RECOMMENDED STRATEGY FOR ON-BOARD EMISSION DATA ANALYSIS AND COLLECTION FOR THE NEW GENERATION MODEL

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1.0 INTRODUCTION

The Office of Transportation and Air Quality (OTAQ) of the U.S. Environmental Protection Agency (EPA) is beginning work to design the "New Generation Model" (NGM) which will be the successor to the Mobile6 highway vehicle emission factor model. Advances in measurement technology have, in the last few years, made possible measurement of vehicle tailpipe emissions during real-world vehicle operation using portable on-board instruments. A key consideration in designing the NGM, therefore, is the role that data obtained from on-board emissions measurements can play. Because the measurement and interpretation of on-board data is a relatively new area, EPA has sought input from three external organizations to provide examples and recommendations of modeling approaches, and to recommend data collection strategies for the NGM. Each of the three organizations is working simultaneously and independently under the same scope of work, and each is preparing its own report. The three organizations are North Carolina State University (NCSU), the University of California at Riverside, and Environ. This report represents the work done at NCSU. The three organizations have not had an opportunity to review each other's reports in preparing final conclusions and recommendations.

1.1 Objectives

This project has several primary objectives:

1. To recommend methods for using tailpipe emissions measurements for Light Duty Gasoline Vehicles (LDGV), Heavy Duty Diesel Vehicles (HDDV), and nonroad vehicles in the development of emission factor models;
2. To develop conceptual models for each of the three vehicle categories using on-board emissions data provided by the U.S. Environmental Protection Agency;
3. To apply the conceptual models to predictions for a "validation" dataset and to interpret the results;
4. To develop recommendations regarding other emissions data that should be used in developing the NGM; and
5. To develop and recommend testing strategies for on-board measurement of emissions in support of the NGM.

These five objectives are supported by four major tasks:

Task 1: Development and Demonstration of a Conceptual Analytical Methodology for Analyzing On-board Emissions Data (supports Objectives 1, 2, and 3)

Task 2: Development of Strategies for Using Alternative Emissions Data (supports Objective 4)

Task 3: Development of Testing Strategies for On-Board Data (supports Objective 5)

Task 4: Documentation of Results and Presentation to EPA (supports all objectives)

This chapter provides: (1) an overview of current approaches to measuring and modeling emission factors; (2) motivation for the use of on-board emissions data; (3) a brief review of previous work at NCSU regarding on-board emissions measurements; (4) a review of several alternative concepts for estimating emissions in the NGM; and (5) an introduction to the general approach to modeling that is employed in this work.

1.2 Overview of Conventional Emissions Measurement and Estimation Approaches

The most common methods for measuring vehicle emissions have been the use of dynamometer tests in a laboratory test facility or roadside, remote sensing at specific on-road locations, and tunnel studies. The current generation of emission factor models, including the EMFAC series of models used in California, and the MOBILE series of models developed by EPA, are based upon emissions data for selected driving cycles. A driving cycle is composed of a unique profile of stops, starts, constant speed cruises, accelerations and decelerations and is typically characterized by an overall time-weighted average speed (TRB, 1995; NRC, 2000). Different driving cycles are used to represent driving under different conditions. The emission measurements for a driving cycle are typically conducted on a dynamometer in the laboratory. A concern with driving cycles is that they may not be sufficiently representative of real-world emissions (Kelly and Groblicki, 1993; Denis *et al.*, 1994; Barth *et al.*, 1996; NRC, 2000; EPA, 1993). The MOBILE6 model is an improvement over the previous versions of the MOBILE model, because it is based upon driving cycles obtained during recent activity studies in various cities. However, because the data obtained from driving cycles is typically reported only a trip average basis, such as in the Mobile Source Observational Database developed by EPA, it is not possible to estimate emissions at smaller time or spatial scales. Thus, typical driving cycle data cannot be used to evaluate microscale or mesoscale vehicle emissions. For example, improvements in traffic flow (e.g., signal coordination and timing) cannot be evaluated with driving cycle-based models (NRC, 2000).

In order to estimate effects associated with driving dynamics, the modal operation of a vehicle and related emissions need to be analyzed. Modal emissions-based models relate emissions directly to the operating mode of vehicles. The operating modes include cruise, acceleration, deceleration, and idle (NRC, 2000; Barth and Norbeck, 1997; Frey *et al.*, 2001; Tong *et al.*, 2000). Several research studies have been performed using dynamometers and instrumented vehicles producing second-by-second emissions data to investigate vehicle emissions associated with modal events (e.g., Cicero-Fernandez and Long, 1994). By testing a small set of newer technology vehicles, these studies found that CO and HC emissions are greatly affected by various acceleration modes.

Several researchers have developed modal-emissions models. One way of developing a modal-emissions model is to set up a speed-acceleration matrix in order to characterize vehicle operating modes of idle, cruise, and different levels of acceleration/deceleration and to determine corresponding emissions (West and McGill, 1997). According to Barth *et al.* (1996), the problem with such an approach is that it does not properly handle other variables that can affect emissions, such as road grade or use of accessories. Another disadvantage is that the vehicle history is not properly considered, as the vehicle emissions in a given second might be a function of the previous second's speed and acceleration (NRC, 2000). In statistical terminology, this refers to autocorrelation in the time series of second-by-second emissions measurements.

Another type of modal-emissions model is based on engine mapping. The conceptual approach is to translate real-time speed and route information into instantaneous vehicle rpm and load parameters, use an engine map to look-up the instantaneous emission rates for the specific rpm and load conditions, and continuously integrate the instantaneous emission rates to estimate the total emissions from a given set of vehicle activities. A potential weakness is that emissions occurring under transient conditions may not be adequately represented by the emissions map that is derived under steady-state conditions. Mapping models have been developed by LeBlanc *et al*., (1994); Shih and Sawyer, (1996); and Shih *et al*., (1997).

The aggregate modal modeling approach used by the Georgia Institute of Technology for the Mobile Emission Assessment System for Urban and Regional Evaluation (MEASURE) model is similar to emission mapping, but it is based upon emissions 'bag' data to derive modal activities (Washington, 1997). The model estimation data consisted of more than 13,000 laboratory tests conducted by the EPA and CARB using standardized test cycle conditions and alternative cycles (Bachman, 1999). Hierarchical tree-based regression analysis was applied to the database using several vehicle technologies and operating characteristics as variables to explain variability in emissions. Vehicle activity variables include average speeds, acceleration rates, deceleration rates, idle time, and surrogates for power demand.

The Center for Environmental Research and Technology at University of California Riverside (UCR-CERT) has developed a modal emissions model that reflects Light-Duty Vehicle (LDV) emissions produced as a function of the vehicle's operating mode. The model predicts second-by-second tailpipe (and engine-out) emissions and fuel consumption for different vehicle categories in different states of condition (e.g., properly functioning, deteriorated, and malfunctioning) (Barth *et al.*, 1997). In developing the model 315 vehicles from 24 different vehicle/technology groups were tested on the FTP (Federal Test Procedure) test, EPA's high-speed driving cycle (US06), and a newly developed modal driving cycle (Barth *et al.*, 1997).

In the UCR-CERT model second-by-second tailpipe emissions were modeled as the product of three components: fuel rate (FR), engine-out emission indices ($g_{emission}/g_{fuel}$), and time-dependent catalyst pass fraction (CPF). The model is composed of six modules: (1) engine power demand; (2) engine speed; (3) fuel/air ratio; (4) fuel-rate; (5) engine-out emissions; and (6) catalyst pass fraction. Power demand was estimated using environmental parameters (wind resistance, road grade, air density, and temperature), and vehicle parameters (velocity, acceleration, vehicle mass, cross-sectional area, aerodynamics, vehicle accessory load, transmission efficiency, and drive-train efficiency). Power demand was combined with other engine parameters (gear selection, air/fuel ratio, and emission control equipment) to develop dynamic vehicle or technology group emission rates (Barth *et al.*, 1996). The model uses a total of 47 parameters to estimate vehicle tailpipe emissions.

In the fuel-based method, emission factors are normalized to fuel consumption and expressed as grams of pollutant emitted per gallon of gasoline burned instead of grams of pollutant per mile. In order to obtain an overall fleet-average emission factor, average emission factors for subgroups of vehicles are weighted by the fraction of total fuel used by each vehicle subgroup. The fleet-average emission factor is multiplied by regional fuel sales to compute pollutant emissions (Singer and Harley, 1996). The fuel based approach is amenable to the use of emissions data collected for on-road vehicles using either remote sensing or tunnel studies, as opposed to relying on laboratory tests in the driving cycle approach. Therefore, this approach may yield a key benefit of being more representative of on-road emissions. Emissions can be calculated by vehicle class by applying the multiplication separately for each class. The accuracy of a fuel-based model depends on how well the vehicles and driving modes from which emission factors were measured represent the entire area under study. The accuracy of the age distribution used to weight emissions data from each vehicle model year is another important consideration. NCSU has conducted two on-road studies using remote sensing. One resulted in fuel-based emission factors for CO and HC for school and transit buses (Frey and Eichenberger, 1997), and the other resulted in fuel-based emission factors for a variety of light duty vehicles (Rouphail *et al*., 2000).

1.3 Motivation for Use of On-Board Emissions Data

The National Research Council (2000) reviewed the structure and performance of the Mobile model, investigated ways to improve the model, and made recommendations for the NGM. One of the recommendations of the NRC study is to develop the capability to estimate emissions at different scales such as microscale, mesoscale, and macroscale. To be able to develop this kind of model, new measurement techniques are needed. On-board emissions measurement is one of these techniques and is widely recognized as a desirable approach for quantifying emissions from vehicles, since data are collected under real-world conditions at any location traveled by the vehicle. Until recently, on-board emissions measurement has not been widely used because it has been prohibitively expensive. Therefore, instrumented vehicle emissions studies have typically focused on a very small number of vehicles (Kelly and Groblicki, 1993; Cicero-Fernandez and Long, 1997; Gierczak *et al.*, 1994; Tong *et al.*, 2000, as well as the work of Richard Shores, Bruce Harris, and others at EPA). In other studies, researchers have measured engine parameters only (Denis *et al.*, 1994; LeBlanc *et al.*, 1994; Guensler *et al.*, 1998; West *et al.*, 1997). However, in the last few years, efforts have been underway to develop lower-cost instruments capable of measuring both vehicle activity and emissions (Scarbro, 2000; Vojtisek-Lom and Cobb, 1997). More recently, the concepts employed by Vojtisek-Lom and Cobb have been commercialized by Clean Air Technologies International, Inc., which markets the OEM-2100™ portable emissions measurement system. Other companies are also entering the on-board emissions measurement market with instruments of their own.

1.4 Previous Work at NCSU Regarding On-Board Emissions Measurements

NCSU has been a pioneer in the use of on-board emissions measurement systems. For more than two years, NCSU has deployed portable on-board emissions measurement systems to measure real-world, on-road tailpipe emissions of light duty vehicles (Frey *et al*., 2001). The objectives of the study were to: (1) evaluate a new low-cost approach for measuring on-road tailpipe emissions of highway vehicles; (2) investigate factors that affect the amount and variability of on-road emissions, using statistical methods; and (3) devise and demonstrate methods for designing and conducting observational experiments that realistically evaluate pollution prevention strategies for on-road vehicles.

Portable instruments were used for measuring carbon monoxide (CO), nitric oxide (NO), and hydrocarbon (HC) emissions and vehicle activity (e.g., vehicle speed, engine parameters) on a second-by-second basis. Data collection, quality assurance, reduction, and analysis protocols were developed. Field data collection occurred in a pilot and an evaluation phase. In total, over 1,200 one-way trips were made with more than 20 vehicles, 4,000 vehicle-miles traveled, 160 hours of second-by-second data, and 10 drivers. The pilot study was used to identify key factors influencing on-road emissions and as input to the design of the evaluation study. In the evaluation study, data were collected intensively with a small number of vehicles on two corridors before and after signal timing and coordination changes were implemented. For the first corridor, changes in signal timing and coordination did not result in a significant change in traffic flow or emissions. However, substantial reductions in emissions were estimated for uncongested versus congested traffic flow when comparing travel in the same direction at different times of day. For the second corridor, there were significant improvements in traffic flow and some reduction in emissions for three of the four time period and travel direction combinations evaluated.

The impact of signal timing and coordination changes with respect to non-priority movements involving cross-streets was evaluated. For the first corridor, there was no statistically significant observed change in emissions for non-priority movements. For the second corridor, there typically was a decrease in average speed and an increase in emissions for non-priority movements; however, many of the observed changes were not statistically significant.

The study also demonstrated other analysis methods, including: (a) macro-scale analysis of trip average emissions and traffic parameters; (b) micro-scale analysis of second-by-second emissions and vehicle operation; (c) meso-scale analysis of modal emission rates; and (d) spatial analysis of emissions at specific locations along the corridors. Both statistical and theoretical-based approaches were evaluated. The implications of the study results for pollution prevention strategies were discussed. Conclusions were presented regarding instrumentation, protocols, analysis techniques, and case study-specific findings. Recommendations were given regarding future applications of on-board measurements.

Of the most common approaches to emissions data collection, the emerging area of on-board emissions measurement is perhaps the most promising. Although not without limitations, on-board emissions data measurement enables collection of representative real-world data at any location and in any weather, which remedies many of the shortcomings of laboratory based methods and of field-based methods such as remote sensing and tunnel studies, which are limited in siting. At the same time, because real-world data collection is observational, it is not possible to collect data under controlled conditions as in the laboratory. Therefore, there will continue to be role for multiple sources of data in developing the NGM.

1.5 Possible Conceptual Approaches for Estimating Emissions in the NGM

EPA has suggested several approaches for the Emission Rate Estimator (ERE) of the NGM. These approaches can briefly be summarized as:

Approach 1: Use of high frequency (e.g., second-by-second) data to develop microscale (e.g., second-by-second) emission estimates, with aggregation as appropriate for mesoscale (e.g., modal) and macroscale (e.g., trip average emissions) estimates. This model would be highly data intensive. If implemented as a neural network, it would not be very transparent to the user in terms of the underlying physical principles. If implemented as a physical-based model, it may require a substantial amount of design data or other input assumptions that are not readily observed using portable on-board emissions measurement systems or using existing infrastructures for collecting vehicle registration and traffic data.

Approach 2. Use of statistical methods to process raw data to generate mesoscale and macroscale estimates. EPA characterizes this as a "descriptive" method.

Approach 3. Development of an extensive data set and use of the ERE to simply query the database when emissions estimates are needed.

All three of these approaches have validity and in some cases overlap with each other. For example, NCSU has employed regression tree approaches to develop emission estimates based upon remote sensing data (Rouphail *et al.*, 2000). Regression tree approaches effectively involve binning the data but do not require fitting of a model to the data. Thus, such an approach is a combination of Approach 2 and Approach 3.

As part of previous work, NCSU has explored in some detail the use of neural networks to process on-board emissions data collected during a study for NCDOT (Frey *et al*., 2001). Neural networks offer some advantages of flexibility of functional form in representing data. They require a good training data set. However, the process of selecting appropriate inputs for training of the neural network model is a subjective one. The time it takes to get good results during training is a function of the *a priori* assumptions made by the analyst regarding which explanatory variables to include in the model. In addition, since there is some autocorrelation in second-by-second activity and emissions data, it is necessary to consider multiple time steps when training the neural network. A key shortcoming of neural networks is that they do not provide direct measures of sensitivity nor do they provide clear equations that reveal the key physical relationships among the inputs and outputs. Techniques exist for trying to interpret the results of a neural network model, but for most users such models are likely to be impenetrable "black boxes" providing no insight other than what a user obtains for himself or herself through sensitivity analysis.

Physical-based models are perhaps the most intellectually satisfying of the approaches mentioned above. Such models would enable prediction of emissions based upon design and activity data for the vehicle. For example, knowledge of the engine displacement, number of cylinders, compression ratio, intake air pressure, equivalence ratio, volumetric efficiency, and many other parameters could form a basis for predicting fuel consumption and emissions with an appropriately calibrated model. The problem with a model such as this as there can be a very large number of inputs that are not typically measured in vehicle activity studies. Therefore, it would be impractical to use such models for estimating fleet average emissions or for many other purposes. There is a temptation with such models to include lots of input variables. However, it is perhaps equally or more important to tease out which ones really matter and which ones really do not. Such models are useful for providing insights into key factors that affect emissions, but they may not be practical for use on a national scale or even on an urban scale for emissions predictions by local, state, and federal agencies.

Perhaps the most practical approach, and the approach pursued by NCSU in this project, involves a combination of some of the above. Specifically, it is important that physical insight play a role in the development of an emissions model. At the same time, it is also critically important that there be a good empirical basis for the model. It is typically the case for many models that the model outputs are most critically sensitive to only a subset of all possible model inputs. Therefore, it is not necessary, useful, or practical to exhaustively include all possible inputs. Cullen and Frey (1999) and others discuss issues of model complexity, aggregation, and exclusion that are relevant here. A model should have a clear data quality objective and clear criteria regarding the desired domain of applicability. The domain over which the model is valid should ideally correspond to the domain for which model predictions are desired.

The complexity of a model is characterized by the number of compartments, pathways, or states represented in the model, by the number of inputs, and by the function form of the equations. Complexity and size are two different issues, however. A model may be large but simple in that it may be composed of a large number of inputs but have a linear functional form. A model can be small and complex because it might be highly nonlinear with extensive interactions among the components. Complex systems are often hierarchies, which can be described in terms of the "span" of each level in the hierarchy and in terms of the number of levels. A simple model may have repetitive components at only one level. It is generally believed that simple models are more limited in their applicability than complex models. For example, if a simple model is a local linearized version of a more complex model, then the simple model will provide accurate predictions close to some specific point but the accuracy of the predictions will degrade as the model is extrapolated farther away from the calibration point.

There are various trade-offs between simplicity and complexity in models, and such trade-offs should be acknowledged and made consciously. Complex models are often intended to represent the science as well as possible. Simpler models are often intended for more widespread use. Complex models may be more accurate than simpler models. Accuracy here refers to convergence of the average predictions of the model to the true value. In going from simple to more complex models, uncertainty due to the structure of the model may be reduced. However, uncertainty associated with perhaps a larger number of inputs or with the error propagation properties of the complex formulation can lead to a loss of precision.

For policy purposes, some say that models should be made "as simple as possible, but no simpler" (Morgan and Henrion, 1990). This means that models should not contain any extraneous features that have no real bearing on the policy applications of the model. Thus, if a model is to be used for development of modal or macroscale emission inventories involving averages over a fleet of vehicles, for example, then it may be extraneous to include excessive design details regarding individual vehicle make and model among the inputs to the model. The typical user would only be frustrated by such demanding data input requirements. However, this does not mean that such considerations should not enter into the process of developing the model. It only means that the final model should be of an appropriate level of complexity consistent with its intended use. For example, a complex, detailed physical-based model could be developed initially to obtain fundamental insights regarding key relationships that should be preserved in the final model, perhaps using surrogate variables that are more readily measurable. Various methods, such as response surface techniques or other sensitivity analysis methods (e.g., see Frey and Patil, 2002 for a review, as well as Cullen and Frey, 1999, and Bharvirkar and Frey, 1998) can be used to identify key relationships in the complex model that should be preserved in a more simplified model intended for wider use.

1.6 Summary

On-board emissions measurements have emerged as a promising new approach for obtaining representative real-world tailpipe emissions data based upon actual on-road driving. The increasing availability of instrumentation for performing on-road emissions studies, the development of data collection and analysis protocols, and the increasing availability of example on-board studies suggests that on-board data collection is a potentially practical and useful source of data for the NGM. Therefore, this study is aimed at exploring the potential of on-board data to play an important role in the NGM, and to make recommendations for the development of models and measurement of data needed to support the NGM. Based upon the key considerations regarding conceptual approaches to estimating emissions described here, Chapter 2 will present in more detail the general approach to modeling that is employed in this study. Chapter 3 focuses on development and demonstration of a conceptual model for LDGVV emissions. Chapters 4 and 5 have a similar focus with respect to HDDV and nonroad vehicles, respectively. Predictions made with conceptual models for all three mobile source categories are given in Chapter 6 and a comparison is made to observed values. Recommendations regarding the use of alternate emissions data are addressed in Chapter 7, and recommendations for testing strategies for on-board data are addressed in Chapter 8.

2.0 GENERAL TECHNICAL AND MODELING APPROACH

To support Objectives 1, 2, and 3, and to meet the requirements of Task 1, an overall approach as well as specific procedures for analyzing on-board emissions data must be developed and demonstrated. This chapter provides an overview of the general technical and modeling approach employed in this work. The approach is applied to two categories of on-road vehicles, LDGV and HDDV, and to a single category representing nonroad vehicles.

EPA provided on-board measurement data sets for selected LDGV, HDDV, and nonroad vehicles. The HDDV vehicles for which data were provided are diesel transit buses. The non-road vehicles for which data were provided are construction equipment. It is important to point out that NCSU had no role in the design or execution of the on-board measurement studies. Thus, NCSU had no role in selection of vehicles, drivers, routes, time of day, and other scheduling aspects, nor regarding the calibration, maintenance, and operation of the measurement equipment. Thus, the focus of this chapter is on methods for evaluating and analyzing data after they have been collected. However, the development of a model is conditional on the data used to calibrate the model. Therefore, the quality of the model will be influenced by the study design for the data collected for model calibration. Important considerations in designing on-board data collection studies are addressed in Chapter 8.

2.1 Overview of General Technical and Modeling Approach

The general modeling approach employed by NCSU involves the following key considerations:

1. Visualize the data!
2. Iterative approach to model development, including consideration of physical and empirical (statistically significant) relationships observed in actual data, informed by *a priori* theoretical constructs.
2. Quantification of variability and uncertainty in model predictions.

When evaluating a data set and when developing a model from the data set, it is important to begin with hypotheses regarding relationships based upon physical insights. Such insights might be obtained based upon previous work. For example, parametric experiments in laboratory settings provide some indication of what are the key sensitivities of emissions to various factors, such as engine load, engine speed, air temperature, accessory use, and so on. Knowledge of these factors is important in identifying "independent" or input variables to use in initial model development.

The first step of data visualization typically includes developing multiple pairwise scatter plots of the candidate input and output variables to look for possible empirical relationships among them. Statistical software such as SPLUS is well-suited to this type of work and has been used extensively in previous studies involving both remote sensing and on-board emissions measurement data (e.g., Rouphail *et al.*, 2000; Frey *et al.*, 2001). The process of visualization of data also gives the analyst an appreciation for the variability in the data that may not be explained by any of the candidate input variables.

Both physical and statistical relationships between emissions and explanatory variables are explored. Examples of statistical methods used in previous work include ANOVA, regression trees, and regression analysis. Past work at NCSU has typically employed procedures most similar to Approach 2 described in Section 1.5; however, data have also been analyzed in terms of key physical parameters (e.g., fuel equivalence ratio) in order to obtain key physical insights regarding relationships in the data. For example, HC emissions from diesel vehicles have a dependence on equivalence ratio, as do CO emissions from LDGV. However, although emissions may be better explained by some physical variables such as equivalence ratio, such variables are not readily observable for those who are likely users of the NGM. Therefore, rather than develop a model based upon input parameters for which data are not likely to be readily available, it is important to seek surrogate variables that are related to the key physical variable of interest but for which data may be more readily available. For example, a key focus of previous work has been to evaluate the predictive power of readily observable traffic parameters with respect to emissions (e.g., Rouphail *et al.*, 2000).

