	0.001089	-52	0.000673	-71	1.114641	0.653819	-41	0.596964	-46	0.037055	0.017076	-54	0.007536	-80
2103	0.001682	0.001174	-30	0.001481	-12	0.003115	0.001064	-66	0.000707	-77	0.713377	0.508459	-29	0.588173	-18	0.028625	0.011217	-61	0.011063	-61
2104	0.003339	0.00162	-51	0.001267	-62	0.002869	0.001942	-32	0.000965	-66	1.171887	0.711085	-39	0.587889	-50	0.05007	0.026471	-47	0.013628	-73
2105	0.004665	0.002149	-54	0.001593	-66	0.002939	0.00126	-57	0.000973	-67	1.288537	0.823675	-36	0.613453	-52	0.066924	0.031311	-53	0.012323	-82
2106	0.006577	0.002846	-57	0.002235	-66	0.003766	0.00141	-63	0.001123	-70	1.360129	0.737997	-46	0.56076	-59	0.082777	0.021256	-74	0.014604	-82
2107	0.008025	0.003665	-54	0.002943	-63	0.004028	0.001526	-62	0.001221	-70	1.498808	0.809143	-46	0.675402	-55	0.08088	0.023906	-70	0.022786	-72
2108	0.009009	0.005018	-44	0.003925	-56	0.003551	0.001595	-55	0.001195	-66	1.644394	0.802907	-51	0.725539	-56	0.101806	0.029478	-71	0.028732	-72
2109	0.01072	0.005428	-49	0.005163	-52	0.0052	0.001935	-63	0.001437	-72	1.811788	1.301192	-28	1.036041	-43	0.146791	0.040071	-73	0.042312	-71
2110	0.013533	0.008557	-37	0.006739	-50	0.004841	0.002246	-54	0.001466	-70	1.959334	1.247208	-36	1.169198	-40	0.208775	0.055964	-73	0.061325	-71
2111	0.016326	0.010608	-35	0.008615	-47	0.006874	0.002737	-60	0.002002	-71	2.303041	2.134836	-7	1.86914	-19	0.331085	0.112855	-66	0.128683	-61
2112	0.016636	0.009201	-45	0.009319	-44	0.007075	0.004083	-42	0.004147	-41	2.454817	2.221742	-9	2.195417	-11	0.664957	0.508908	-23	0.587978	-12
2113	0.018636	0.009346	-50	0.008606	-54	0.008143	0.005669	-30	0.004974	-39	3.00003	2.826129	-6	2.735825	-9	0.917957	0.906304	-1	1.037041	13
2114	0.018182	0.012218	-33	0.008621	-53	0.009979	0.012121	21	0.009851	-1	3.192905	3.65873	15	3.427465	7	1.255385	1.425734	14	1.612373	28

Table A-5. Continued

Bin[a]	NO[b]					HC[b]					CO_2[b]					CO[b]				
	Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg		Time-Avg	Trip-Avg		Vehicle-Avg	
	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.	std. dev.	std. dev.	diff.	std. dev.	diff.
2201	0.002025	0.000981	-52	0.000666	-67	0.005724	0.001843	-68	0.001068	-81	0.613904	0.273568	-55	0.263742	-57	0.114323	0.041109	-64	0.018576	-84
2202	0.001373	0.001018	-26	0.000437	-68	0.001315	0.001012	-23	0.000366	-72	0.675646	0.401726	-41	0.118576	-82	0.076183	0.044768	-41	0.007651	-90
2203	0.001812	0.000953	-47	0.000498	-73	0.002487	0.000827	-67	0.000309	-88	0.662243	0.237542	-64	0.22642	-66	0.08347	0.02829	-66	0.005443	-93
2204	0.004017	0.004185	4	0.003048	-24	0.000901	0.001069	19	0.000361	-60	0.7346	0.861998	17	0.345979	-53	0.062257	0.052883	-15	0.009072	-85
2205	0.008341	0.00692	-17	0.007591	-9	0.004297	0.002034	-53	0.00079	-82	0.88572	0.871532	-2	0.460997	-48	0.069947	0.062257	-11	0.02374	-66
2206	0.011656	0.009697	-17	0.0106	-9	0.002485	0.001831	-26	0.001041	-58	1.082677	0.935579	-14	0.745519	-31	0.120335	0.071032	-41	0.040804	-66
2207	0.01327	0.012669	-5	0.013467	1	0.004035	0.002652	-34	0.001958	-51	1.347016	1.10976	-18	1.145355	-15	0.196119	0.092674	-53	0.073024	-63
2208	0.017788	0.01643	-8	0.017134	-4	0.011091	0.00444	-60	0.004399	-60	1.439746	1.04263	-28	1.20379	-16	0.429698	0.191461	-55	0.175101	-59
2209	0.019972	0.020016	0	0.019755	-1	0.00739	0.003756	-49	0.003978	-46	1.495146	1.094696	-27	1.235369	-17	0.329428	0.119911	-64	0.115394	-65
2210	0.026059	0.023848	-8	0.02638	1	0.009476	0.004503	-52	0.004976	-47	1.831227	0.851895	-53	1.134458	-38	0.651197	0.220715	-66	0.250122	-62
2211	0.032955	0.033371	1	0.032509	-1	0.010611	0.007382	-30	0.006424	-39	2.135363	1.230785	-42	1.433405	-33	0.706309	0.266176	-62	0.297055	-58
2212	0.04661	0.04875	5	0.047183	1	0.016814	0.012329	-27	0.012946	-23	1.624249	1.219954	-25	0.913632	-44	1.294249	0.671993	-48	0.717117	-45
2213	0.049311	0.048572	-1	0.048572	-1	0.017884	0.013392	-25	0.013392	-25	2.386484	1.472577	-38	1.472577	-38	1.427208	0.894934	-37	0.894934	-37
2214	0.057202	0.051111	-11	0.051111	-11	0.032672	0.026775	-18	0.026775	-18	2.102866	1.50871	-28	1.50871	-28	2.051322	1.561656	-24	1.561656	-24

[a] First two digit of VSP Bins: 11: odometer < 50,000 miles and engine size < 3.5 liter; 12: odometer < 50,000 miles and engine size > 3.5 liter; 21: odometer > 50,000 miles and engine size < 3.5 liter; 22: odometer > 50,000 miles and engine size > 3.5 liter.
[b] Unit of standard deviation: g/sec; Unit of diff.: %.