The development of the functional form of a model should be informed not only by *a priori* assumptions based upon theoretical expectations, but also upon relationships that are inferred from the data. When only *a priori* assumptions guide model development, it is typically the case that the model can become too complex or fragmented. For example, in the nonroad source categories, emission factors are often subdivided by type of equipment, type of application, size of equipment, and other factors. In the specific case of CFI equipment, for example, agencies such as EPA propose to separate 2-stroke equipment by size, and to develop emission factors separately for each size range. However, a statistical analysis of data for the different size ranges reveals that there is not a statistically significant difference in emissions for two size ranges reportedly under consideration (Frey and Bammi, 2002). Therefore, there is no obvious benefit to creating multiple size ranges for this source category.

Similarly, Kini and Frey (1997) performed a statistical evaluation of the driving cycle data used to develop the speed correction factor in the Mobile5 model. The average emissions estimated from several driving cycles were found to be not statistically significantly different than the average emissions estimated from other cycles. For example, this was found in a comparison of the LSP1, LSP2, and LSP3 cycles. Since all three cycles produce essentially the same emissions, these three cycles are redundant. Time and effort can be saved by not creating an unnecessary demand for data and by not using redundant data in model development. Model development is simplified if unnecessary categories are avoided.

It is important to consider both variability and uncertainty when analyzing data and developing a model. Previous work at NCSU has demonstrated that there is substantial variability in emissions for a given mobile source category, whether it be an on-road source (e.g., Frey *et al.*, 1996; Kini and Frey, 1997; Frey and Eichenberger, 1997; Frey *et al.*, 1999; Frey *et al.*, 2001) or a nonroad source (e.g., Bammi and Frey, 2001; Frey and Bammi, 2002a&b). However, for emission inventory purposes, one is typically less interested in inter-vehicle variability in emissions and more interested in uncertainty regarding fleet average emissions. Therefore, it is necessary to statistically analyze emissions data so that estimates of uncertainty in average emission factors can be produced. NCSU has demonstrated approaches for quantification of variability and uncertainty in both on-road and nonroad sources, as referenced above. Such approaches are employed in this work.

One of the key reasons to address uncertainty in model predictions is to enable comparisons. For example, in this project EPA provided NCSU with a "modeling" dataset was used for model development. These data are also referred to here as "calibration" data, because they were used to calibrate the model. Separately, EPA provided a "validation" data set that is incomplete. The validation data contained only selected activity data, and NCSU was required to make predictions using the model developed from the pilot modeling data set using the activity data of the validation dataset. EPA withheld information regarding the observed emission values for the validation data set until after NCSU reported the predictions made by the conceptual models developed in this project.

In making predictions, estimated ranges of variability and/or uncertainty in the predictions are reported. When comparing the model predictions to the true values of emissions for the validation case, the precision of the model should be considered. It is also critically important to consider the data quality objectives of the prediction. In this study, the calibration data set is based upon a relatively small number of vehicles for each of the three source categories: LDGV, HDDV, and nonroad. For each of the three categories, EPA requested predictions of emissions for individual vehicles and for a "fleet" average. When making predictions for individual vehicles, it is important to evaluate the precision of the model in terms of the portion of the observed inter-vehicle variability from the calibration data set that is unexplained by the model.

For example, suppose that a conceptual emission factor model is used to estimate the total trip emissions for a single vehicle. Activity data for the vehicle, in the form of a second-by-second speed trace, may be available, along with second-by-second data for a small number of other possible explanatory variables. The conceptual model might be structured so as to predict second-by-second emissions and sum them to obtain an estimate of the total trip emissions. The estimated trip emissions can then be compared with the observed trip emissions, and the difference between the two is an indication of the model prediction error. However, a key question is whether the model prediction error in a specific case is within the expected error of the model. If it is, then the prediction is considered to be acceptable. If it is not, then there may be some important discrepancy that should be investigated and corrected. Because the model is not likely to be able to predict emissions with no error, some prediction error is expected. Possible causes of error in model predictions include the following:

- The model may be incomplete in that it does not have a sufficient set of explanatory variables;
- the model may not have the most appropriate functional form;
- the model may have been calibrated with data that contained measurement errors;
- the validation data may contain measurement errors for either the explanatory variables and/or the observed emissions; and/or
- the validation data set may have been obtained under conditions substantially different than those for the data used to calibrate the model.
- data entry errors.

If the validation data were for conditions different then those under which the calibration data were collected, the model was extrapolated. The predictions of a model that has been extrapolated can have very large errors and/or be meaningless. In developing the predictions for the validation data set, the range of values of the explanatory variables were compared to those in the calibration data sets to determine if there were any potential problems with model extrapolation.

2.2 Technical Approach for On-Road Vehicles

This project features the development of methodologies for using on-board emissions data as the basis for estimating emissions for both on-road and nonroad sources. This is essential in developing the EPA's NGM since data representative of real-world conditions need to be utilized for better emissions predictions. The overall philosophical approach that we will use has been described in the previous section. In this section, we provide some additional detail and examples regarding the approach in this work for dealing with on-road vehicles.
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This study involves methodologies that will be used for estimating on-road vehicle emissions of hydrocarbon (HC), carbon monoxide (CO), and nitrogen oxides (NO_X). First, conceptual analytical modeling techniques will be presented with example analyses applied to on-road data collected in previous work at NCSU using an on-board emissions measurement device as part of an NCDOT-funded project.

The first task of this project, Development and Demonstration of a Conceptual Analytical Methodology for Analyzing On-Board Emission Data, is divided into two subtasks. One is the development of a conceptual analytical methodology, and the other involves application of the methodology to an example case study. The general approach for both is addressed in this section.

In discussing on-road vehicles, the examples focus upon gasoline-fueled (spark ignited engine) vehicles. Of course, diesel-fueled (compression ignited engine) vehicles are also of importance. The on-board emissions measurement technique used at NCSU for gasoline-fueled vehicles is similar to the on-board emissions measurement technique for diesel vehicles. Both techniques involve collection of vehicle activity data, typically through an on-board diagnostic (OBD) data link and measurement of gaseous tailpipe emissions for pollutants such as CO, NO, hydrocarbons, and CO_2. An additional consideration for diesel vehicles, which was not part of the scope of this project, is particulate matter (PM) emissions. The methods described in the following sections can include analysis of PM data. We note that EPA did not provide such data in the pilot modeling data set, and that the EPA is requesting only composite emission estimates for HC, CO, NO_x, and CO_2 for on-road equipment, and for NO_x and CO_2 for nonroad equipment.

2.2.1 Microscale Analysis for On-Road Vehicles

Microscale analysis refers to estimation of emissions for specific corridors and intersections for project level and hot-spot analyses (EPA, 2001). The temporal profile of vehicle activity and emissions provides important insights regarding potential factors that can explain variation in vehicle emissions and, in particular, explain high emissions events or "hot spots". A "hot spot" would be a location at which emissions tend to be high because of the influence of roadway, traffic control, or other traffic characteristics at that location.

To illustrate the type of data available from on-board emissions measurement and the insights they provide, an example of an individual one-way vehicle trip for a 1999 Ford Taurus collected by the NCSU research team on August 30, 2000 at a site in North Carolina is presented. Figure 2-1 shows vehicle speed versus elapsed time of the trip. The figure is labeled with the location of the vehicle at specific times. The trip took place on Chapel Hill Road between Cary, NC and Research Triangle Park. The trip began south of Morrisville Parkway and ended a short distance north of Airport Boulevard. There is notation in the figure indicating when the vehicle entered the queue for an intersection, and when the vehicle crossed the center of the intersection, such as at Aviation Parkway. The travel time on the corridor was approximately 13 minutes. The instantaneous speed ranged from zero to approximately 50 mph, and the average speed was 11 mph. The longest waiting times occurred in the queue at the intersection with Morrisville Parkway. The specific location of the vehicle was measured in this case based upon the speed trace and time stamps.

An example emission trace for a measured pollutant is shown in Figure 2-2 for CO. It is clear that the highest emission rates, on a mass per time basis, occur during small portions of the trip. For example, for CO, the emission rate exceeds 0.02 grams per second only five times during the trip, and emissions exceed 0.10 grams per second only one time. The largest peak in the emission rate occurs at the same time as the acceleration from zero to approximately 40 mph as the vehicle clears the intersection with Aviation Parkway. In fact, most of the peaks in CO emission rate tend to coincide with accelerations. The CO emission rate remains below 0.02 grams per second for the first ten minutes of the trip, corresponding to a period of stop-and-go travel with speeds ranging from zero to less than 25 mph. These data suggest that the CO emission rate during idling or crawling are comparatively low compared to the CO emissions during acceleration. Thus, an important insight is that high emissions may not necessarily be associated with heavily congested traffic flow, as is often assumed. Instead, high emissions may occur at a specific location because of the influence of traffic control and traffic regulations (e.g., speed limit) at a specific site. This type of insight emphasizes the tremendous importance of on-road emissions data. This example also serves as a cautionary tale that the insights obtained from an on-board emissions data-based model may contradict "conventional wisdom" obtained from mistaken interferences based upon extrapolation of dynamometer data-based models (e.g., Frey *et al.*, 1996; Kini and Frey, 1997; Frey and Eichenberger, 1997; Rouphail *et al.*, 2000; Frey *et al.*, 2001).

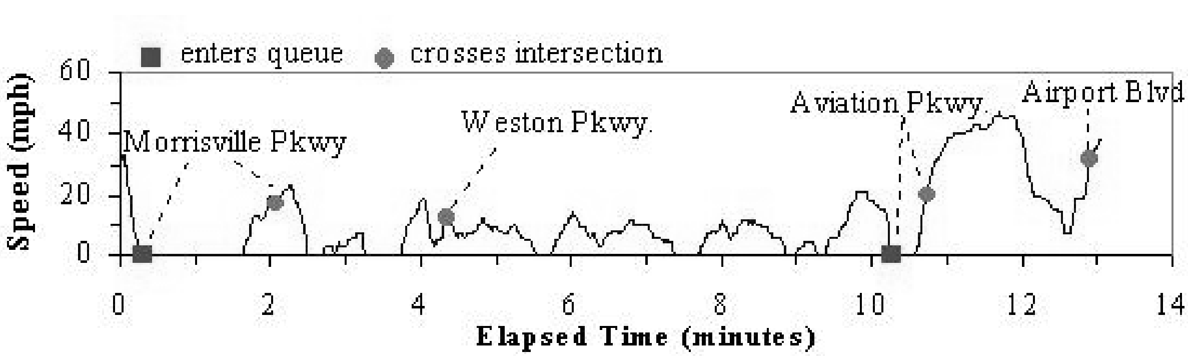


Figure 2-1. Vehicle speed versus elapsed time of the trip (Source: Frey *et al.*, 2001).

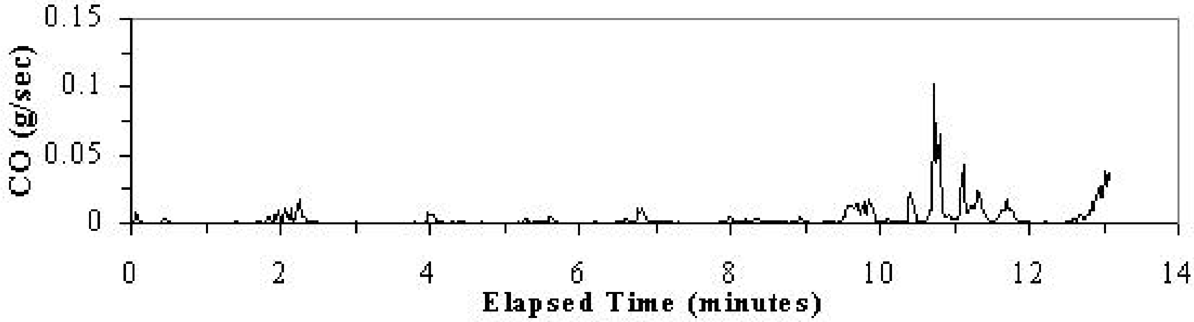


Figure 2-2. Vehicle CO emissions versus elapsed time of the trip (Source: Frey *et al*., 2001).

In general, the time traces for all four measured pollutants, including HC, NO, and CO_2 (not shown here but documented in Frey *et al*., 2001) indicate that there is a relatively large contribution to total emissions from short-term events at certain locations. This implies that efforts to have accurate predictions should consider these events. Using these data one can develop temporal distributions of emissions as given in Figure 2-2. This would be the first step in identifying "hot-spots" and parameters that are responsible for these "hot-spots". In order to understand what causes emissions hotspots on a route, it is important to understand the fundamental relationships between vehicle operation and emissions.

For example, short-term episodes of high CO emissions are typically associated with "fuel enrichment." Fuel enrichment refers to periods of vehicle operation in which the fuel-to-air ratio is higher than during normal operation. During normal vehicle operation, the fuel-to-air ratio is almost exactly stoichiometric. During fuel enrichment, there is not enough air to completely combust the fuel. Therefore, the emissions leaving the engine during enrichment will include more products of incomplete combustion, especially CO. The catalytic converter normally is capable of oxidizing CO to CO_2. However, under fuel enrichment, there is not sufficient oxygen in the exhaust gas for this oxidation reaction to go to completion.

An example of the effect of fuel enrichment on CO emissions obtained from on-board instruments as the vehicle, 1999 Ford Taurus, was driven on a test corridor is shown in Figure 2-3. The CO emission rate in terms of grams of CO emitted per gram of fuel consumed on a second-by-second basis is compared with the vehicle fuel equivalence ratio. An equivalence ratio close to one denotes stoichiometric combustion. An equivalence ratio of greater than one indicates fuel enrichment. The figure clearly demonstrates that high CO emissions occur only during fuel enrichment. The equivalence ratios were calculated from data reported by the OEM-2100™ on-board emissions measurement system used at NCSU, including fuel flow rate and intake air flow rate. In the current study, insufficient data were available from which to calculate equivalence ratio for many of the vehicles in the calibration data set; therefore, it was not possible to perform a similar analysis on a consistent basis for all of the vehicles provided in the EPA database. However, for the final model, surrogate variables that reflect the influence of these key physical factors may be needed, since it is not likely that equivalence ratio or fuel flow will be readily available activity data in practice. Since high equivalence ratio tends to be associated with high engine loads such as occurring during acceleration, one surrogate for equivalence ratio used in this work is to define separate driving modes (acceleration, cruise, deceleration, and idle) and to calculate emissions separately for each mode.

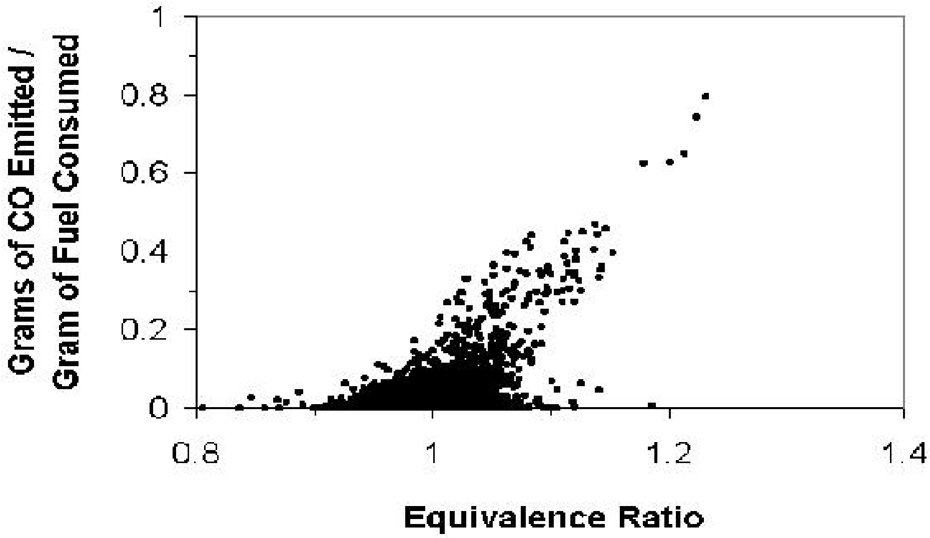


Figure 2-3. Comparison of CO Emission Rate Versus Equivalence Ratio (higher equivalence ratio reflects greater fuel enrichment) for a 1999 Ford Taurus (Source: Frey *et al*., 2001).

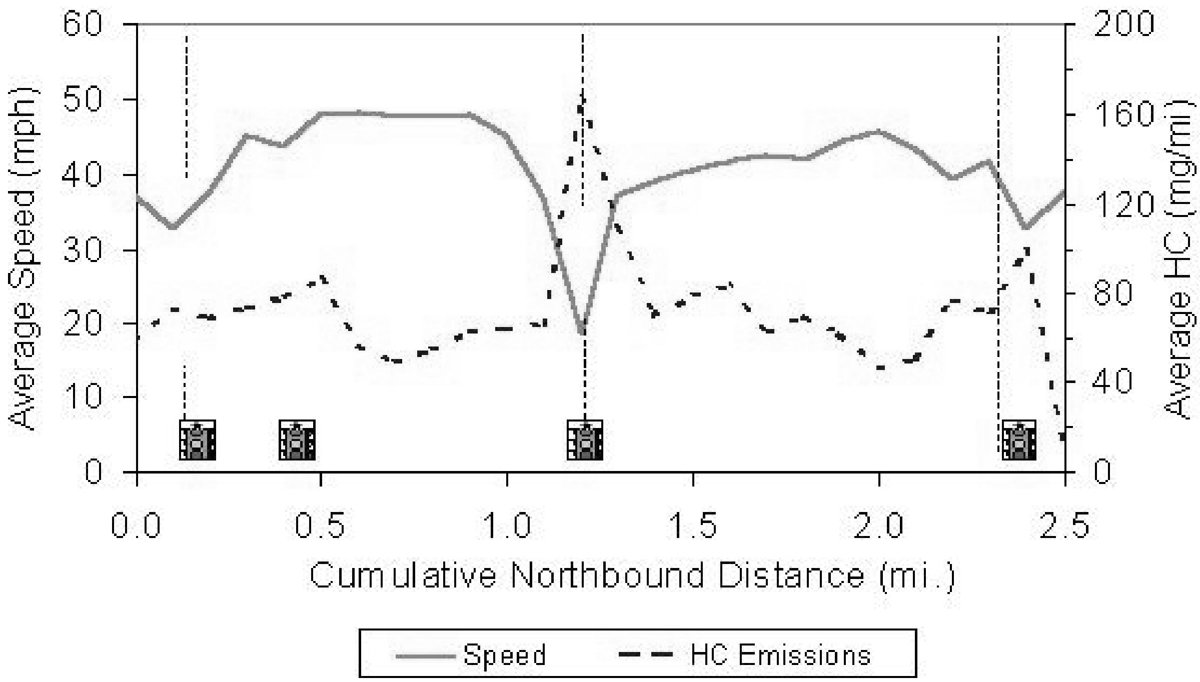


Figure 2-4. Illustration of Spatial Distributions of Emissions Based upon Averages of over 100 vehicle runs on a selected corridor (Source: Frey *et al*., 2001).

Another way to identify hot-spots is look at the spatial distribution of emissions. The spatial location of emissions can be estimated by assigning a location to the vehicle for each second of the trip, which can be obtained from GPS. An example of spatial analysis is shown in Figure 2-

4, where emissions averaged over 100 vehicle runs on a selected corridor with 1999 Ford Taurus is given with the locations of traffic signals.

Figure 2-4 displays the average speed and average HC emissions for a corridor approximately 2.5 miles long and shows the locations of signalized intersections. This example illustrates the presence of an emission hotspot associated with a specific intersection, at approximately 1.25 miles. The spatial distribution of emissions can also be used to estimate emissions for segments of routes representing different roadway functional classes. Thus, the influence of functional class on emissions can be evaluated. In addition, the influence of other possible explanatory factors can be explored, such as road grade, traffic control devices, and others.

Even if not included in this study, in the future consideration should be given to characterization of traffic control devices with respect to emissions. For example, while there could be a default emission estimate for vehicle emissions on a primary arterial functional class of roadway, the emission estimate could be modified based upon knowledge of the density of traffic signalization along the corridor (e.g., number of signals per mile). We recommend that EPA give serious attention to collecting activity data regarding roadway functional class and traffic control devices in future on-board emissions data collection. Alternatively, emissions can be estimated as a function of roadway classification, with subcategories representing vehicle movements within an influence zone of an intersections as distinct from vehicle movements that are not influenced by intersections (e.g., midblock).

The considerations above generally apply to both light duty and heavy duty on-road vehicles. However, for heavy duty vehicles, emissions may typically be influenced by other factors that are not readily observable, such as the vehicle payload. For example, work by Bruce Harris at EPA has explored the effect on emissions of vehicle payload in the trailer of a tractor-trailer rig. While such information could be observed in principle in the process of collecting data, the user of a model would have to make assumptions about the distribution of vehicle loads.

Diesel engines have different emission characteristics than do gasoline engines. Because diesel engines operate at much higher pressure ratios and with excess air, they have higher NO_x emissions than do gasoline engines. Flagan and Seinfeld (1986) indicate that equivalence ratio is an important explanatory factor for diesel engine emissions. For example, HC emissions tend to be low for equivalence ratios greater than approximately 0.5, but increase sharply as equivalence ratio decreases to values less than approximately 0.3. CO emissions tend to be lowest at equivalence ratios of approximately 0.4 to 0.5, and to increase if the equivalence ratio is either higher or lower than these values. NO_x emissions tend to increase as the equivalence ratio decreases. One implication of the data shown by Flagan and Seinfeld is that HC emissions are relatively insensitive to equivalence ratio for a wide range of variation of equivalence ratio. This implies that HC emissions may be relatively constant, on average, as a function of the available explanatory variables (e.g., speed, acceleration) compared to the other pollutants.

2.2.2 Mesoscale Analysis for On-Road Vehicles

Mesoscale analysis refers to analysis at regional and sub-regional (corridor) levels as stated by NRC (2000). These analyses should be for fine resolution estimation of emissions using vehicle-operating conditions as input parameters. It should be noted that there might be some overlap between mesoscale and microscale analyses (EPA, 2001).

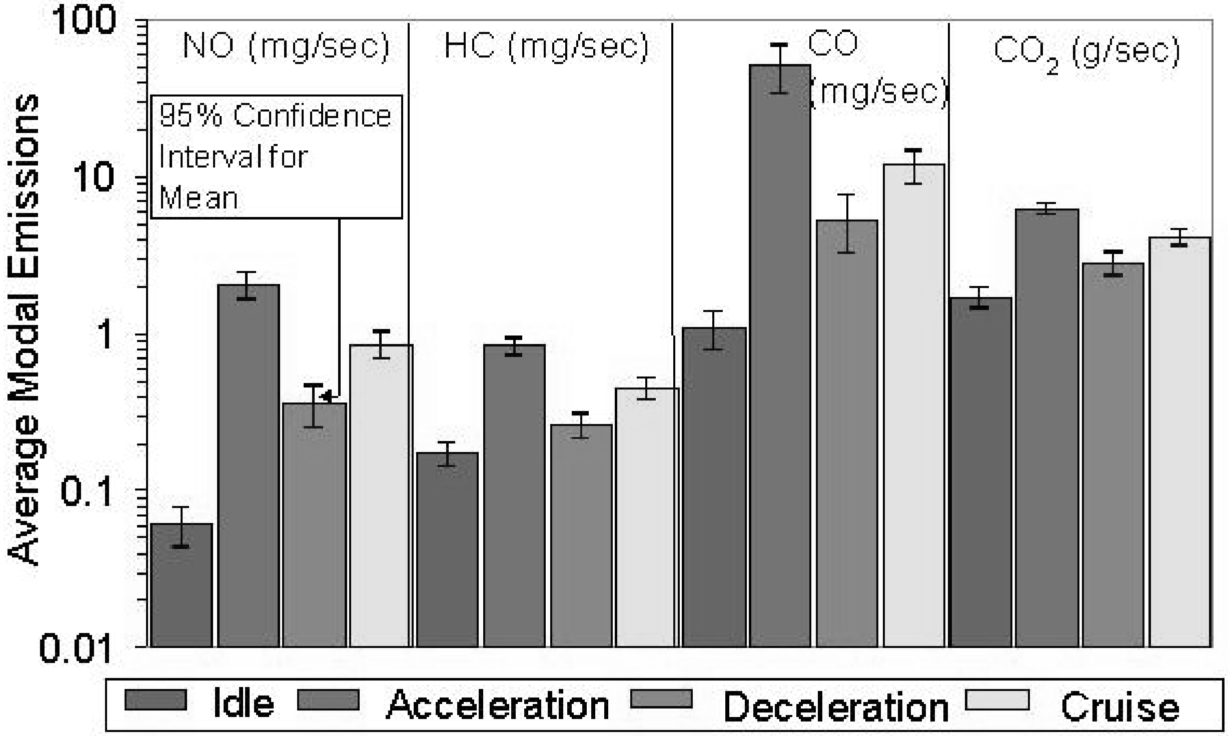


Figure 2-5. Mean Modal Emissions of Four Pollutants and 95 Percent Confidence Intervals on Mean Emission Rates (Source: Frey *et al*., 2001).

Mesoscale analyses would allow developing accurate assessment of TCMs and Transportation Improvement Plans (TIPs). One method that enables such results is modal analysis. The research team at NCSU has developed modal analysis methods based upon empirical definitions of operating modes of vehicles using vehicle speed and acceleration as input variables (Frey *et al*., 2001).

As part of previous work, a program was written in Microsoft Visual Basic that calculates the driving mode for second-by-second data and determines the average value of emissions for each of the driving modes and for the total trip. In order to illustrate the types of results obtained from modal analysis of the emissions data, example results are developed based upon 72 one-way trips obtained using a 1999 Ford Taurus on Chapel Hill Road. A comparison of the average modal emission rate for each of four pollutants is shown in Figure 2-5, along with estimates of the 95 percent confidence intervals on the mean emission rates.

For each of the four pollutants, the four modal emission rates are significantly different from each other at the 0.05 significance level. Thus, from the graph in Figure 2-5, one can conclude that the acceleration mode produces the highest emission rate for all four pollutants studied. The idle mode produces the lowest emission rates. The fact that all of the modes are statistically significant from each other means that these modes do offer explanatory power. These results suggest that the *a priori* modal definitions assumed here are reasonable. These results suggest that measures that reduce the frequency or intensity of acceleration events may have significant benefits.

Modal emission rates tend to be similar for the same vehicle even if the distribution of the amount of time spent in each mode differs. Thus, modal emissions can be used as a means for benchmark comparison of the same driver/vehicle pair operating on different routes. If the modal emissions are similar, as is expected, then differences in trip emissions will be attributable to differences in the distribution of driving modes. Thus, in addition to being a useful output of a model, evaluation of modal emissions is important in developing the model and understanding factors that lead to differences in mesoscale emissions predictions.

The above considerations typically apply both to light duty and heavy duty vehicles. However, for heavy duty vehicles, as previously discussed, other factors may potentially be significant, such as the passenger/cargo load. The modal behavior of diesel engines may differ from that of gasoline engines, such as for HC emissions. As previously noted, the emission rate of HC tends to be insensitive to large variations in equivalence ratio. Because the average equivalence ratio may differ among the driving modes, but within the range for which HC emission rates are relatively insensitive, it is also likely that diesel HC emissions may not differ substantially among the driving modes. Therefore, the modal definitions used for heavy duty vehicles may produce different results from those obtained for light duty vehicles.

2.2.3 Macroscale Analysis for On-Road Vehicles

Macroscale refers to analysis over a large regional area (e.g., county, state, nation), for which emissions are estimated using aggregated analysis techniques (NRC, 2000; EPA 2001). As a general rule, it is preferred to obtain macroscale estimates based upon aggregate of data from a finer resolution scale. Specifically, for example, it is better to start with second-by-second on-board emissions data than it would be to start with trip-average based dynamometer test data. With finer resolution data, there is always the option of partitioning or analyzing the data in ways to take into account key explanatory microscale or mesoscale variables that might affect macroscale emissions, or that might allow the same data and model to be used for multiple purposes in analyzing problems at all three scales. For example, because real world emissions are often highly influenced by localized high emission rates, macroscale emissions may be influenced by peak measures of vehicle equivalence ratio, fuel use, or power demand, rather than average values of these. At the same time, it is still possible to look at the effect of trip-average explanatory variables. Relations between emissions and explanatory variables such as trip average speed and average ambient temperature might be examples for this type of analysis. Some of these variables, such as ambient temperature, do not fluctuate substantially during a typical trip and therefore are more naturally treated as trip-average or macroscale variables.

As part of previous work, researchers at NCSU developed relations between emissions and explanatory variables including average speed, ambient temperature, humidity, air condition usage, traffic flow, vehicle type, driver effect, and signal coordination condition using Analysis of Variance (ANOVA) techniques (Frey *et al*., 2001). Based upon these analyses significant parameters were identified and their relation to emissions were developed. As just one example, in Figure 2-6 a relation between corridor average speed and HC emissions are given for repeated runs of one of the tested vehicles driven on a specific corridor.

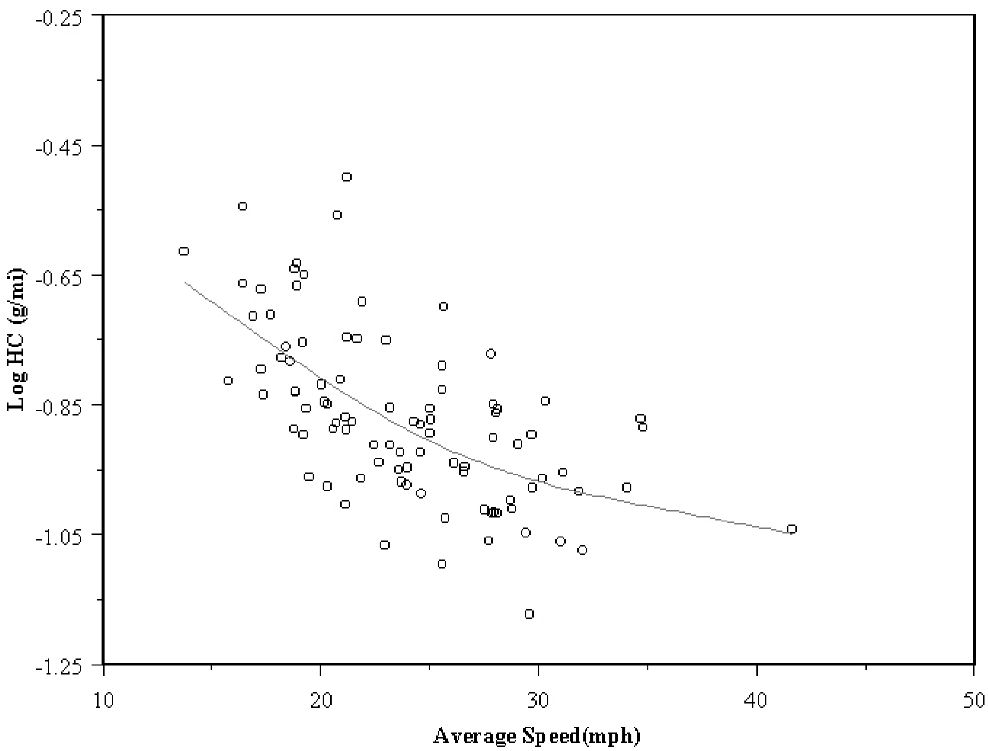


Figure 2-6. Illustration of a Macroscale Relationship between Corridor Average HC emissions and Corridor Average Speed (Source: Frey *et al.*, 2001).

Each point in Figure 2-6 represents run-based averages of HC emissions, given in a log grams per miles basis, as collected by on-board equipment corresponding to the corridor average speed measured for that run. HC emissions vary from 0.08 to 0.35 grams per mile whereas speed varies from 15 to 40 mph for this particular vehicle over the multiple runs. There is an inverse relation between HC emissions and average speed, as indicated by non-parametric regression fit to the data. There is also substantially variability in the data not explained by the trend line, indicating that a model based only on average speed has limited explanatory power. For example, for a given average speed, the unexplained variability in HC emissions is approximately plus or minus 30 percent.

Previous work by the project team (Frey *et al.*, 2001) has revealed that there are statistically significant trends between trip or segment emissions with respect to macroscopic traffic parameters such as number of stops and control delay. Thus, these macroscopic traffic parameters offer some explanatory power with respect to emissions.

Chapters 3 and 4 provide the details of the data and analyses employed to develop conceptual models for both LDGV and HDDV, respectively.

2.3 Technical Approach for Nonroad Vehicles

The previous section has focused on on-road vehicles. In this section, the focus is on nonroad vehicles. There are some key differences in the factors that influence nonroad vehicle emissions that lead to substantial differences in how such vehicles should be analyzed, compared to on-road vehicles.

It is useful to begin with some examples of nonroad vehicles as a basis for discussing approaches for estimating their emissions. It should be noted that there is a great deal of variability among nonroad vehicle categories, and a three-month project is not able to address all of these. EPA provided data for only three compression ignition (CI) construction vehicles as the basis for exploring conceptual approaches to model development. Thus, it is not possible to explore *quantitatively* a methodology for spark ignition (SI) nonroad data in this project. An example of an important SI nonroad source category is lawn and garden equipment. At the same time, it should be noted that the current laboratory-based approaches for measuring emissions from both CI and SI nonroad sources share many similarities. Test procedures based upon weighted averages of emissions measured over multiple steady state modes are commonly used. The testing modes are typically characterized by a specified engine load range, sometimes in combination with a specific engine RPM. Frey and Bammi (2002a) report on development and analysis of a lawn and garden (L&G) equipment database, while Frey and Bammi (2002b) report on development and analysis of a construction, farm, and industrial (CFI) equipment database, with more specific information regarding specific testing cycles used, such as the SAE J1088 procedure used for lawn and garden equipment and the 21-mode and similar tests used for CFI. Thus, it is conceivable that an approach that has been tested for CI data may also prove useful in the future for SI data. The steady-state modal-based test methods have been applied in the past to both gasoline and diesel nonroad vehicles in many emission source categories. As an additional example, emissions from railroad diesel locomotives are typically measured at one of a limited number of throttle settings, which is also suggestive of a modal approach to emissions measurement. Thus, there is a history in which a modal approach has been used to measure emissions from a variety of nonroad vehicles.

CI nonroad sources are manifold, and it is not likely that a technique developed specific to one will be applicable to another, at least in terms of specific definitions of individual modes. Perhaps stated another way, a single technique applied to all CI sources may help explain some variability in emissions. However, if activity patterns specific to particular CI nonroad source categories are not considered, opportunities may be lost to better explain emissions in individual cases. For example, consider a backhoe versus a railroad locomotive. A backhoe may typically operate over a very small area, with most of the engine load associated with the weight of material in the backhoe's bucket and the range of motion of the backhoe in lifting and turning with the load. In contrast, the railroad "road" locomotive may travel at constant speed over a long distance, with engine load influenced by road grade and the weight and load of the train. Railroad engines that operate over the road are typically operated at specific throttle settings which vary at different points during the trip. Backhoes may typically operate with more transient engine loads.

2.3.1 Microscale Analysis for Nonroad Vehicles

Many nonroad emission sources are measured using "mode" based approaches (e.g., Bammi and Frey, 2002a&b). The definition of modes for nonroad sources is different than that used for on-road sources. For nonroad sources, modes typically refer to specific combinations of throttle setting, engine speed, engine load, and/or torque. Such modes are not directly related to vehicle speed and acceleration as are the modes typically used for on-road sources.

For the prediction (validation) data set, EPA provided data regarding emission rates of NO_x and CO_2, and regarding relative humidity, ambient temperature, barometric pressure, engine RPM, and exhaust flow (a surrogate for load). Therefore, these five latter quantities are the available primarily candidates for development of a conceptual model. Static data regarding the characteristics of the nonroad vehicle, such as engine size, number of cylinders, rated power/speed, weight, model year, mileage/hours, fuel delivery system, and fuel type, were also provided. However, because data were provided for only three individual nonroad vehicles, there is not sufficient data to develop a model that is a function of a large number of static attributes.

The analysis of nonroad vehicles will differ in some ways than that for on-road vehicles. For example, vehicle speed is not a useful explanatory variable for many nonroad sources, although it is important for both LDGV and HDDV vehicles. However, comparison of engine parameter traces, such as traces for engine RPM and exhaust flow (a surrogate for engine load) gives some useful information regarding the events causing high emissions for nonroad vehicles. This analysis is likely to be vehicle technology-specific since different vehicle technology classes might have activity patterns that influence emissions (e.g., consider the example of the backhoe versus the railroad locomotive). For this reason, statistical methods and knowledge from current measurement techniques for nonroad vehicles were utilized to help understand and identify these effects.

The main focus of this particular subtask, therefore, is on microscale second-by-second analysis of data to gain fundamental insight into factors influencing variability in emissions, with the purpose of developing a meso-scale model based upon modes. A meso-scale model can be used to estimate emissions at higher levels of aggregation, such as for macroscale analyses. Data visualization includes development of time traces and scatter plots of second-by-second data. Statistical methods were used guided by hypotheses regarding physical principles underlying emissions. A key objective is to identify variables that are more readily observable in order to reduce the data input requirements for estimating nonroad vehicle emissions. It is also possible that static features of the equipment, such as engine size or rated horsepower, may play an important role in dividing the nonroad data into separate categories for analysis.

Although not likely to be directly relevant to the scope of the current project, a long-term area of promise for nonroad sources is the use of GPS-based techniques to identify emissions hotspots. Identification of hot-spots and correlation with other activity data will give more insight to events causing high emissions.

Table 2-1. Test conditions for 13-mode and 21-mode Test Procedures.

Mode	13-mode test			Mode	21-mode test		
	Engine Speed (rpm)	**Load**	**Mode Weight**		**Engine Speed (rpm)**	**Load**	**Mode Weight**
1	Low Idle	None	0.0667	1	Low Idle	None	0.0667
2	*Intermediate	None	0.08	2	*Intermediate	None	0.0444
				3	Intermediate	12.5%	0.0444
3	Intermediate	25 %	0.08	4	Intermediate	25 %	0.0444
				5	Intermediate	37.5%	0.0444
4	Intermediate	50 %	0.08	6	Intermediate	50 %	0.0444
				7	Intermediate	62.5%	0.0444
5	Intermediate	75 %	0.08	8	Intermediate	75 %	0.0444
				9	Intermediate	87.5%	0.0444
6	Intermediate	Full	0.08	10	Intermediate	Full	0.0444
7	Low Idle	None	0.0667	11	Low Idle	None	0.0667
8	Mfr’s. Rated	Full	0.08	12	Mfr’s. Rated	Full	0.0444
				13	Mfr’s. Rated	87.5%	0.0444
9	Mfr’s. Rated	75 %	0.08	14	Mfr’s. Rated	75 %	0.0444
				15	Mfr’s. Rated	62.5%	0.0444
10	Mfr’s. Rated	50 %	0.08	16	Mfr’s. Rated	50 %	0.0444
				17	Mfr’s. Rated	37.5%	0.0444
11	Mfr’s. Rated	25 %	0.08	18	Mfr’s. Rated	25 %	0.0444
				19	Mfr’s. Rated	12.5%	0.0444
12	Mfr’s. Rated	None	0.08	20	Mfr’s. Rated	None	0.0444
13	Low Idle	None	0.0667	21	Low Idle	None	0.0667

* Peak torque speed or 60 % of rated speed, whichever is higher

Source: (Hare and Springer, 1973).

2.3.2 Mesoscale Analysis for Nonroad Vehicles

In developing emissions estimation methodology for nonroad vehicles, one of the approaches is to determine modal emissions rates. Current methodology for nonroad vehicle emissions estimation is based upon laboratory-based modal emissions estimates. For example, for CFI nonroad vehicles test cycles are typically characterized by a number of steady-state "modes." Each steady-state mode typically involves operation at a specified engine speed or type of speed and load (i.e. idle, low, intermediate or rated) for a given length of time. For CFI engines, the typical tests used include the 8-mode, 13-mode, 21-mode and 23-mode procedures. As an example of this type of test, the modes are summarized for both the 13-mode and 21-mode tests in Table 2-1. These two tests are used for CI-based CFI sources. In these cases, engine speed (RPM) and engine load are the key determinants of each mode.

Modal analysis can be developed using engine RPM, and load as indicated in Table 2-1, and based upon the lessons learned from microscale analysis of the data. For example, from second-by-second traces of emissions versus time compared with engine RPM versus time, engine load versus time, and other time traces, it is possible to identify, qualitatively, situations that lead

Table 2-2. Results of the Uncertainty Analysis of Mean NOx and THC Emission Rates for Diesel and Gasoline fueled CFI Engines in units of g/hp-h.

Category	Pollut-ant	Units	# of Data	Fitted Distri.	Mean [a]	95% CI on Mean [b]	Relative Uncertainty [c]
Gasoline	NO_x	g/hp-hr	4	WE	4.58	3.11 – 6.33	-32% to+38%
	THC	g/hp	4	WE	10.5	8.22 – 12.3	-22% to+17%
Diesel 2S	NO_x	g/hp	4	WE	16.8	13.2 – 20.2	-21% to+20%
	THC	g/hp	4	WE	1.49	0.78 – 2.22	-48% to+49%
Diesel 4S	NO_x	g/gal	15	LN	149	126 – 177	-15% to+19%
		g/hr	20	GA	1670	1220 - 2140	-27% to+28%
		g/hp-hr	37	LN	8.46	7.62 – 9.37	-10% to+11%
	THC	g/gal	15	GA	16.7	11.5 – 22.3	-31% to+34%
		g/hr	20	GA	133	90.3 – 176	-32% to+32%
		g/hp-hr	37	WE	1.25	0.93 – 1.58	-26% to+26%

[a] Mean of 500 Bootstrap Samples
[b] Numbers shown here are for the 95 percent confidence interval of the mean obtained from bootstrap simulation in terms of absolute emission rates
[c] Numbers shown here are for the 95 percent confidence interval of the mean obtained from bootstrap simulation in terms of relative deviation from the mean.
WE ≡Weibull, LN≡ Lognormal, GA ≡ Gamma

to periods of high emissions. With this insight, definitions of modes are developed and tested to arrive at a set of modes that lead to statistically significant differences in emissions wherever possible. We seek to avoid creating a large number of modes that are redundant with each other, as well as to avoid creation of modes that are sparsely populated with data. For example, the modes in Table 1 were clearly defined *a priori* based upon arbitrary engine speeds and engine loads. We have not seen any evaluation that offers comment as to whether it is really necessary to have as many as 13 or 21 modes to explain variability in emissions. Nor is there information reported in the emissions test studies as to whether CFI vehicles typically operate in all of the *a priori* defined modes during real world operation.

Consistent with our objective of quantifying both variability and uncertainty, the range of variability in the data and the portion of observed variability that cannot be explained by the model were characterized. Although there were not sufficient data in this project to estimate emission factors for a large range of emission sources, examples of recently developed uncertainty estimates for nonroad emission factors are reported in Table 2-2. The examples are for CFI emissions for nitrogen oxides and total hydrocarbons for CFI (Frey and Bammi, 2002b). The variability in emissions was quantified using empirical and parametric distributions. Bootstrap simulation was used to characterize confidence intervals for the fitted distributions. Table 2-2 gives results of the uncertainty analysis of mean NO_x and THC emission rates for diesel and gasoline fueled CFI engines in units of g/hp-h.

Results presented in Table 2 show that relative uncertainty in emission rates for THC and NO_X range from plus or minus 10 percent to almost plus or minus 50 percent. As stated by NRC (2000), determining uncertainty and variability for emissions estimates is important for users to interpret emission estimates and the appropriate use of those estimates, and can provide confidence to policy-makers making decisions based on associated analyses.

2.3.3 Macroscale Analysis for Nonroad Vehicles

Current nonroad modeling techniques, such as EPA's NONROAD and California Air Resources Board's (ARB) offroad models, are based upon macroscale analysis (EPA, 2001). In this study, results obtained from microscale and mesoscale estimates are used and aggregated data are utilized for macroscale level analysis, such as to predict emissions for an entire "trip" or for a typical period of operation. In macro-scale analyses using current models, emission factors are typically divided into categories by equipment type and engine size. There is not sufficient data in this project to explore such categories. In future work, with larger data sets representing a larger number of different pieces of equipment, it will be important to explore whether the pilot data support disagregation by equipment type and engine size. Possibly, there are some other factors that should be considered to which emissions may be sensitive, such as the variation in the distribution of engine load, which in turn might be a function of the application of the engine. Examples of applications include bulldozers versus backhoes, which would have different activity patterns.

Chapter 5 provides the details regarding the data and analysis for the nonroad examples provide by EPA. Several specific approaches were explored for each of three pieces of equipment, including the development of a time series model, development of a simple modal model, development of a modal model with linear regressions in each mode, and development of a multiple linear regression model. These are detailed in Chapter 5.

2.3.4 Comments on Other Pollutants: PM, Greenhouse Gases, and Air Toxics

EPA did not provide data regarding PM, greenhouse gases (other than CO_2), or air toxics as part of this project. Therefore, emissions of these pollutants cannot be analyzed quantitatively as part of this work. The general methods and procedures demonstrated for HC, CO, NO_x, and CO_2 for on-road sources, and for NO_x and CO_2 for nonroad sources, are a useful starting point for developing techniques for modeling PM, greenhouse gases other than CO_2, and air toxics. However, without data it is not possible to make other than general statements about what methods can be used for these other pollutants. However, it must be recognized that there are substantial data gaps, as limited data are available only for a subset of key air toxics identified in EPA's list of 33 urban air toxics or in the larger list of almost 200 HAPs. Methods for measuring these other pollutants using on-board emissions measurement systems are not yet well-developed. Thus, there will likely continue to be a reliance on alternate emissions data for these pollutants for some time, as discussed in Chapter 7.

2.4 Summary

This chapter has presented a general approach for analyzing and modeling emissions from selected mobile source emission categories, and has provided illustrative details and discussion regarding specific analysis and modeling methods. Key aspects of the approach used in this work include visualization of data, the use of statistical methods for model development, and quantification of variability and/or uncertainty in model predictions. The next three chapters focus on the details of the analysis and model development for LDGV, HDDV, and nonroad vehicles, respectively.

3.0 CONCEPTUAL MODELING APPROACH FOR LIGHT DUTY GASOLINE VEHICLES

In this section, the conceptual model development approach for Light-Duty Gasoline Vehicles (LDGV) is presented. On-board data for selected LDGVs were provided by EPA as the basis for developing and demonstrating a methodology for modeling CO, NO_x, HC, and CO_2 emissions. NCSU had no control over study design or data collection pertaining to the LDGV data.

The following section presents data post-processing methods that were required to form an accurate emissions and explanatory variables database. Quality checks were also conducted on data in order to identify and remove any errors from the database. Exploratory analysis of the data is described in Section 3.2. Section 3.3 describes the development of conceptual model. A summary of the development and demonstration of the model is given in Section 3.4.

3.1 Data Post-Processing

In this section, methods for data post-processing are discussed. This work is important in developing an accurate database, and it includes developing protocols for data post-processing, discussion of possible errors in the dataset, and methods for making corrections.

3.1.1 Database Formation

Data for Light-Duty Gasoline Vehicles (LDGV) were provided by EPA to NCSU in comma delimited format. These files were converted into Microsoft Excel^{TM} format since Microsoft Excel^{TM} was used as the main environment for data analysis and model development.

A total of 12 files were provided for the purpose of model development. Each file represents data collected with a different vehicle. These vehicles are of model years between 1996 and 1999 and have an engine size ranging from 1.9 liters to 3.1 liters. All of these vehicles are fuel injected (FI) and have 3-way catalysts.

Preliminary analysis of individual files indicated that the format for some files was different although the same data were reported. A Visual Basic program was written to read files with different formats and create new files with a consistent format so that a database with a single format is obtained. The data fields included in each file are summarized in Table 3-1.

Each Excel file included data for one vehicle driven on different trips. Trips were separated into different worksheets for each file using a Visual Basic program. This is essential since a trip is the basic unit for our analysis. After separating data into different trips it was observed that the number of trips is not the same for each vehicle. For example, seven trips were conducted with Vehicle 2, whereas only one trip was driven using Vehicle 18. The durations of the trips were not the same. The duration of the trips ranged from 124 seconds, for Trip 3 conducted with Vehicle 12, to 4,249 seconds with Vehicle 18.

In the next step of data-processing, variables which might be helpful in explaining variability in vehicle emissions, but that were not provided in the original data set, were estimated. These variables include acceleration and power demand.

Table 3-1. List of Parameters given in LDGV Data Set Provided by EPA

Category	**Parameters**
Vehicle Characteristics	Engine Size; License number; Instrument configuration number
Ambient Conditions	Relative humidity (%); Ambient temperature (in both °C and °F unit); Barometric pressure (in both kPa and in Hg unit)
Roadway Characteristics	Latitude (degree); Longitude (degree); Altitude (feet); Grade (%)
Vehicle Activities	Mass Air flow (g/sec); Intake air temperature (°F); Intake air temperature Ford (°F); Coolant Temperature (°F); Engine load (%); Percent throttle (%); Date; Time; Vehicle speed (mph); Engine RPM; A/C (on/off); Fuel Consumption rate (lb/sec); Intake manifold pressure (in Hg); Short-term fuel trim bank 1 and 2, lambda bank 1 and 2; Transmission _gear; MIL status, Number of diagnostic trouble codes
Vehicle Emission	HC, CO, NO, CO_2 and O_2 emission (in PPM, g/sec, g/kg fuel, g, g/mi units)

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 is 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:

$$\text{Acceleration (mph/sec)} = 22.15\,\text{(mph/sec)} \times \text{Gradient (\%)} \qquad (3\text{-}1)$$

where 22.15 (mph/sec) represents the acceleration due to gravity. For example, a vehicle that maintains a constant speed along a four percent road grade must accelerate 0.89 mph/sec to counteract deceleration due to gravity. In this study, second-by-second observed acceleration as well as acceleration due to gravity were estimated using a Visual Basic program and were incorporated to the data set.

Vehicle emissions are product of the engine combustion process which is the result of power requirement or demand from the engine. Previous studies have shown that a relation between power demand and emissions of some pollutants, such as CO, can be established (e.g., Barth *et al.*, 1997; Bachman, 1999).

Several different approaches have been proposed by others for estimating power demand. These approaches range from complex models where power demand is estimated for different specific components of engine load to coarse approximations. The selection of an appropriate model depends on the type of data available. Complex models require detailed information regarding the vehicle and its environment, such as wind resistance, air density, transmission efficiency and drive-train efficiency. In this study an approximation widely used by researchers is employed (e.g., Barth *et al.*, 1997; Bachman, 1999). The equation used for power demand estimation is:

$$P = v \times a \tag{3-2}$$

where:

P	=	Power Demand (mph^2/sec)
V	=	Vehicle speed (mph)
A	=	Vehicle acceleration (mph/sec)

For each trip, second-by-second power demand was estimated with a program written in Visual Basic.

3.1.2 Data Quality Assurance/Quality Check

For quality assurance purposes, the data set for each vehicle trip was screened to check for errors or possible problems. The types of errors typically encountered from on-board data collection of vehicle emissions are explained in elsewhere (Frey *et al*., 2001). In developing an experimental design one should consider possible sources of errors for data collection. Since the experimental design in this study was not developed by NCSU, the NCSU study team had no control over these errors. Therefore, in this study the focus was to check for errors and correct them if possible. The most common errors indicated by Frey *et al*. (2001) are: loss of data; negative emissions estimates; synchronization errors between engine and gas analyzer data; errors in instrument reporting updates; and drift in emissions data. Each of these is reviewed here.

Loss of Data: There might be several reasons for loss of data. On occasion, communication between instruments might be lost, leading to loss of data. Another reason for missing data may be the failure of a particular vehicle to report a particular variable. In this study, a Visual Basic program was written to look for partial or full loss of data in each trip for all available emissions and explanatory variables. Table 3-2 summarizes the result of this check.

As seen in Table 3-2, some of the parameters are missing in nearly all of the data sets. For example, manifold absolute pressure is missing for eight out of the 12 vehicles. Similarly, throttle percent is missing for eight of the vehicles. The absence of some of these variables meant that other possible explanatory variables, such as equivalence ratio, could not be estimated.

Negative Emissions Values: Because of random measurement errors, on occasion some of the measured concentrations might have negative values that are not statistically different from zero or a small positive value. However, in situations where zeroing may have occurred in the presence of reference air containing significant amounts of a pollutant, the instrument may systematically report negative emission values. In this study, a program in Visual Basic was written to check for the presence of negative emissions estimates in the data set. It was found that some trips contained a large frequency of negative values for HC emissions. The trips which had negative emissions estimates and the number of seconds of such estimated are reported in Appendix A. For example, Vehicle 12 Trip 1 has 2,036 seconds of negative HC emissions values, where as the total trip lasted for 2,160 seconds. This problem was discussed with Sensors Inc., company responsible for data collection. It was suggested by Sensors that negative data should be set to zero. Therefore, negative HC emissions were set to zero for all of the cases where negative data were found.

Table 3-2. Summary of Loss Data Check

Parameters	**Vehicles**	**Trips**	**Notes**
Mass Air Flow (g/sec)	5,7,15,16	All	Missing
Manifold Absolute Pressure (Hg)	2,6,11,12,13,14,17,18	All	Value equals to zero
Coolant Temperature (ºF)	7	All	Missing
Throttle (%)	2,7,11,12,13,14,17,18	All	Missing
A/C compressor (On/Off)	6,7,15,16	All	Missing
MIL (On/Off)	7,11,12,13	All	Missing
Exhaust Temperature (ºF)	All the vehicles	All	Value equals to zero
Torque (ftlbs)	All the vehicles	All	Value equals to zero
Inlet Air Temperature (ºF)	2,11,12,13,14,15,17,18	All	Missing
Altitude (ft)	7	1	Value equals to zero

Synchronization Errors: From previous research (Frey *et al*., 2001) it is known that in some cases, such as because of blockages in the gas sampling line, the time delay of the response of the gas analyzer may increase, leading to a discrepancy in the synchronization of the gas analyzer and the engine data streams. It was found from the previous research that the relation between the time series of CO emissions and engine RPM could indicate the presence of a synchronization error. CO emissions tend to increase at the same time as a rapid increase of engine RPM. Some spot checks were conducted on the data files for synchronization errors. An example plot of CO emissions versus engine RPM is presented in Figure 3-1 where part of the trip for Vehicle 12 Trip 1 is used.

As seen in Figure 3-1, at the 1699th second there is an increase in engine RPM from 1082 rpm to approximately 3900 rpm in seven seconds. For the same period CO emissions increase from 0.1 to 5.1 volume percent. There seems to be delay of 2 seconds in the CO data. After contacting Sensors on this issue, it was reported that during data collection the transfer time for collection of gas is measured and data are aligned based upon the measured time delay. From the Frey *et al*. (2001) work, it was found that small errors in synchronization do not substantially impact estimate of total trip emissions. Therefore, it is assumed that there is no significant error due to synchronization in these data.

Freezing of instrument: From previous research, it is known that during data collection sometimes the instrument “freezes” and does not update the readings each second although the vehicle is moving and there is a change in engine and environmental conditions. A lack of change in reported emissions concentrations might occur when emission readings are very low and the instrument cannot detect any changes. However, if "freezing" occurs at high emission values, then there may be an instrument error. A Visual Basic program was written which checks variables for this kind of error. Variables checked for this error included: Mass Air Flow; Engine RPM; Torque; Latitude; Longitude; Fuel Consumption (lb/sec); HC emission (g/sec); CO emission (g/sec); CO_2 emissions (g/sec); and NO emissions (g/sec). All of the cases where the variables were not updated for more than 60 seconds were recorded in a table. In some of these cases emission levels were very small. In such cases, changes in emissions were most probably below the detection limit of the instrument and the instrument could not update the readings.

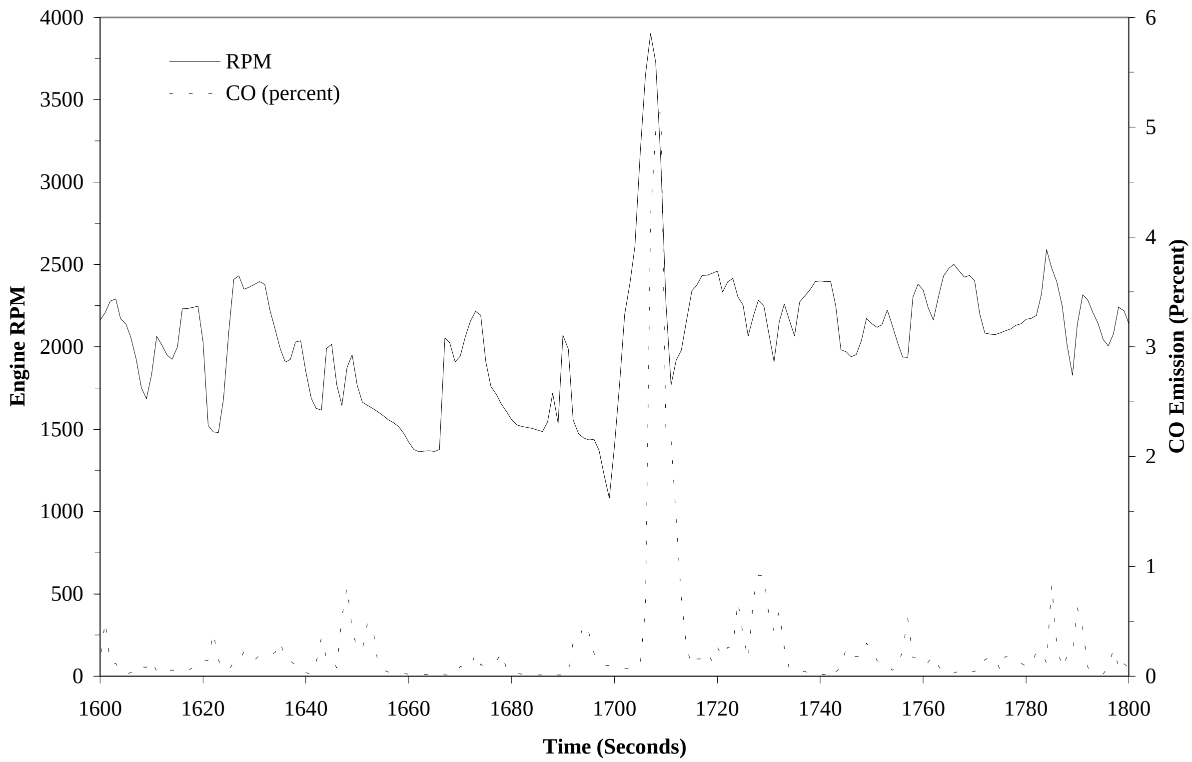


Figure 3-1. Comparison of Engine RPM with CO Emissions for Checking the Presence of Synchronization Error for Vehicle 12 Trip 1.

Table 3-3. Summary of Freezing Check for Instrument Readings

Vehicle	Trip	Parameter	Number of Seconds without Update	Frozen Value
7	1	Latitude (deg)	1495	42.304
7	1	Longitude (deg)	1495	-83.711
12	1	NO (ppm)	308	149
13	2	NO (ppm)	All	0
15	2	NO (ppm)	79	369
15	2	NO (ppm)	126	137
16	5	NO (ppm)	231	139

These cases were not considered as errors. However, cases where the emission readings did not update for more than 60 seconds and stayed at high values were considered as errors. Table 3-3 presents the findings where emission levels are stuck high values as well as parameters that have the same value throughout the trip.

Table 3-3 summarizes the cases where freezing of the instrument occurred at non-zero values or, in one case, for an entire trip. For Vehicle 7 Trip 1, the GPS device reported the same reading for

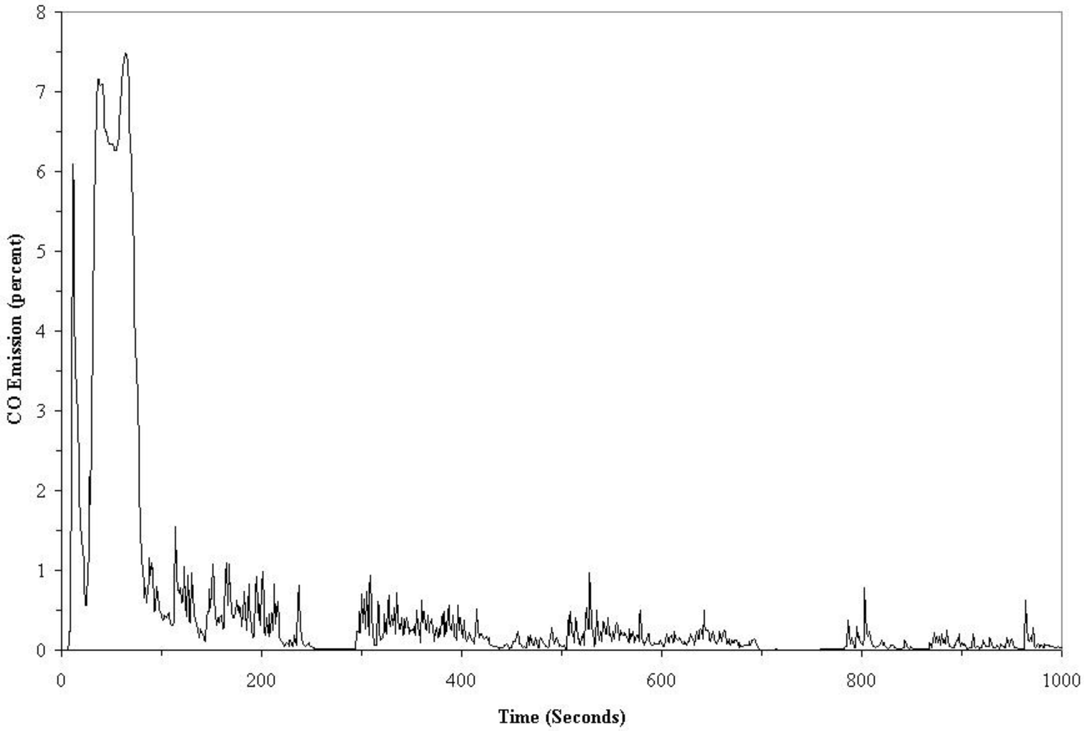


Figure 3-2. Example Check for Drift Error for Vehicle 2 Trip1 for CO Emissions

the entire trip. Therefore GPS data for this trip were not used. There are four cases where NO emissions were stuck at high values for more than 130 seconds. After discussing with Sensors, these data were excluded from analysis since this was probably caused by an error in the instrument. For Vehicle 13 Trip 2, it was found that NO emissions were reported as zero throughout the entire trip. Data for NO emissions for this trip were also excluded from analysis. It was observed that data collected for Vehicle 13, except for the first trip, had a problem reflected in the O_2 measurements. In these data sets, the O_2 measurements were in the range of eight to nine volume percent. The O_2 level should be much lower than this. The high O_2 level is an indication of a leakage of ambient air into the system during data collection. After discussion with Sensors Inc., data for Vehicle 13, except for the first trip, were excluded from analysis since an error in O_2 level would effect measurements of all other pollutants.

Drift in data: From previous research it was found that a drift in emissions data might occur due to instrument error. In order to check this problem, one can look at time series plots of emissions data. If there is a clear indication of downward or upward trend in the data, and if this trend can not be explained by changes in explanatory variables, then one might suspect a drift error in the data set. In this study, spot checks were made to see whether this kind of error was present in the database. Figure 3-2 presents an example check conducted for Vehicle 2 Trip1 for CO emissions. During the first 300 seconds of the trip CO emissions are relatively high. This is due to the cold-start process. After the first 300 seconds, the emissions stabilize. The minimum emission values in any time interval after the cold-start are consistent, indicating no drift. Similar checks were conducted for each vehicle and it was determined that there was no drift error in this data set.

3.2 Exploratory analysis

After database formation and screening the data for errors, an exploratory analysis was conducted to better understand the variability of vehicle emissions and the basic trends between explanatory variables and vehicle emissions. This exploratory analysis is a necessary step before developing any relationships between vehicle emissions and explanatory variables.

This section first presents a summary of the data provided for emissions and engine related variables. Then variability in the emissions data is presented. Scatter plots were utilized for data visualization purposes. Spatial analysis of emissions is also given. Identification of cold-start is subsequently discussed. Finally, the findings of the exploratory analysis are summarized.

3.2.1 Data Summary

After the post-processing procedure was completed, 51 valid trips were obtained for 11 different vehicles. An example of the summary of the emissions and activity data as well as of environmental and roadway characteristics is given for Vehicle 2 in Table 3-4. Summary tables for the other vehicles are given in Appendix A.

The data in Table 3-4 are divided into several categories. These categories include: vehicle characteristics; variables related to vehicle operation; environmental characteristics; and roadway characteristics.

There were seven trips conducted with Vehicle 2 as shown in Table 3-3. Five of these trips were conducted on the same day and two of them on another day. The durations of the trips ranged from 927 seconds to 2,026 seconds. The average speed of the trips differed from each other. The slowest average speed occurred for Trip 2, with an average speed of 29.8 mph, whereas the fastest average speed occurred for Trip 3, with an average of 57.9 mph. Ambient weather conditions during these trips were similar. The average temperature ranged between 19.8 ^{0}C and 29.3 ^{0}C and average humidity varied between 29 percent and 40 percent. Changes in operation conditions as well as changes in environmental conditions and roadway conditions resulted in differences in average emissions. For HC emissions, the highest average emission rate is more than four times higher compared to the lowest average emission rate. The ratio of the highest trip average emission rate to the lowest trip average emission rate is smaller for the other pollutants for Vehicle 2. However, there are other vehicles which have ratios higher than 15, as in the case of HC emissions for Vehicle 17 when comparing Trip 1 and Trip 5, as shown in Appendix A. These results indicate that there is a considerable amount of variability in the data. The next section will present this issue in more detail.

Table 3-4. Summary of Data for Vehicle 2

Vehicle No	**2**						
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip4*	*Trip5*	*Trip6*	*Trip7*
Vehicle Characteristics							
Plate No	5CCN62						
Vehicle Make	FORD						
Vehicle Model	TAURUS GL						
Vehicle Model Year	1997						
Engine Displacement(l)	3						
Transmission Type	AUTO						
GVWR	4687						
Vehicle Operation							
Average Speed (mph)	38.4	29.8	56.0	57.9	34.8	30.7	28.8
Average Engine Load (%)	30	29	33	34	32	32	33
Average RPM	1692	1530	2171	2241	1591	1550	1520
Average Throttle (%)	0	0	0	0	0	0	0
Average Inlet Air Temperature (F)	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Average Coolant Temperature (F)	200	199	202	198	198	187	179
Average MAF (g/sec)	1590	1425	2196	2364	1541	1557	1595
Average Fuel (lb/sec)	0.0024	0.0021	0.0033	0.0036	0.0023	0.0024	0.0024
Average Power Demand (s*a)	0.69	1.48	0.45	0.44	1.14	1.17	0.85
Average HC (g/sec)	0.0035	0.0021	0.0009	0.0029	0.0034	0.0031	0.0028
Average CO (g/sec)	0.0436	0.0329	0.0361	0.0389	0.0428	0.0351	0.0398
Average CO2 (g/sec)	3.3882	3.0126	4.6758	5.0972	3.2764	3.3537	3.4104
AverageNO (g/sec)	0.0091	0.0096	0.0124	0.0121	0.0075	0.0100	0.0081
Environmental Characteristics							
Average Ambient Temperature (C)	29.3	25.3	28.2	26.5	24.3	19.8	21.7
Average Ambient Pressure (kPA)	99.0	99.0	99.0	99.0	99.0	99.0	99.0
Average Humidity (%)	29	35	30	34	39	39	40
Roadway Characteristics							
Average Latitude (degree)	42.25	42.13	42.28	42.28	42.12	42.12	42.12
Average Longitude (degree)	-83.70	-83.72	-83.61	-83.61	-83.72	-83.71	-83.71
Average Altitude (feet)	921	810	858	845	772	772	784
Average Grade (%)	-0.040	-0.251	-0.090	0.028	0.221	-0.216	0.117
Time of Day	17:41:11	18:57:25	19:37:49	22:00:52	23:28:22	3:09:14	7:48:36
Day of Week	9/20	9/20	9/20	9/20	9/20	9/21	9/21
Number of Seconds of Data	1115	1086	2026	1931	927	1051	1118

3.2.2 Variability in Emissions Data

In this section, data are presented to illustrate the variability in observed data. For this purpose, trip-average emissions rates were utilized. First, inter-vehicle variability is presented. In estimating inter-vehicle variability, average emission rates were estimated for each vehicle using the trip-based averages. For vehicles which have multiple trips, a confidence interval for the mean was estimated. Figure 3-3 presents inter-vehicle variability for CO emissions. Inter-vehicle variability for other pollutants is given in Appendix A. Confidence intervals for the mean could not be estimated for Vehicles 13 and 18 since there was only one trip in the screened

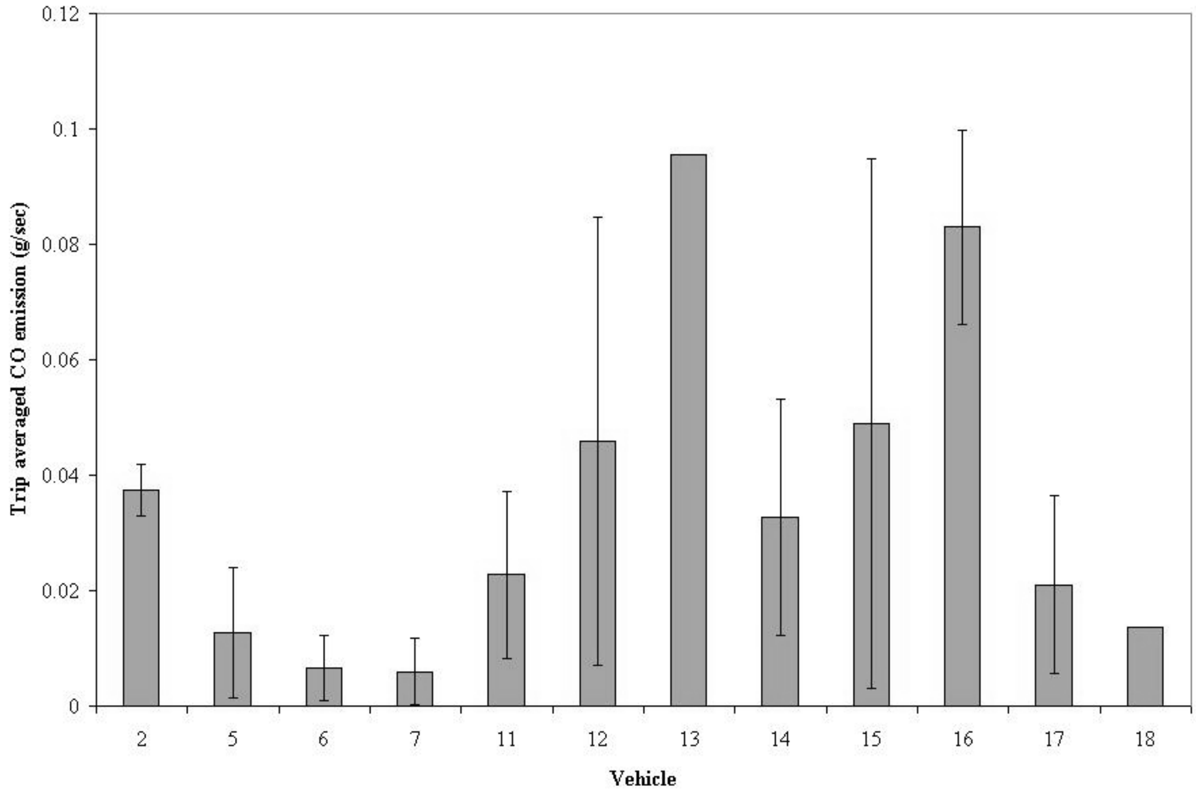


Figure 3-3. Trip-Based Mean CO Emission Rates for Light-Duty Gasoline Vehicles

data set for these vehicles. As noticed in Figure 3-3, the confidence interval on the mean is typically large on a relative basis since the maximum number of multiple runs with the same vehicle is nine, for Vehicles 14 and 16. On a relative basis, the typical narrowest confidence interval for the mean is for Vehicle 2, at plus or minus 12 percent, and the widest confidence interval is at plus or minus 98 percent, for Vehicle 7. Therefore, for most of the cases there are not statistically significant differences between the average CO emissions rates for different vehicles. However, there are some cases in which a given vehicles appears to be emitting more than others. For example, the average CO emission rate for Vehicle 2 is significantly higher than average CO emission rate for Vehicles 5, 6, and 7, since the confidence intervals for the mean values of Vehicle 2 do not overlap with the confidence intervals on the mean for Vehicles 5, 6, and 7. The effects of ambient conditions, roadway conditions and vehicle operation conditions were not controlled during data collection, and these factors may account for some of the observed differences in average vehicle emissions.

Inter-trip variability was analyzed. The purpose of this analysis was to characterize the range of variability in trip average emissions among all of the vehicles, to determine whether the data set is relatively homogeneous, and to gain insight into whether all of the vehicles can be treated as one group for purposes of analysis and model development. The trip average HC emission rate was 0.0018 g/sec for 51 trips conducted with 11 different vehicles. The 95 percent confidence interval for this mean value ranges from 0.0017 g/sec to 0.0023 g/sec, or a range of approximately plus or minus 15 percent. Approximately 90 percent of the values are below

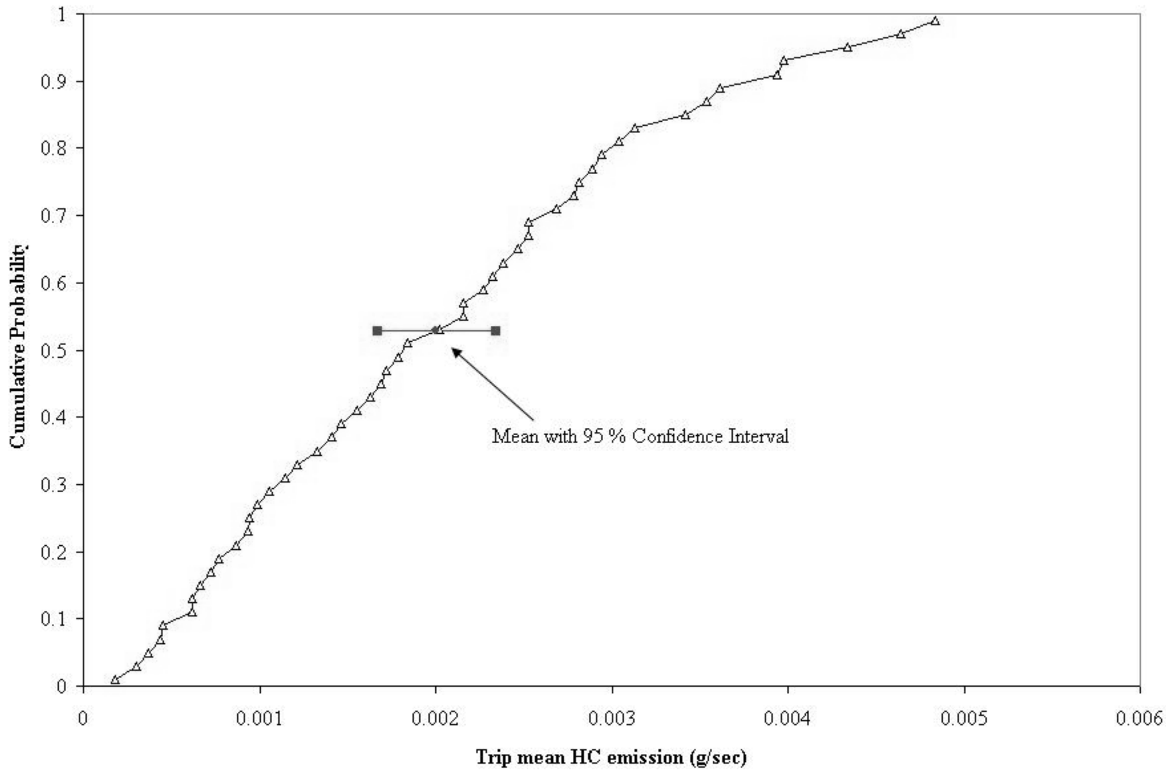


Figure 3-4. HC Inter-Trip Variability and Mean Estimate for Light-Duty Gasoline Vehicles

0.0040 g/sec. Most of the emissions estimates are within a range of an order-of-magnitude (e.g., ranging from 0.00030 to 0.0046 g/sec over a 95 percent probability range). In Figure 3-4, the cumulative distribution function of the data is almost a straight line for data at less than approximately the 80^{th} percentile, which indicates that these data are approximately uniformly distributed. Although there is some skewness in the distribution as suggested by the upper tail, there are no data points that are obvious outliers. Thus, there are no obvious "high-emitter" cases in this data set. Therefore, this data set is deemed to be sufficiently homogeneous that all of the vehicles within it can and should be treated as a single group for purposes of analysis and model development. It should be noted that there are some vehicles that have as much variability among trips as is observed in the overall dataset. For example, for Vehicle 5, the average HC emissions rate ranges from 0.0007 g/sec to 0.0048 g/sec.

Similar results were obtained for CO, NO and CO_2 emissions. Most of the emissions estimates are within a range of an order-of-magnitude for all these pollutants. For CO, emissions range from 0.0027 to 0.096 g/sec over a 95 percent probability range. For CO_2, this range is between 0.66 to 5.1 g/sec. Emissions for NO ranges from 0.00057 to 0.012 g/sec over a 95 percent probability range. Probability distributions for CO, CO_2, and NO are given in Appendix A.

3.2.3 Identification of Explanatory Variables

In this section, factors influencing vehicle emissions are summarized as cited in the literature. There are mainly four groups of parameters that affect vehicle emissions as indicated by Guensler (1993). These groups are: (i) vehicle parameters; (ii) fuel parameters; (iii) vehicle operating conditions; and (iv) vehicle operating environment.

Vehicle Parameters

Vehicle parameters are related to vehicle technology and include vehicle class (i.e., weight, engine size, horse power), model year, vehicle mileage, fuel delivery system, emission control system, and on-board computer control system. Studies have shown that vehicle make and model year are significantly related to vehicle emissions. For example, vehicle emissions are generally higher for older vehicles (Pollack *et al.*, 1992; Rouphail, 2000; Barth *et al.*, 1997; Stedman and Bishop, 1999). The effect of other vehicle parameters are investigated in several other research projects (Bart *et al.*, 1997; Bachman, 1999).

Fuel Parameters

Fuel parameters include fuel type, oxygen content, fuel volatility, hydrocarbons content as indicated by Guensler (1993). The composition, physical and chemical properties of the fuel can have significant effects on vehicle emissions (Guensler, 1993).

Vehicle Operating Conditions

The starting mode of the vehicle (cold or hot), average vehicle speed, modal activities that cause enrichment, load (i.e., air condition, heavy load), and driver behavior are examples of vehicle operating conditions (Guensler, 1993). Cold-start emissions are significantly higher than hot-start emissions (Singer *et al.*, 1999; An *et al.*, 1996). The magnitude of emissions is a function of commanded air/fuel ratios, catalyst temperature, and engine temperature (Heywood, 1988; Joy, 1992; Pozniak, 1980). In most vehicles, the on-board computer control systems initially demand a rich fuel mixture to prevent the engine from stalling (Bachman, 1999).

The equivalence ratio is defined as the ratio of the actual fuel-to-air mass ratio in the engine divided by the stoichiometric (sometimes referred to as "theoretical") fuel-to-air mass ratio. If the engine is operating at stoichiometric fuel-to-air ratio, the equivalence ratio is one. If the engine is operating with an excess of fuel compared to the air intake, then the engine is running "fuel-rich" and the equivalence ratio will be greater than one. Conversely, if the engine is running "fuel lean", the equivalence ratio will be less than one (Degobert, 1995). Gasoline-fueled vehicles equipped with a three-way catalyst are computer-controlled to operate very close to an equivalence ratio of one during most driving. However, if higher vehicle performance is required, such as during hard acceleration, the engine will operate in a fuel-rich mode, referred to as "enrichment." It is well known that CO emissions increase during enrichment. NO emissions, on the other , are highest when the equivalence ratio is approximately one (Degobert, 1995). Catalytic converters must reach “light-off” temperatures of roughly 300 ^{0}C to work efficiently (Bachman, 1999). Until the catalyst reaches this temperature, the tailpipe emissions are the same as the engine-out emissions. Once the catalyst warms up, it is effective at substantially reducing emissions of CO, HC, and NO. In order to protect the catalyst from overheating during periods of high engine power demand, the on-board computer of the vehicle commands the engine to operate fuel-rich. This results in insufficient oxygen in the exhaust to allow for CO and HC to be oxidized. Thus, under fuel rich conditions, the catalyst effectiveness is substantially reduced, and emissions are potentially much higher than during normal vehicle operation.

One of the events that causes enrichment is use of the air conditioner. Air conditioners place an additional load on the engine. This load increases the fuel consumption and can increase the emissions for a given vehicle speed and road load (EPA, 1993;NRC, 2000).

Driver behavior may also have a significant effect on vehicle emissions since it has an effect on the frequency and magnitude of enrichment events. Aggressive driving appears to cause significantly higher emissions (TRB, 1995; Shih *et al.*, 1997; Shih and Sawyer, 1996; and LeBlanc *et al.*, 1995).

Vehicle average speed is one of the parameters that has been used as the main explanatory variable in regulatory models such as the Mobile and EMFAC models. The relation between emissions and average speed are based upon dynamometer tests using standardized driving cycles. Speed correction factors were developed based upon driving cycles with different mean speeds. The FTP emissions (at the mean FTP speed of 19.6 mph) are multiplied by the speed correction factor for a desired speed to give the emissions at the desired speed. Speed correction factors are function of vehicle, model year, and pollutant species (NRC, 2000).

Vehicle Operating Conditions

Vehicle operating conditions include the environmental conditions under which the vehicle is operated, such as humidity, ambient temperature, and road grade.

Ambient temperature is known to affect vehicle emissions. Studies have been conducted to determine this effect and include them in vehicle emissions models (NRC, 2000). FTP tests are conducted at 75°F. In order to account for other temperatures, the MOBILE model includes temperature-correction factors. It has been found by EPA that CO and HC increase gradually (typically 10-30 percent) with decreasing temperatures from about 80°F to 50°F. Below 50°F, emissions increase non-linearly (NRC, 2000). Lax (1994) found that there is a 60 percent increase in HC from 55°F to 35°F (or 3 percent per °F), and a 100 percent increase in CO from 55°F to 35°F (or 5 percent per °F). Humidity is another environmental parameter that might have an effect on vehicle emissions. Humidity was used with ambient temperature to develop a heat index parameter that is used in Mobile 6 to model the effect of A/C (NRC, 2000).

Another parameter that can have an effect on vehicle emissions is road grade. Road grade affects vehicle emissions by impacting the load on the engine. Gravity exerts a force on a vehicle that must be counteracted to maintain a constant speed (Bachman, 1999). In a study conducted by Cicero-Fernandez and Long (1997), it has been found that there is about 0.04 g/mile increase for HC for each 1 percent increase in road grade. For CO the reported increase is 3 g/mile for each 1 percent grade increment. Recent studies include the effect of road grade by estimating the effect of road grade on acceleration (Bachman, 1999).

Summary

In this section, variables influencing vehicle emissions were summarized. The explanatory variables available for model development represent many but not all of the key influences on emissions identified in the literature review. One of the constraints of this study is that the explanatory variables that are available for model validation purposes are only a subset of the explanatory variables available for model development. Therefore, the conceptual model will not include variables that are not available in the prediction dataset. The focus of this study was on using explanatory variables that are available in the prediction dataset or derived variables that can be estimated from the available ones, such as acceleration and power demand.

3.2.4 Data Visualization

A first step in understanding the relationship between emissions and explanatory variables includes data visualization. This involves developing multiple pairwise scatter plots of the candidate input and output variables to look for possible empirical relationships among them. The process of visualization of data also gives the analyst an appreciation for the variability in the data that may not be explained by any of the candidate input variables. Statistical software such as SPLUS is well suited to this type of work and was used in this study.

As an example for data visualization, a scatter matrix prepared in S-Plus for HC emissions and possible explanatory variables for Vehicle 2 is given in Figure 3-5. Scatter matrices for other pollutants for Vehicle 2 are given in Appendix A. Explanatory variables plotted in this figure are: Vehicle Speed (mph); Vehicle Acceleration (mph/sec); Ambient Temperature (^{0}F); Humidity (grains/lb air); Altitude (feet); Grade (percent); AC (on/off); Power Demand (mi^2/h^2.sec). HC emissions are reported in grams/second. For this figure, second-by-second data collected with Vehicle 2 are combined from seven different trips making a total of 9,254 observations.

The bottom row in Figure 3-5 illustrates the relationship between HC emissions (i.e., y-axis) and explanatory variables. For example, the cell on the bottom left is a scatter plot of HC emissions versus vehicle speed. HC emissions tend to go down as vehicle speed increases. The highest HC emission occurs when vehicle speed is approximately 10 mph. Similarly there is a relationship between acceleration and HC emissions. For negative values of acceleration, HC emissions are very low. The highest HC emissions occur for an acceleration of approximately 2 mph/sec. The relationship between ambient temperature and HC emissions is noisy. The same is true for relationships between humidity or altitude with HC emissions.

HC emissions are highest when road grade is positive and close to zero. This indicates that grade has an impact on HC emissions but the effect is moderate. HC emissions when A/C is on do not appear to be substantially different from when A/C is not used for this particular vehicle. HC emissions are low for negative power demand estimates. HC emissions tend to go up as power demand increases, but the largest HC emissions occur at less than the maximum power demand level. This relation indicates the possible explanatory power of power demand for HC emissions.

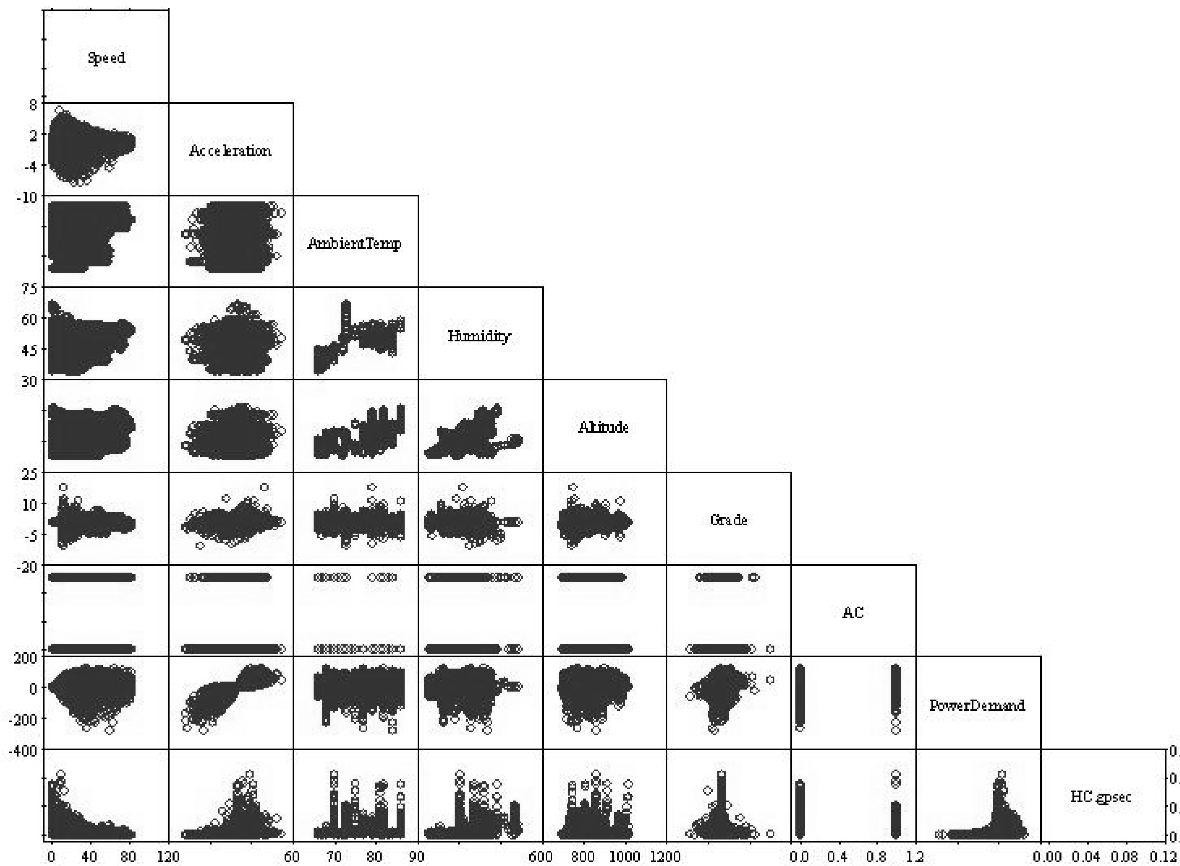


Figure 3-5. Example Scatter Matrix for HC Emissions for Data Collected with Vehicle 2

A scatter matrix not only presents the relationship between explanatory variables and pollutants, but also shows relations among explanatory variables. For example, there is a relationship between power and acceleration, which is shown in the second column and second row from the bottom. This is expected since power demand is estimated from speed and acceleration.

It is clear from investigations of the scatter plots that there is a substantial amount of variability in emissions data and there is not any single explanatory variable that directly explains a large portion of this variability. It is possible that several variables can explain some part of the variability. The relationship between explanatory variables and emissions may be complex. This implies a need to look at a combination of explanatory variables in order to explain variability in emissions. For this purpose, both engineering and statistical techniques need to be applied.

3.2.5 Spatial Analysis

Spatial analysis allows an evaluation of how emissions change spatially. This is important to help identify possible emission hot-spots throughout the trips. The spatial distribution of emissions can also be used to estimate emissions for segments of routes representing different roadway functional classes and to identify variability in traffic flow and emissions for specific roadway functional classes. Thus, the influence of functional class on emissions can be evaluated. In addition, the influence of other possible explanatory factors can be explored, such as traffic congestion, level of service, road grade, traffic control devices, and others.

Second-by-second geographical location of each vehicle is provided since second-by-second x and y coordinates are reported from the GPS system during data collection. A first step in spatial analysis is to visualize the data using Geographical Information System (GIS) software. For this purpose, ArcGIS, developed by ESRI, was utilized. One reason for selecting ArcGIS is that the most recent version includes Visual Basic as the programming environment. This is compatible with other programs that use Visual Basic, such as Microsoft Excel.

This section presents a summary of the procedure applied for visualizing data in ArcGIS. Information is provided on how roadway facility types were determined to enable a comparison of pollutants on different roadway types. Finally, a conceptual approach is given for further spatial analysis.

In order to visualize data spatially, a GIS layer showing roadways is required. GIS layers that show roadways for the U.S. can be obtained from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) system. However, layers available at the TIGER website do not contain roadway classes. Therefore GIS data from TIGER cannot be used to identify roadway functional classes. A search conducted on the internet revealed that the Michigan Department of Natural Resources (MDNR) has roadway layers that have roadway classifications. After contacting MDNR, it was found that the roadway classification they use was based upon United States Geographical Survey (USGS) topographical maps and not upon the Federal Highway Administration (FHWA) classification scheme. The classification scheme used by MDNR has only four classes. Class 1 is a primary route, Class 2 is a secondary route, and Classes 3 and 4 represent a "road or street". In contrast, other classification schemes are more detailed in classifying freeways, primary arterials, minor arterials, secondary roads, feeder/collector streets and others. Since this was the only publicly available roadway layer that could be readily found, the conceptual spatial analysis was based on this data set.

In using the data obtained from MDNR, GPS data were projected to a map projection of the roadway layer. For this reason, trip data were imported to ArcGIS and converted to a GIS layer using the road layer obtained from TIGER. This is required since trip data can only be converted to a layer if it is matched against an unprojected map layer. The trip layer was projected into a specific map projection of a roadway layer obtained from MDNR using a program given by MDNR. Finally, the trip data and the roadway layer with roadway classifications was shown together. An example case for trip data for Vehicle 11, Trip 1 is shown in Figure 3-6.

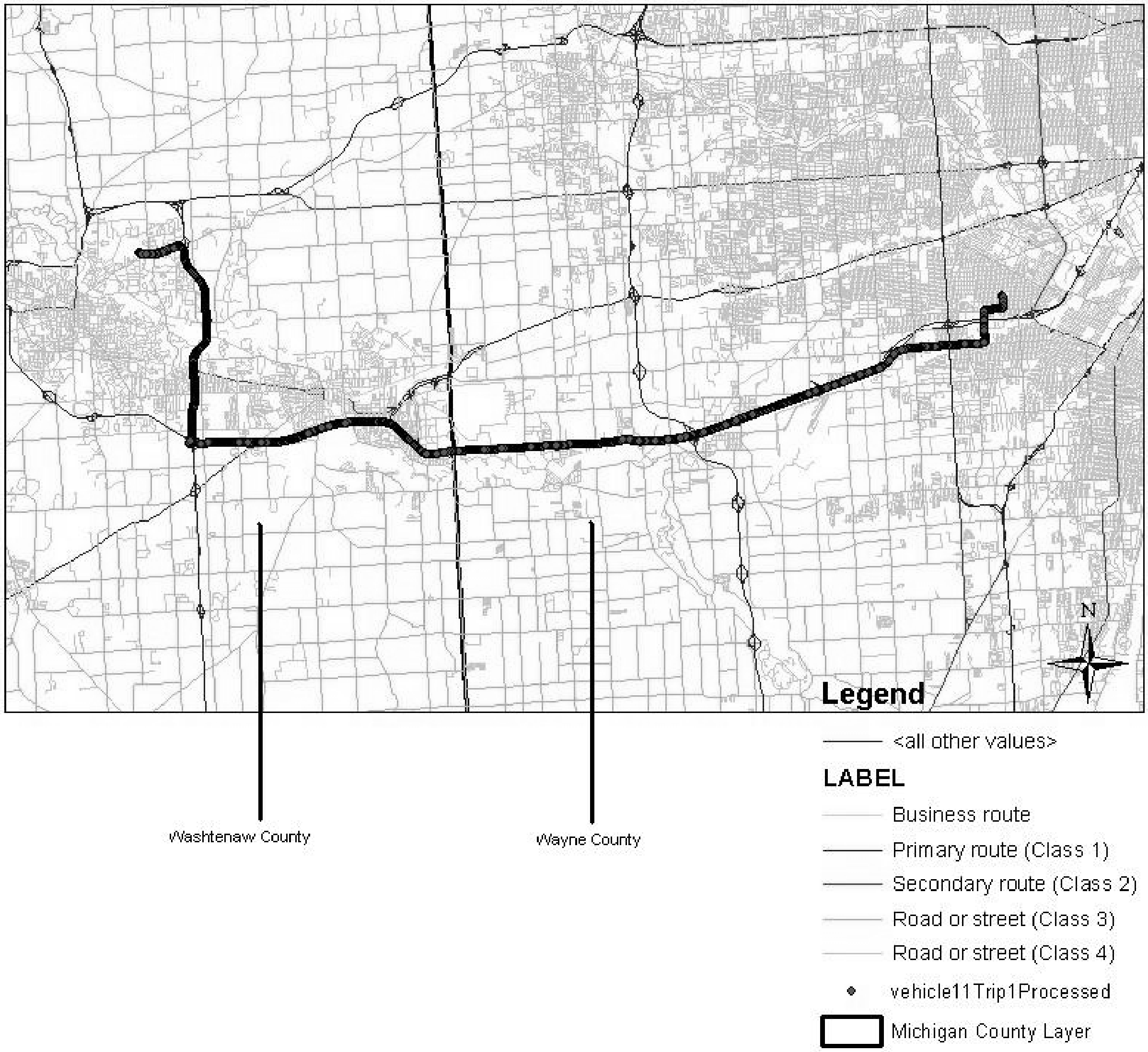


Figure 3-6. Example Spatial Data Visualization for Vehicle 11 Trip 1

In Figure 3-6, there are five different roadway types shown with different colors in the legend. With the help of GIS analysis, one can visualize how the trip was conducted. For this particular trip, the trip started in Washtenaw County and ended in Wayne County. Almost the entire trip was conducted on Class 1 roads with a small part driven on Class 3 roads.

Similar analysis was conducted for all 51 trips. In order to evaluate the effect of roadway classification on emissions, roadway layer and trip layers were spatially joined using a Visual Basic program written in ArcGIS. All of the trips were assigned a roadway type for each second. An analysis of the effect of roadway type was then conducted using the average emission rates for different roadway types. Figure 3-7 presents result of such an analysis for CO emissions, plots for other pollutants are given Appendix A.

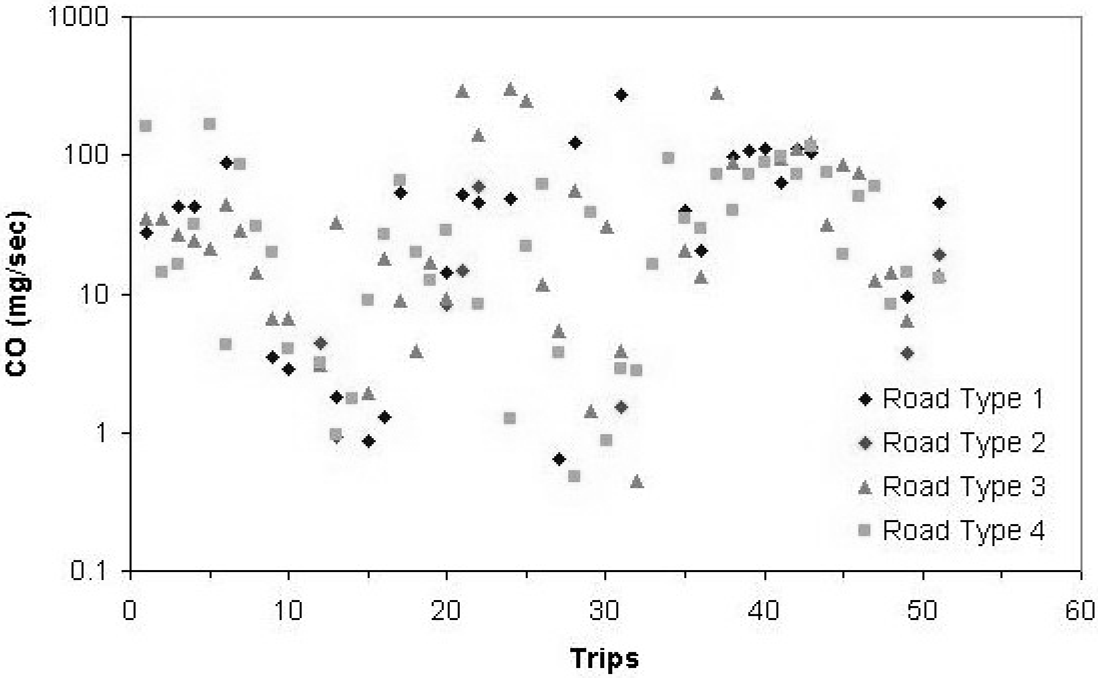


Figure 3-7. Summary for Average CO Emission Rate for Different Roadway Types

In Figure 3-7, there is no clear difference between the roadway types in terms of CO emissions. Roadway type 3 seems to have high values for some trips, but it has low emissions for other trips. Similar results are obtained for other pollutants as well. The available roadway classification may not be the most useful in terms of vehicle emissions. If one wants to determine the effect of roadway types, developing an appropriate emissions-sensitive scheme is important.

Another type of analysis that can be done using GIS is to determine the effect of road intersections on vehicle emissions. Locations of traffic signals were not provided in the data set. There might be GIS layers which contain such information but they are not publicly available. In this study, an example conceptual case study was used as a means to show how an analysis of the influence of intersections on emissions can be conducted in the future using GIS analysis.

One method for determining the location of signalized intersections is to manually locate these points on the map and enter them as a separate layer to ArcGIS. Another method is based upon the fact that roadway lines are drawn from one intersection to another. There are few cases where two lines connect without representing an actual intersections; however, those cases are typically errors in the GIS data and are very rare. Therefore, in this study a program was used to determine the location of intersections by looking at the connection points of roadway lines. After determining these points, they were added as an event theme to ArcGIS map. In order to evaluated the effect of an intersection on emissions, a buffer zone of 200 feet was assumed for each intersection. This number is arbitrary and was used for example purposes. The idea was that the influence of traffic control devices on vehicle movement would occur close to the intersection, and that the control delay and stops at an intersection could influence emissions as

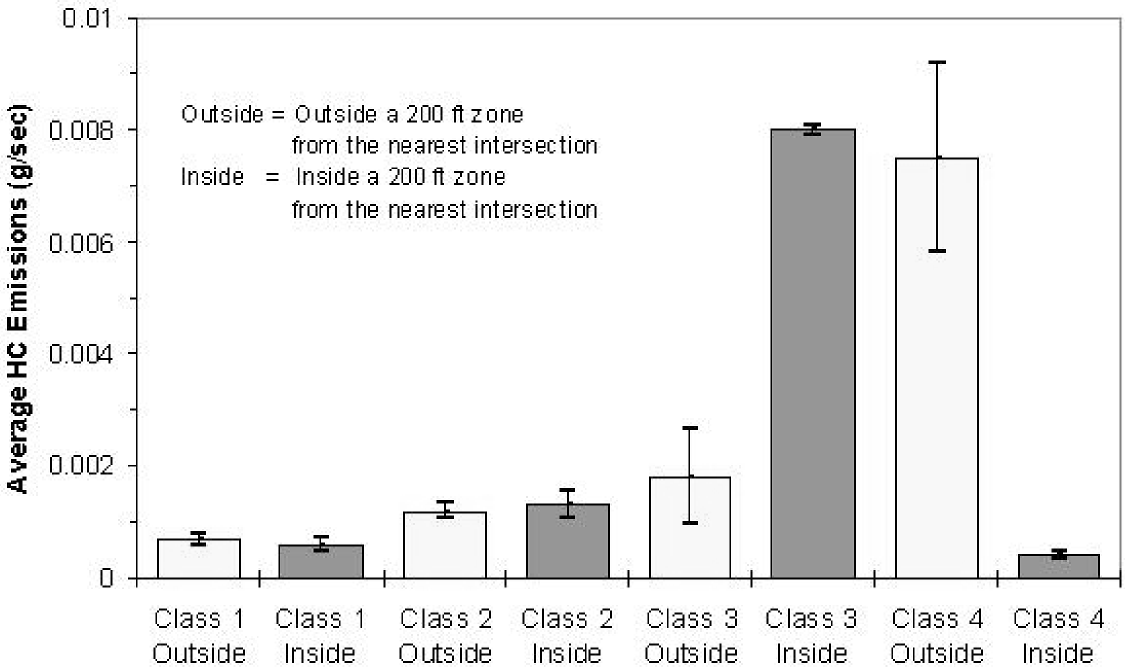


Figure 3-8. Average HC Emissions for Roadway Classes and Intersection Effect

was observed in the Frey *et al*. (2001) study. For each road class, data were separated into categories of "Outside" or "Inside" the intersection influence zone.

Figure 3-8 presents average HC emissions with respect to roadway type and whether inside or outside the intersection zone, along with 95 percent confidence intervals on the mean, for the example of Vehicle 11 Trip 1 data. In Figure 3-8, some modes have narrower confidence intervals than others, because number of data points are different for each mode. For the Class 1 and Class 2 roadways, there was no observed difference in average emissions when comparing locations "Outside" versus "Inside" the intersection influence zone. The average emission rates for Class 1 and Class 2 roadways differ by a factor of approximately two. Class 3 roadways resulted in higher average emissions than for either the Class 1 or Class 2 roadways. For Class 3 roadways, the observed average emissions "Inside" the intersection influence zone were substantially higher than those "Outside" the zone. It is expected that emissions inside of an intersection influence zone are higher than those outside of such a zone because factors such as stops and control delay tend to result in accelerations within the intersection zone that increase emission rates (Frey *et al*., 2001). However, for the Class 4 case, the results are counter-intuitive in that the average emissions "Inside" the zone are estimated to be much lower than those "Outside" the zone. However, this particular result may be an artifact of very small sample size.

The analysis of emissions with respect to roadway functional class and with respect to an intersection influence zone is meant to be illustrate of a general approach that can be explored more thoroughly in the future. The results of the example case study here suggest that some of the variability in emissions can be explained not only by roadway functional class, but also with respect to roadway design or traffic control features.

3.2.6 Identification of Cold-Start Emissions

Cold-start emissions are significantly higher than hot-stabilized emissions as explained in Section 3.2.3. The occurrence of a cold-start and its duration is a function of ambient, engine, and catalyst temperatures. Engine temperature and catalyst temperature were not measured in the on-board study. Instead coolant temperature was measured. Therefore, coolant temperature was investigated for its utility as a surrogate for use in detecting the presence of an cold-start and in estimating its duration. Information regarding soak time was also used.

The relationship between CO emissions and coolant temperature was investigated. Figure 3-9 presents an example of time series of both CO emissions and coolant temperature for Vehicle 5, Trip 2. CO emissions were very high for the first 130 seconds, during which coolant temperature stays lower than 80 °F. At approximately 130 seconds, the coolant temperature and the CO emissions stabilized. Therefore, it can be concluded that this trip had a cold-start duration of approximately 130 seconds. Because coolant temperature is only a surrogate for engine temperature, however, it was decided not to base the identification of the existence and duration of a cold start on the coolant temperature. Instead, an approach was sought in which the presence and duration of a cold start could be determined based upon the second-by-second time series of emissions data obtained from on-board measurements.

Statistical techniques based upon non-linear regression were applied to estimate the duration of a cold-start automatically by determining the time at which emissions stabilized. The objective of the nonlinear regression was to estimate the duration of the cold start, which is quantified as the time t_C. The premise underlying this method for determining cold start duration is that during the cold start, there is a clearly identifiable trend of a decrease in CO emissions with time. However, once the vehicle reaches hot stabilized operation, CO emissions do not change substantially when averaged over time. A program was written in SAS that uses non-linear regression to estimate t_C based upon CO emissions. An example of this analysis is given in Figure 3-10 for the same trip presented in Figure 3-9. There is a downward trend in the regression fit for the first 192 seconds. After that time, the fit is a horizontal line representing average CO emissions during hot stabilized operation. In SAS, it is possible to get 95 percent confidence intervals on the t_C value. For this particular case, the 95 percent confidence interval for t_C ranges from 167 seconds to 216 seconds.

The upper bound of the 95 percent confidence interval was used as the assumed cold start duration, to reduce the probability that cold start data would be mistakenly classified as part of hot stabilized operation. If a cold-start is present, then t_C will typically be a positive number. If a cold start is not present, then t_C will typically be zero or a negative value.

The estimation of cold start duration was conducted also for HC and NO emissions, and not just for CO emissions. The upper limit of the confidence intervals for t_C were compared for all three pollutants. For most of the cases, the results for HC and CO were similar. On the average results obtained for HC are within 20 percent of results obtained for CO.

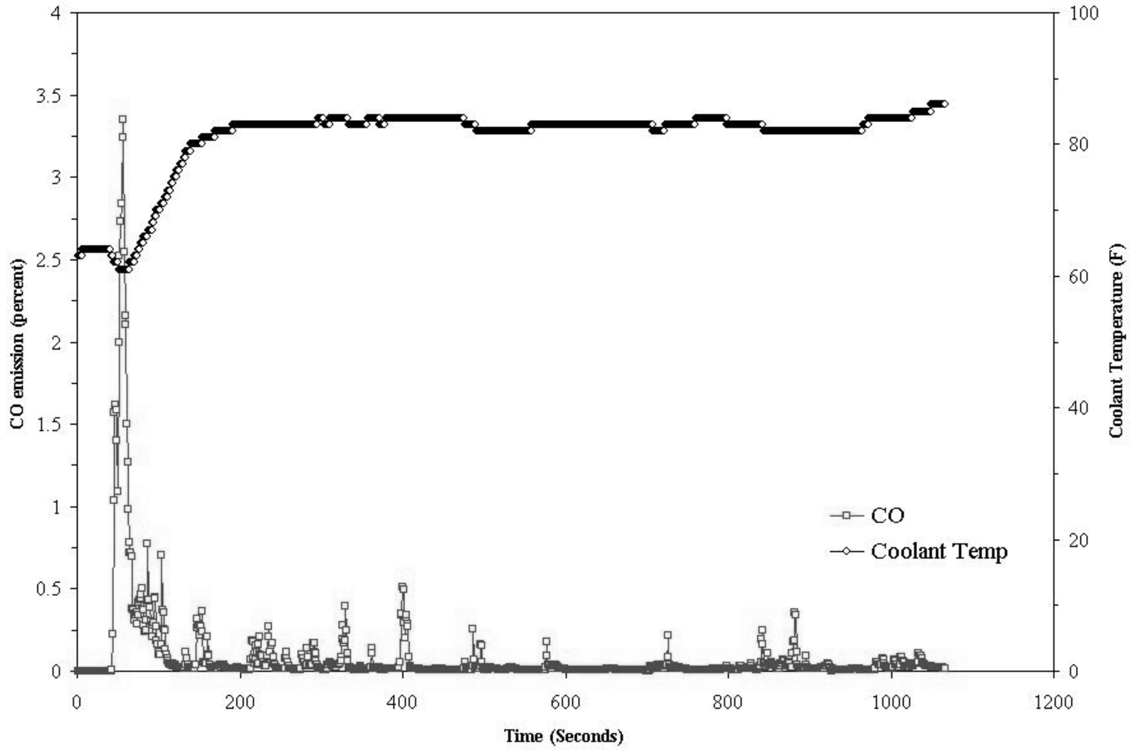


Figure 3-9. Relation between Coolant Temperature and CO Emissions for Vehicle 5 Trip 2

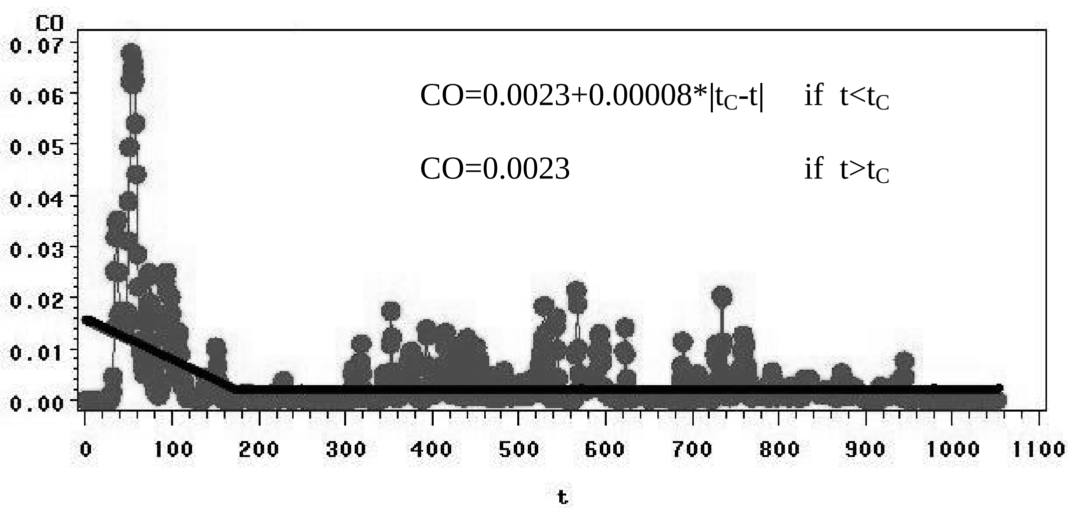


Figure 3-10. Determination of Presence and Duration of Cold-Start using Non-Linear Regression

When deciding the duration of cold-start, values for t_C estimated from all three pollutants were taken into account, however, results from HC and CO were given more emphasis since these pollutants are affected from cold-start more than NO emissions. For cases where different results were obtained for t_C among the three pollutants, data were closely investigated and the soak time between the particular trip and an earlier one was also considered, which were provided in the dataset. Soak time between the trips help identifying the presence of cold-start. For example, if there is less than 10 minutes between trips, it is most probable that there is not a cold-start in the latter trip. For the cases, where different t_C were obtained for different pollutants, generally highest one is selected to make sure that cold-start emissions are not mistakenly taken as part of hot-stabilized emissions. This way a decision was reached for each trip for the presence and duration of cold-start emissions. It was found that 34 of the trips had cold-starts with durations ranging from 70 to 391 seconds. A table summarizing the result of this analysis is given in Appendix A.

Identification of cold-starts was used to categorize data for later analysis, so that hot-stabilized data could be separated from cold-start data.

3.2.7 Summary of Exploratory Analysis

In this section, relationships between possible explanatory variables and emissions were investigated. This is a necessary step before any of the modeling efforts. The insights obtained from this section were utilized to develop a model as explained in the next section.

3.3 Model Development

The objective of this section is presented along with the requirements of the study. The methodology used for model development is discussed. Finally, a summary of the model is given with comparison of observed versus predicted data using the model. Finally, a discussion of unexplained variability and uncertainty is given.

3.3.1 Objective and Preliminary Assessments

In this study one of the objectives is to develop conceptual models for light-duty gasoline vehicles for CO, HC, NO and CO_2 emissions using on-board emissions data provided by the U.S. Environmental Protection Agency. Developed models were subsequently applied to a "validation" dataset and predictions for these datasets were obtained, as described in Chapter 6. As discussed in Section 3.2.3, explanatory variables that were provided in the “validation” dataset were fewer in number than the explanatory variables provided in the “modeling” dataset. Therefore, modeling attempts should take this aspect into account to develop models based upon variables available for prediction purposes. Variables available in the “validation” dataset were: vehicle speed (mph); time/date; a/c (on/off); temperature (^{0}F); humidity (grains/lb air); ambient pressure (in Hg); latitude (deg); longitude (deg); and grade (percent). These variables and others that can be estimated from these, such as acceleration and power demand, were utilized in developing models.

An important issue in developing models is to identify the nature of the data set that will be used for modeling calibration purposes. For example, any correlation in the dataset, including correlation among the explanatory variables as well as autocorrelation if the data are a time series, should be identified before moving to the modeling step. In this study, second-by-second data were collected using the on-board instrumentation. Given the short averaging time of the data, there is a strong likelihood that the data are autocorrelated. Data were checked for autocorrelation using SAS software.

Figure 3-11 presents autocorrelation assessment results both in numerical values and with a graphical representation for CO emissions for Vehicle 5, Trip 2. SAS estimates correlation between CO emissions at time t and t+*k*, which represent a time lag of *k*. In order to determine whether autocorrelations are significantly different from zero, 95 percent confidence intervals are estimated. Since the distribution of autocorrelation is approximately normal, two times the standard error is plotted to the left and right of the vertical axis representing zero autocorrelation, as shown in Figure 3-11. If autocorrelations fall within the range enclosed by plus or minus two standard errors, then they are not statistically different from zero (Warner, 1998). However, most of autocorrelations shown are positive and extend beyond the confidence interval, suggesting the presence of statistically significant autocorrelation for CO emissions for multiple time lags. The autocorrelation values are statistically significant for all time lags up to 21.

The exponential decay trend of the autocorrelation estimates as lag increases suggests the presence of an autoregressive (AR) process, which means that the observation at time t depends on the previous values (at time t-1 for example). However, in order to confirm that an AR model is appropriate, one needs to check partial autocorrelation estimates. The partial autocorrelation at lag k is the autocorrelation between X_t and X_{t-k} that is not accounted for by lags 1 through k-1. Partial autocorrelation function (PACF) cuts off at lag k for an AR(k) process, which means that PACF results are zero after lag k indicating that an AR(k) is suitable for that process. PACF estimates for the example case study given in Figure 3-12.

There are values of the partial autocorrelation at lags 1, 2, 3, and 5, which are outside the 95 percent confidence interval. The appropriate AR process is determined by the largest lag for which statistically significant partial autocorrelation coefficients are observed, even if some of the intermediate lags appear to be insignificant. Thus, the results in Figure 3-12 suggest that CO emissions have a AR process of 5 lags. This means that CO emissions at time t are correlated with CO emissions at times t-1, t-2, t-3, t-4, and t-5, or during the previous five seconds. In order to confirm this, one needs to fit an AR(5) model to the data and analyze the residuals. If the residuals are found to be white noise (i.e., there is no autocorrelation in residuals) by doing statistical tests, such as chi-square tests, then it can be concluded that the identification of the process is correct. Otherwise, different AR models should be fitted until a model which has white noise residuals are obtained. Therefore, this is an iterative process. In this case, an AR(5) model give white noise residuals, proving that CO emissions have an AR (5) process. Checks for other pollutants for this dataset and for other vehicles and/or trips showed that data generally have AR(4) or AR (5) processes.

Time series analysis revealed that data available in this study have autocorrelation and therefore need to be treated carefully. For example, ordinary least squares regression should be used only if the residuals are uncorrelated with each other (Brocklebank and Dickey, 1986). Autocorrelation in the data set might violate this assumption. One method to check whether

```
                                    Autocorrelations

 Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

   0     0.0012949        1.00000    |                    |********************|             0
   1     0.0012137        0.93728    |                   .|******************* |      0.030643
   2     0.0011115        0.85837    |                  . |*****************   |      0.050880
   3     0.0010467        0.80833    |                 .  |****************    |      0.063027
   4    0.00099004        0.76459    |                 .  |***************     |      0.072107
   5    0.00089314        0.68975    |                 .  |**************      |      0.079355
   6    0.00078665        0.60751    |                 .  |************        |      0.084798
   7    0.00070739        0.54630    |                .   |***********         |      0.088791
   8    0.00064155        0.49545    |                .   |**********          |      0.091892
   9    0.00057243        0.44207    |                .   |*********           |      0.094367
  10    0.00050747        0.39191    |                .   |********            |      0.096292
  11    0.00045207        0.34912    |                .   |*******             |      0.097779
  12    0.00040863        0.31558    |                .   |******              |      0.098942
  13    0.00038101        0.29424    |                .   |******              |      0.099883
  14    0.00036310        0.28041    |                .   |******              |      0.100693
  15    0.00034618        0.26734    |                .   |*****               |      0.101424
  16    0.00032398        0.25020    |                .   |*****               |      0.102083
  17    0.00031176        0.24077    |                .   |*****               |      0.102658
  18    0.00029456        0.22748    |                .   |*****               |      0.103187
  19    0.00027290        0.21075    |                .   |****                |      0.103656
  20    0.00024692        0.19069    |                .   |****                |      0.104058
  21    0.00021657        0.16725    |                .   |***.                |      0.104386
  22    0.00018575        0.14345    |                .   |***.                |      0.104637
  23    0.00015922        0.12296    |                .   |** .                |      0.104821
  24    0.00013448        0.10386    |                .   |** .                |      0.104957

                               "." marks two standard errors
```

Figure 3-11. Autocorrelation Estimation Result for CO Emissions for Vehicle 5 Trip 2

```
Partial Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                  1        0.93728    |                   .|******************* |
                  2       -0.16571    |                 ***|.                   |
                  3        0.21827    |                   .|****                |
                  4       -0.04860    |                   *|.                   |
                  5       -0.24672    |               *****|.                   |
                  6       -0.02039    |                   .|.                   |
                  7        0.04391    |                   .|*                   |
                  8       -0.01636    |                   .|.                   |
                  9        0.03341    |                   .|*                   |
                 10        0.02855    |                   .|*                   |
                 11       -0.03224    |                   *|.                   |
                 12        0.03492    |                   .|*                   |
                 13        0.08405    |                   .|**                  |
                 14        0.02625    |                   .|*                   |
                 15        0.00863    |                   .|.                   |
                 16       -0.04336    |                   *|.                   |
                 17        0.03095    |                   .|*                   |
                 18       -0.09779    |                  **|.                   |
                 19        0.01338    |                   .|.                   |
                 20       -0.02382    |                   .|.                   |
                 21       -0.06343    |                   *|.                   |
                 22        0.01003    |                   .|.                   |
```

Figure 3-12. Partial Autocorrelation Estimates for CO Emissions for Vehicle 5 Trip 2 errors are autocorrelated or not is to fit a regression and get residuals and look at the ACF and PACF to whether there is an autocorrelation in the residuals (Brocklebank and Dickey, 1986). These analyses can be done in one step in SAS. Because the time series emissions data for the LDGV variables can be described by an AR(4) or AR(5) time series model, one possible modeling approach is to use time series methods to develop functional relationships between explanatory variables and emissions. However, a key problem in using time series models is that the parameters of such models can be estimated only from a continuous time series. One can overcome this problem by fitting time series models for each data file, which is a continuous time series in itself, then deciding on a general time series model by analyzing the parameters of the individual time series models. However, this is impractical and also is very difficult to achieve. It is impractical because fitting a time series model is an iterative process and would take substantial time and effort. It is difficult to obtain one time series model from several models for individual datasets, because of the high variability in the data. Even if a similar time series model is fit to several datasets, such as an AR model, the coefficients of the variables would probably be very different from each other. If one is interested in developing relations between a response variable and predictor variables, but also needs to consider the history of the predictor variables, simple time series models can not be used. Time series models referred to as transfer function models need to be used in such cases (Brocklebank and Dickey, 1986). These models require fitting time series models for each predictor variable and development of a relationship between the predictor variable time series models and the response variables using transfer functions. Another important aspect of time series models is that it is very difficult to work with missing data in the time series methodology. Thus, although time series approaches offer some theoretical appeal, they were deemed to be impractical as the basis for development of a model such as the NGM, which will require input data from a large number of vehicles and trips.

Because time series modeling is deemed not to be a preferred method for practical reasons, alternatives must be explored. A key criterion for selecting a modeling approach is to find techniques will which essentially destroy the autocorrelation in the data. Although there may be some loss of explanatory power associated with ignoring or destroying autocorrelation, it will be possible to use other modeling approaches that are more practical for taking advantage of the variety of sources of data available for model development.

One method for reducing the influence of autocorrelation is to bin the data so as to disrupt the time series. For example, data can be binned with respect to speed and acceleration criteria to represent different driving modes (e.g., idle, acceleration, cruise, deceleration). Although it is still possible to have segments of time series within a given bin, the effect of autocorrelation will be diminished and may be small enough for practical purposes so as not to compromise the integrity of the model. The potential trade-off between the explanatory power of a time series approach, and the explanatory power of a binned or modal approach, can be evaluated by comparing both approaches. This is done more easily for the nonroad data sets and is addressed in Chapter 5.

With the motivation of removing the influence of autocorrelation, a combination of techniques based upon modal analysis, regression, and time series methods were employed. In general, the first step employed was to bin the data, so as to disrupt the time series. Regression methods were then applied to data within the bins. The methods are briefly reviewed in the next section, followed by their application to the LDGV database.

3.3.2 Methods used for Modeling

In this study engineering as well as statistical methods are utilized to develop emissions estimation models. One of the statistical methods that is used here is Hierarchical Tree-Based Regression (HTBR). Ordinary Least Squares (OLS) regression is also used for modeling purposes. For some part of the data, particularly pertaining to cold starts, regression modeling with time series errors is also applied. In this section, background information on these statistical methods is given.

Hierarchical Tree-Based Regression

Hierarchical Tree-Based Regression (HTBR) 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, HBTR 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, HBTR 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 of the response?; and (2) which value of the selected variable (discrete or continuous) results in the maximum reduction in variability 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).

In order to explain the method in mathematical terms, the definitions presented by Washington *et al.* (1997) are used. The first step is to define the deviance at a node. A node represents a data set containing L observations. The deviance, D_a, can be estimated as follows:

$$D_a = \sum_{l=1}^{L} \left(y_{l,a} - \bar{x}_a \right)^2 \qquad (3\text{-}3)$$

where,

D_a	=	total deviance at node a, or the sum of squared error (SSE) at the node
$y_{l,a}$	=	l^{th} observation of dependent variable y at node a
$\bar{x}_a$	=	estimated mean of L observations in node a

For each of k variables, the algorithm seeks to split the domain of a variable, X_i, (where i has a value from 1 to k) into two half-ranges at node a, resulting in two branches and corresponding nodes *b* and *c*, each containing M and N of the original L observations (M + N = L) of the variable X_i. The reduction in deviance function is then defined as follows:

$$\Delta_{(allX)} = D_a - D_b - D_c \qquad (3\text{-}4)$$

where:

$\Delta_{(allX)}$ = the total deviance reduction function evaluated over the domain of all X_i's (i.e. for k number of X variables)

$D_b = \sum_{m=1}^{M} \left(y_{m,b} - \bar{x}_b\right)^2$

$D_c = \sum_{n=1}^{N} \left(y_{n,c} - \bar{x}_c\right)^2$

D_b = total deviance at node b

D_c = total deviance at node c

$y_{m,b}$ = m^{th} observation of dependent variable y in node b

$y_{n,c}$ = n^{th} observation of dependent variable y in node c

$\bar{x}_b$ = estimated mean of M observations in node b

$\bar{x}_c$ = estimated mean of N observations in node c.

The method seeks to find X_k and its optimum split at a specific value of X_k, $X_{k(i)}$, so that the reduction in deviance is maximized.

The maximum reduction occurs at a specific value $X_{k(i)}$, of the independent variable X_k. When the data are split at this $X_{k(i)}$, the remaining samples have a smaller variance than the original data set. Numerical methods are used to maximize (Equation 3-4) by varying the selection of which variable to use at a basis for a split and what value to use at the split point.

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 node size at which the last split is performed; or (2) minimum deviance criteria at a node have been met. Some software, such as S-Plus™, allow the user to select either criteria. More information on regression trees and its application to vehicle emissions can be found in Unal (1997).

Ordinary Least Squares Regression

Ordinary Least Squares (OLS) regression is a common statistical technique for quantifying the relationship between a continuous dependent variable and one or more independent variables. The dependent variables may be either continuous or discrete. This method has been used since the late 19^{th} century by many analysts. Part of the reason that OLS is so popular is that it is easy to comprehend, it is incorporated into most statistical packages, and its statistical properties are well understood (Washington, 1997). The basic OLS regression equation for a single variable regression can be written as follows;

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_i \times X_i + \varepsilon_i \qquad (3\text{-}5)$$

where;

$\hat{Y}_i$ = value of the response variable in the i^{th} trial

$\hat{\beta}_0, \hat{\beta}_i$ = estimators of regression parameters

X_i = value of the predictor variable in the i^th trial

ε_i = random error term, generally required to be normally distributed with a mean of zero and a variance of σ^2.

The parameters of the OLS regression equation, $\hat{\beta}_0$ and $\hat{\beta}_i$, are found by the method of least squares which requires that the sum of squares of errors be minimized.

In order to fit a linear regression there are key assumptions that should be valid. These include:

(1) X and Y values should be randomly selected
(2) The error terms are normally distributed
(3) The error terms have a constant variance
(4) The error terms are independent
(5) The error terms are normally distributed

If the above assumptions are violated the regression equation might yield biased results. A detailed discussion and presentation on OLS methods is not provided here because of the widespread knowledge of OLS techniques. For further information, Neter *et al.* (1996) can be consulted.

Combination of HTBR and OLS

HTBR methods do not use *a priori* information on the number of variables and their relationship with the dependent variable. These models use their data mining properties to identify the relevant variables. Complex relationships contained in the data can be captured via the process of stratification of the data inherent in the approach. However, HBTR can also result in repetitive and apparently arbitrary stratification of data. For example, it could repeatedly stratify the data based upon speed and acceleration. This would indicate that some combination of speed and acceleration are important, but that data should be binned taking both into account simultaneously.

As suggested by Washington (1999), HTBR lacks some desirable properties of OLS procedures, such as available statistical tests which might be used to test the differences in HTBR model formulations. Without estimated parameters and their related properties, it is difficult to determine whether patterns identified in the data are likely to be explained by long-term stable patterns showing the real relationships in the data, or whether they are just noise reflecting spurious relationships by random fluctuations in the sample. In other words, there are not explicit measures of the statistical significance of HTBR results.

In this study, a priori definitions of driving modes were used to bin the data. HBTR was used for the data for each driving mode to identify which explanatory variables would be most useful in further stratifying the data. OLS regression was done to capture relationships within the data strata.

Time Series Methods

Time series is a wide field in statistics and includes a variety of modeling techniques. The type of time series model that is used here is "Regression with Time Series Errors" (Brocklebank and Dickey, 1986). This method is suitable for data with autocorrelation and where a regression equation between response and predictor variables is sought. This is very similar to OLS regression except errors are estimated using autoregressive (AR) or moving average (MA) models. The model is given as

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 \times X_{1t} + \hat{\beta}_2 \times X_{2t} + ... + \hat{\beta}_k \times X_{kt} + Z_t \qquad (3\text{-}6)$$

where Z_t is a time series. The assumption of non-correlation for error terms is implied in Equation (3-6) since after the fitting the time series to the error terms for the predicted variable, only white noise should be left. Identification of the time series model requires looking at autocorrelation and partial autocorrelation estimates for residuals after fitting the regression, which was explained briefly in Section 3.3.1. Statistical software such as SAS can provide this information directly. After deciding on the type of time series model for the errors, one should identify significant parameters for regression equation. This procedure needs to be iterative (Brocklebank and Dickey, 1986). Detailed theoretical information on time series models and applications can be found in Wei (1990).

3.3.3 Data Segregation Using Modal Analysis Approach

Average emissions of vehicles are different in different operational modes of the vehicles. The analysis of emissions with respect to driving modes, also referred to as modal emissions, has been done in several recent studies (Barth *et al*., 1996; Tong *et al.*, Barth *et al.*, 1997; Bachman, 1999; Frey *et al*. 2001). Driving can be divided into four modes: (1) acceleration; (2) cruise; (3) deceleration; and (4) idle. In this work, the second-by-second emissions data were divided into these four modal categories and the average emissions rates for each mode were calculated.

The defining characteristics of a driving mode are somewhat arbitrary. As an *a priori* assumption, the following definitions have been used, based upon the definitions used by Frey *et al*. (2001) with the exception of the cold start mode, whose definition is introduced here. Cold start has been defined as a mode based upon the duration of the cold start as defined in Section 3.2.6. For hot stabilized operation, four modes of idle, acceleration, deceleration and cruise are defined. 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 had 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 deceleration are classified as cruising. Thus, cruising is approximately steady speed driving but some drifting of speed is allowed. These definitions are not the same as those used in other studies. However, whether these definitions are useful or not can be evaluated by analyzing the emissions data.

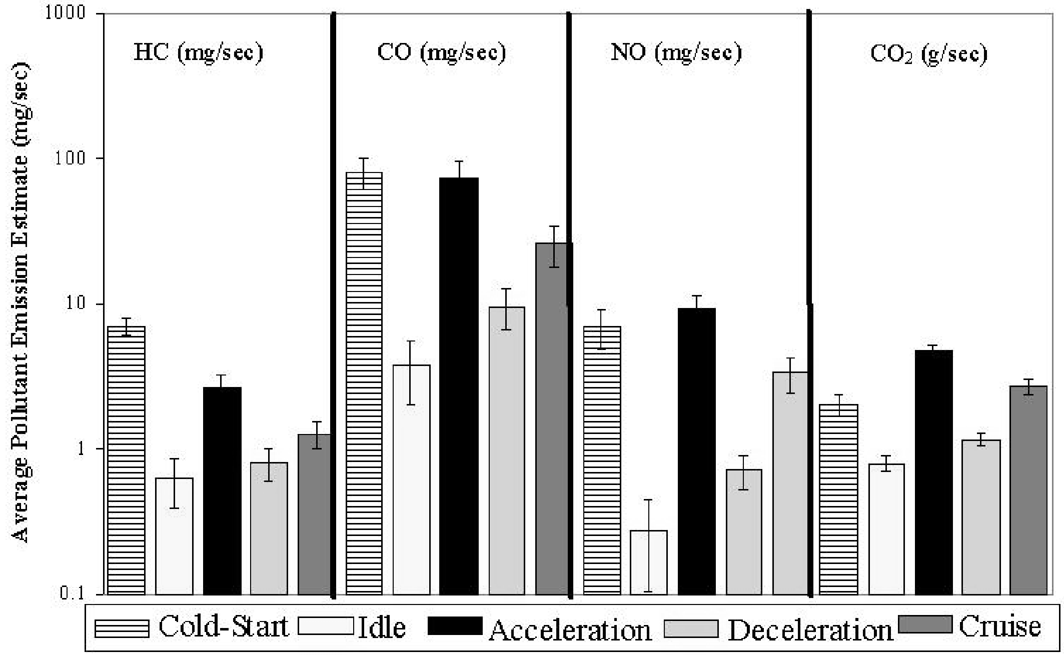


Figure 3-13. Average Modal Emission Rates for All Trips

A program was written in Microsoft Visual Basic that determines the driving mode for second-by-second data and estimates the average value of emissions for each of the driving modes. The program also calculates the total emissions for the trip. In order to determine whether modal analysis has exploratory value or not, average modal emission rates were estimated for each trip. The average of the estimates for each mode was calculated based upon all vehicles and trips in the database. A comparison of the average modal emission rates for each of four pollutants is shown in Figure 3-13, along with estimates of the 95 percent confidence intervals on the trip mean emission rates. The modes shown are cold start, and the four hot stabilized modes of idle, acceleration, deceleration, and cruise. The cold start mode includes all vehicle activity that took place during the cold start duration. For example, some vehicles were driven during the cold start.

It is clear from Figure 3-13 that the average emission rate during cold start is approximately comparable to the average hot stabilized acceleration emission rate. For example, for CO, the average cold start and hot-stabilized acceleration emission rates are not statistically significantly different from each other. These two rates are also nearly the same for NO. For HC the average cold start emission rate is substantially higher than that for hot stabilized acceleration. The results for CO_2 are somewhat different in that the cold start emission rate is less than the acceleration emission rate and is approximately comparable to the cruising emission rate.

Setting aside the cold start mode, and focusing only on the four hot stabilized modes, the comparisons reveal similar trends among all four pollutants and are similar to the findings obtained with different vehicles in the study by Frey *et al*. (2001). The emissions during the acceleration mode are significantly higher than for any other driving mode for hot-stabilized emissions, for all four of the pollutants measured. Conversely, the emission rate during idling is

Table 3-5. Result of Pairwise Comparison for Modal Average Estimates in terms of p-value

P-Values for Pairwise T-test				
	Modes	*Acceleration*	*Deceleration*	*Cruise*
HC	*Idle*	0.000	0.000	0.000
	Acceleration		0.000	0.270
	Deceleration			0.000
CO	*Idle*	0.000	0.895	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000
NO	*Idle*	0.000	0.590	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000
CO_2	*Idle*	0.000	0.008	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000

the lowest of the four modes for all four pollutants. The cruising emission rate is typically slightly higher than the deceleration emission rate.

In order to check whether average modal emission rates are statistically significantly different from each other, pairwise t-tests were estimated. Results of the t-tests are presented in Table 3-5 in terms of p-values. P-values less than 0.05 indicate that the particular pair has statistically significant differences in average estimates. For example, the t-test between idle and acceleration modes for HC emissions gave a p-value of 0, indicating that average HC emissions are different for these two modes. Out of 24 possible pairwise comparisons, only three of them gave p-values higher than 0.05, indicating that average emissions rates for these pairs are not statistically different from each other. Two of these cases occurred for comparisons of the idle and deceleration modes for both CO and NO emissions. The other one occurred between acceleration and cruise modes for HC emissions.

The modal emissions analysis results suggest that the *a priori* modal definitions assumed here are reasonable. These modal definitions allow some explanation of differences in emissions based upon driving mode, as revealed by the fact that, in most cases, the average modal emission rates differ from each other. The analysis also indicates that the average acceleration emission rates for CO and NO are more than a factor of 10 higher than the average idling emission rates, and that the average acceleration emission rates for CO_2 and HC are approximately a factor of five higher than the average idling emission rates. These findings are very similar to those of Frey *et al*. (2001) for a different set of LDGVs. These substantial differences in emission rate have important implications for traffic and air quality management. It should be noted that CO_2 emissions are highly correlated with and are a good surrogate for fuel consumption.

3.3.4 Improving Driving Mode Definitions

Modal definitions have a power to explain variability in emissions since average emission rates for different modes were found to be statistically significant from each other. A further step is taken here to improve these modes by stratifying the data within each mode so that emissions within each strata are more nearly homogeneous.

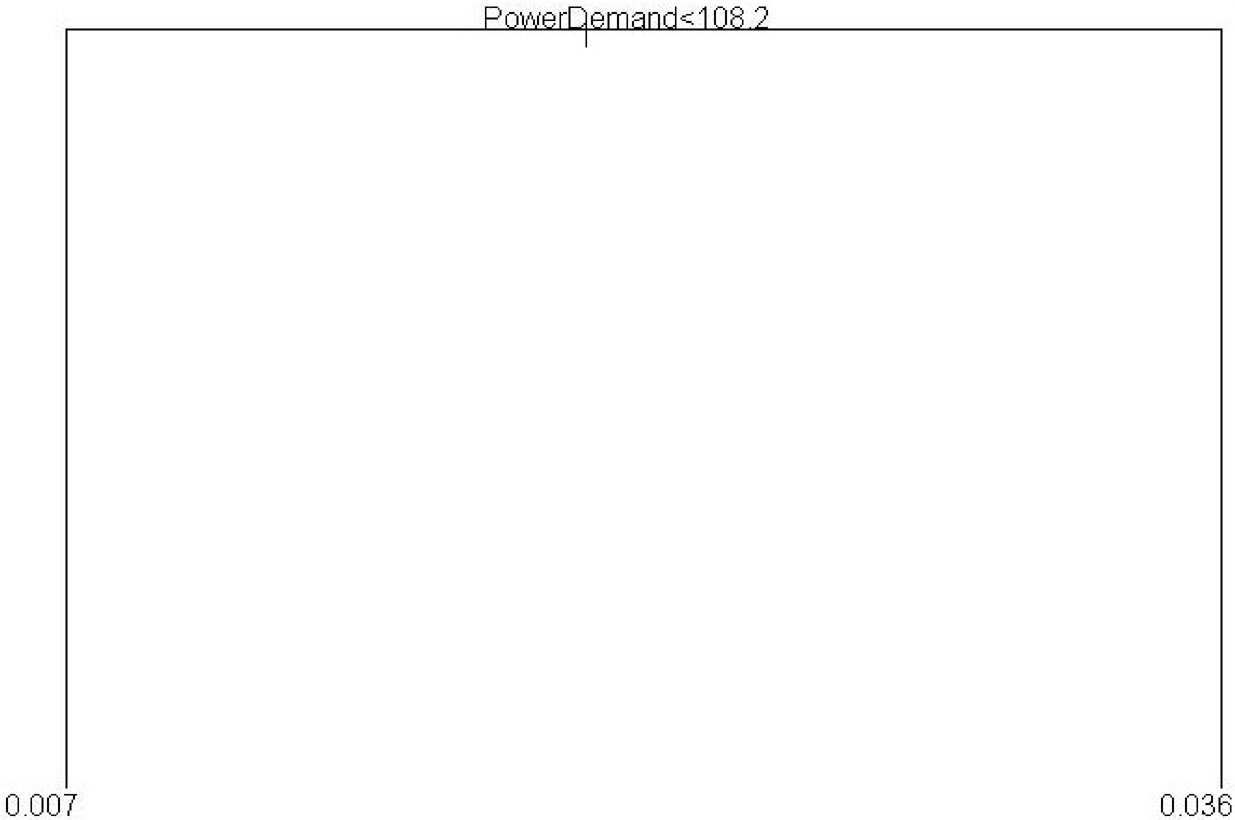


Figure 3-14. Example Regression Tree Output for NO Emissions for Acceleration Mode using Data for Vehicle 11

In order to improve the driving mode definitions, the HTBR technique was utilized. Trip data for each vehicle were combined together and exported to S-Plus for analysis. Then regression trees were formed using explanatory variables related to vehicle operation and vehicle characteristics such as vehicle speed, acceleration, power demand, grade, and vehicle engine size. For each vehicle, regression trees were formed separately for CO, NO, and HC emissions for each driving mode. For CO_2 emissions, the original modes were considered to be adequate for their explanatory power.

An example regression tree output for NO emissions during acceleration for Vehicle 11 is given in Figure 3-14. As seen in Figure 3-14, the first split on emissions occurs for a power demand cutoff point of 108.2 mi^2/h^2.sec. In regression trees, the left branch of the tree represents data with explanatory variable less than the cutoff point, and the right branch represents cases where the explanatory variable has values higher than the cutoff point. For this case, data with power demand higher than 108.2 mi^2/h^2.sec is split to the right and data with power demand less than 108.2 is split to the left. The data in the higher power demand strata have average NO emissions of 0.036 g/sec. The data in the lower power demand strata have an average emission rate of 0.007 g/sec. Thus, the average NO emission rate for high power demand strata is more than 5 times higher than for the low power demand strata. Therefore, the stratification with respect to power demand appears to account for some of the variability in the data.

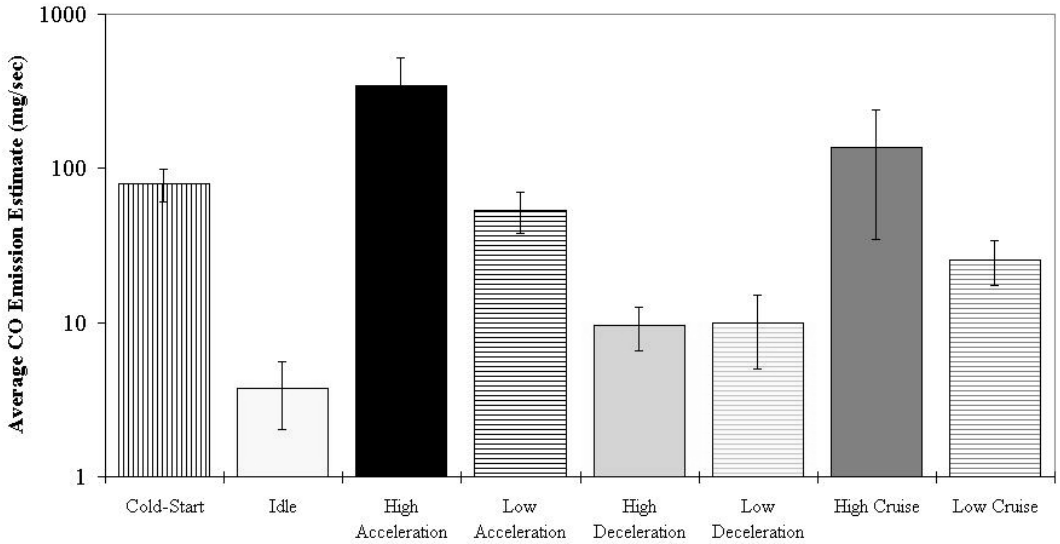


Figure 3-15. Improved Average Modal Emission Rates for All Trips for CO

In the HBTR analysis, a maximum number of four nodes or end points, were sought. However, only two nodes are shown in Figure 3-14 because the first stratification in the tree provided the most benefit as far as reducing the deviation of the data within each node. There was little explanatory benefit to extending the tree to another set of sub-strata and the cost of doing so would have been the requirement to segregate data into a larger number of bins.

HBTR analysis was applied individually to all vehicles, all driving modes, and to the NO, CO, and HC pollutants. In most cases, the first split in the tree was based upon power demand, but the specific numerical value by which the data were stratified varied. However, in order to simplify model development, a decision was made to select one cut-off point for a given driving mode and apply it to all pollutants. Therefore, a representative cut-off point for each driving was selected based upon a review of the results for all pollutants. For example, a cutoff point of 100 mi^2/h^2.sec was used for the acceleration mode. For deceleration, the cutoff point was chosen as -100 mi^2/h^2.sec. For cruise mode, the chosen cut-off was 60 mi^2/h^2. For the idle mode, the HBTR analysis did not reveal any stratification that would be useful.

In order to see whether the newly identified strata have potential benefit in explaining variability in emissions, the average modal emission rates for these new modes were estimated and are compared in Figure 3-15 for the example of CO emissions. Results for other pollutants are given in Appendix A. It is clear from the comparison of both averages and confidence intervals for the averages that the stratification within the modes yields statistically significant bins for both acceleration and cruising. However, there is no significant difference between the high and low deceleration modes. Thus, although there is no apparent benefit to stratify deceleration based upon power demand, it appears to be useful to stratify acceleration and cruise based upon power demand.

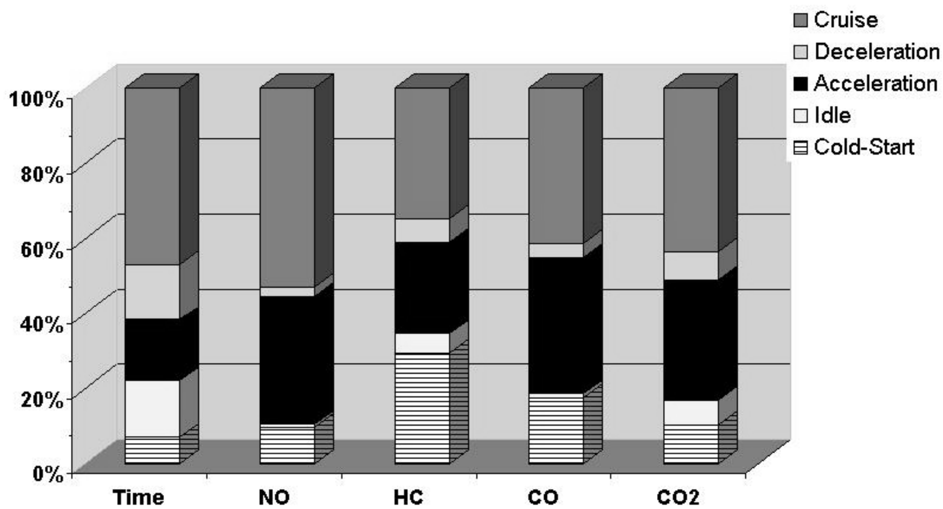


Figure 3-16. Average Distribution of Time and Emissions with respect to Modes

In addition to developing modes that are statistically significantly different from each other, another consideration in model development is to create modes that are useful in explaining a substantial contribution to total trip emissions. Figure 3-16 illustrates the distribution of time spend in each of the five original modes, 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 four pollutants compared to cruise, acceleration, and cold start emissions. Therefore, there is 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. Cruising, which accounts for approximately 50 percent of the time of an average trip in the calibration database, accounts for almost 60 percent of NO emissions, 50 percent of CO_2 emissions, 45 percent of CO emissions, and 40 percent of HC emissions. Acceleration accounts for only approximately 15 percent of the time of the trip but for approximately 30 percent of NO, CO, and CO_2 emissions and approximately 20 percent of HC emissions. Cold start accounts for an average of only five percent of the time of a trip, but for approximately 10 to 15 percent of NO, CO, and CO_2 emissions and more than 20 percent of HC emissions. In contrast, idle and deceleration combined account for typically less than 10 percent of total trip emissions for each of the pollutants even though they account for approximately 30 percent of the time of an average trip. The modal distributions for both time and emissions for each trip are given in Appendix A.

3.3.5 Fitting OLS Regressions

After developing modal definitions, OLS regressions were fit for each mode using selected explanatory variables. The reasons for selecting explanatory variables were explained in Section 3.2.3. These explanatory variables are: speed; acceleration; power; engine size; ambient humidity; ambient temperature; altitude; and road grade. Second and third powers of speed and acceleration were also included in regression analysis.

In fitting regressions to data, a stepwise regression technique was applied in SAS. This technique allows the selection of the best model based upon selected criteria. One of the criteria is to choose a regression model that has the highest R^2 value. Another criteria is to choose a regression equation that has the lowest Akaike's Information Criterion (AIC). AIC penalizes for extra parameters included in the model. One can get incremental but sometimes insignificant improvements in the R^2 value by adding more explanatory variables. Therefore selecting a model based upon lowest AIC will help balance the number of explanatory variables with useful improvements in the explaining capabilities of the model associated with adding more inputs.

Regressions were fit to each modal data set for each pollutant using SAS. The result from SAS is a statistically significant model with statistically significant parameters. The coefficients of the regression equations for CO emissions obtained from this analysis is given in Table 3-4. Results for other pollutants are given in Appendix A.

As seen in Table 3-4, some of the coefficients are zero. This means that those variables were not selected in the regression fits. Table 3-4 also presents R^2 values for each regression equation, given in the next to last row. The lowest R^2 value is 0.1, for the idle mode, and the highest R^2 value is 0.43 for the high acceleration mode. These R^2 values are low to moderate. However, given that only a selected set of explanatory variables are available for inclusion in the regression models, it is not surprising that there is a large portion of variability in the data within each mode that remains unexplained. Furthermore, it must be kept in mind that these models are only for bins of data, and that the process of binning the data also accounts for a portion of the variability in the on-board emissions data.

In the last row of Table 3-4, the correction factor for each regression equation is given. The correction factor is needed because a natural logarithm transform of emissions was used when developing the regression equations. It is known that when the regression result is back transformed to estimate grams/sec from a natural logarithm scale, results will be biased in the absence of a correction. Essentially, the regression for the transformed data is predicting the median emission rate, and the correction is needed to adjust from the median in the log-transformed case to the mean of the g/sec case. This problem of back-transformation is not uncommon in the environmental field, where log transformations are used frequently, as reported by Gilbert (1987). The regression model was in the form of:

$$\ln CO = \text{linear model} + \varepsilon \qquad (3\text{-}6)$$

where ε is the residual error term for the linear regression equation which has a mean of zero and variance of σ^2. Zero mean and constant variance for the residual terms are the key assumptions for the OLS regression. However, when we back transform the equation to calculate CO in terms of grams/second from natural logarithm scale, the residual term is also transformed as shown in Equation 3-7 below:

$$CO = \exp(\text{linear model}) \times \exp(\varepsilon) \qquad (3\text{-}7)$$

If we refer to the term $\exp(\varepsilon)$ as ε', then the new residual term ε' is biased and the new residuals do not have a zero mean. In order to solve this problem several methods have been proposed. One is to modify the regression methodology so that when it is back-transformed the results are not biased (Heien, 1968; Bradu and Mundlak, 1970). Another approach is to develop a

Table 3-6. Results of Regression Fit for CO Emissions

Variable	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
Intercept	-1.448	-12.9628	1.7659	-0.0358	2.6553	17.8749	3.7128
Engine Size (l)	-0.96	0.9781	-0.1541	-0.5107	-0.3358	0	-0.1935
Humidity	0	0	-0.0672	-0.0706	-0.0776	-0.1014	-0.0872
Speed	0	0.1649	0.0376	0.0445	0	0	0.0425
Speed^2	0	-0.0013	0	0	0	-0.0074	0
Speed^3	0	0	0	0	0	0.0001	0
Accel	0	0	-0.7249	-0.1892	0	0	-0.5009
Accel^2	0	0.0207	0.3437	0	0	0	0.1897
Accel^3	0	0	-0.0363	0	-0.0024	0	0
Temperature	-0.034	-0.0513	-0.0671	-0.0621	-0.0778	-0.0874	-0.0967
Altitude	-0.0008	0.0047	0	0.0015	0	0	0.0004
Grade	0	-0.1478	-0.1095	0	0.0981	0	0.0187
AC	0	0	0	0.0062	-0.0052	0	0.0239
Power	0	0.0257	0	0.0146	0	0	0
R-square	0.10	0.43	0.28	0.20	0.26	0.32	0.30
Correction Factor	3.9	2.3	9.7	5.7	5.1	2.5	3.9

correction factor for the reverse transformed regression equation. To do that, the individual residual terms were back transformed from the natural logarithm scale to grams/second and their average was calculated. The average value of the transformed residuals is the correction factor for the regression equation for calculating the average emissions estimate. The emissions estimates from the transformed linear regression should be multiplied by the correction factor in order to calculate a correct average in units of grams per second. As seen in Table 3-6, engine size is selected as a significant parameter for all of the modes for CO, except for the high cruise mode. However, the coefficient of engine size changes from one case to another. For example, for high acceleration the coefficient for engine size is 0.98 whereas it is -0.15 for low acceleration mode. These numbers suggest that the influence of engine size with respect to CO emissions may be different for different types of operation, or engine size might be functioning as surrogate for some other explanatory variable that is not directly observable in this study.

3.3.6 Modeling Cold-Start Data

For cold-start emissions, conventional regression cannot be used directly since data for this mode is comprised of consecutive seconds of data that are autocorrelated. One way to overcome this problem is to fit a regression model with time series errors. Time series methods were explained in Section 3.3.1. Although time series models are typically fit to data that represent only one continuous time series, it is possible to take a simpler approach to capturing some autocorrelation in a regression model by including error terms for the predicted variable based upon time lags. If data from multiple sources (e.g., different vehicles and trips) can be assumed to originate from the same process, then it is possible to combine the data. In this case, there are data regarding cold start emissions from 34 trips. For illustrative purposes, it will be assumed that all cold-starts are from the same process and that the cold start data from the 34 trips can be combined into one data for analysis. The validity of this approach can be judged based upon the comparison of trip-average emission rates predicted using this model versus the observed data.

After combining the cold-start data, a regression model with time series errors was fit to the data. In this process, explanatory variables that were listed in Section 3.2.3 were utilized. Coolant temperature was also included since it was shown earlier that coolant temperature varies inversely with emissions during the cold start and, therefore, may be useful in explaining some of the variability in cold start emissions. Using SAS, regressions with time series errors were fit to CO, NO, and HC data. It was found that acceleration, engine size, ambient temperature, and coolant temperature were the significant predictive variables for HC emissions. The time series errors, were modeled using an AR(2) model for HC. For CO emissions, speed, power demand, and coolant temperature were found to be significant predictive variables, and an AR(2) model was fit to the error terms. For NO, speed and power were the only predictive variables that were found to be significant. The error terms for NO emissions were modeled as an AR(4) model. The model fitted to CO emissions is given in Equation (3-8):

$$CO = 0.175 - 0.00083 \times Coolant + 0.0013 \times Speed + 0.0002 \times Power - 1.197 \times \varepsilon_{t-1} - 349 \times \varepsilon_{t-2} \qquad (3\text{-}8)$$

where;

Coolant = Coolant Temperature (^{0}F)
Speed = Vehicle Speed (mph)
Power = Power Demand (mi^2/h^2.sec)
ε_k = Error term

Comparison of cold-start emissions predicted using the model given in Equation 3-8 with the observed data for trip averages is given in Figure 3-176 for CO emissions. The results of other pollutants are given in Appendix A. The R^2 value is 0.33, which means that the model can explain 33 percent of variability in average cold start CO emissions. R^2 value for NO was found to be 0.53 and it was 0.09 for HC emissions.

In order to use an equation such as (3-8) for making predictions, it would be necessary to know the coolant temperature. However, for the model validation activity, coolant temperature was not available, and in general coolant temperature would be unknown. Therefore, a method is needed that enables predictions of cold start emissions without having to know the actual coolant temperature history for a given vehicle. An approach is explored here in which the cold start duration is estimated as a function of soak time. The estimated cold start duration can then be used to "look up" a coolant temperature profile for the appropriate vehicle technology group that corresponds most closely to the estimated cold start duration.

Figure 3-18 presents the relationship obtained between cold start duration and soak time based upon the available calibration data. The R^2 value for the relationship was found to be 0.43. It is possible that the predictive ability of a model such as this could be improved by including other explanatory variables, such as ambient temperature and engine characteristics.

The approach used for making predictions of cold start emissions was to estimate the cold start duration based upon the known soak time of the vehicle, and to find a coolant temperature profile corresponding most closely to the estimated cold start duration. In finding a similar dataset, one should check the ambient temperature and soak time in order to find a matching data file.

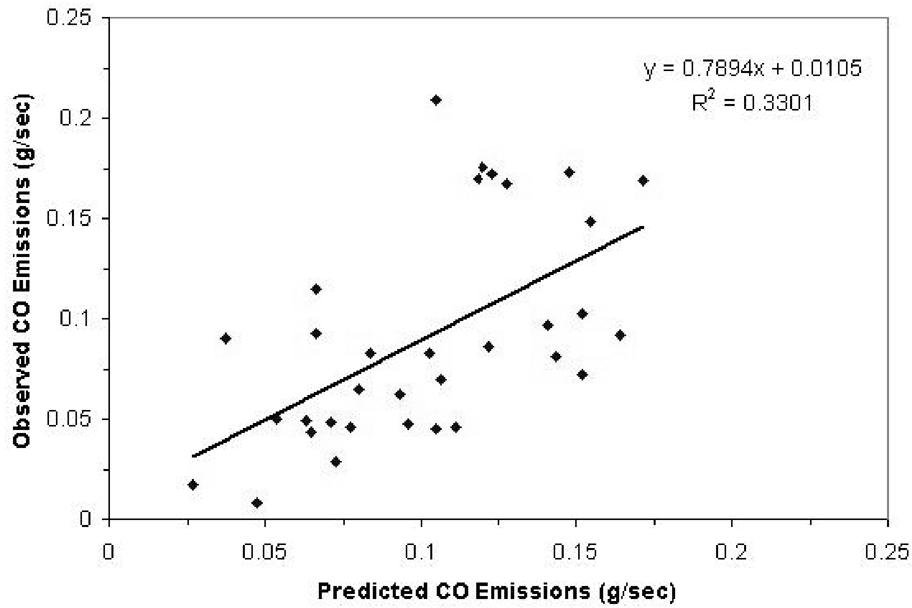


Figure 3-17. Comparison of Cold-Start CO Emissions for Predicted and Observed Data for Cold-Start

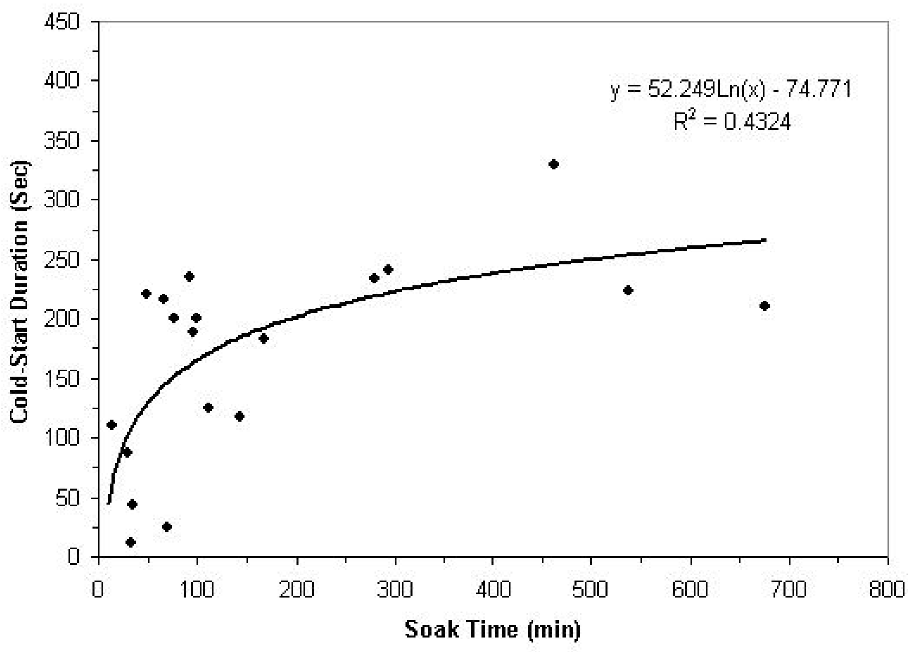


Figure 3-18. Relationship between Soak Time and Cold-Start Duration

3.3.7 Comparison of Observed and Predicted Data

The conceptual models developed for each pollutant are based upon estimation of emissions at a meso-scale for each of the five modes previously defined (cold start, idle, acceleration, deceleration and cruise). In some cases, the modes were further divided based upon power demand, such as for acceleration and cruise. OLS regression equations were used to provide a microscale predictive capability within the modes. Cold start was treated differently because of the autocorrelation of emissions within this mode. Thus, for cold start, OLS regression with time series errors was used to develop a microscale predictive capability.

Table 3-7 summarizes the methods used for each pollutant. For example, OLS regressions with time series errors was used for modeling HC emissions during cold-start. HC emissions during idle were modeled with OLS regression. OLS regressions were used to model HC emissions in each improved driving mode, such as high acceleration and low acceleration modes. For CO_2, OLS regressions were used for the original driving modes (i.e., idle, acceleration, deceleration, and cruise). The models for each of the four pollutants were used to predict emissions for the calibration data set based upon the values of the explanatory variables reported in the calibration dataset. The performance of the models was evaluated by comparing model predictions and actual observations for trip average emission rates based upon the calibration data set. In Chapter 6, the models were applied to make predictions for a validation data set that was different from the calibration data set.

In this section, parity plots are presented to help visualize how well the models are able to make predictions based upon the calibration data. An example of a parity plot is given for HC emissions in Figure 3-19. The parity plots display the observed (actual) trip average emission rates on the vertical axis versus the predicted emission rates on the horizontal axis. There are 51 points in the figure, representing 51 different trips.

The performance of the model can be evaluated in terms of precision and accuracy. The R^2 value is an indication of precision. Higher R^2 values imply a higher degree of precision, and less unexplained variability in model predictions, than lower R^2 values. The slope of the trend line for the observed versus predicted values is an indication of accuracy. A slope of one indicates an accurate prediction, in that the average prediction of the model corresponds to an average observation. The R^2 value for Figure 3-19 is 0.45, and the slope of the trend line is 0.77. These results indicate that the model can explain approximately half of the variability in the data, and that there is some bias in the model predictions. The bias can be corrected using the slope and intercept from the trend line to convert a model prediction more closely to match the observed emissions.

Figure 3-19 also shows the confidence interval on the mean prediction value. The confidence interval for the mean prediction was estimated using SAS. Details on estimation of confidence interval for the mean prediction can be found in literature (Neter *et al.*, 1996). As seen in Figure 3-19, confidence interval is narrowest in the average of the prediction, at around 0.002 g/sec for the predicted HC emissions and widens as moves away from the mean. The range of uncertainty in the mean for a predicted emission rate of approximately 0.002 g/sec is approximately plus or minus 15 percent. For a predicted emission rate of approximately 0.001 g/sec, the range of uncertainty in the mean is approximately plus or minus 25 percent. For a predicted emission rate

Table 3-7. Summary of Model Developed for Each Pollutant for LDGV

Driving Modes	*Improved Modes*	**HC**	**CO**	**NO**	**CO_2**
Cold-Start		OLS w/ TSE*	OLS w/ TSE	OLS w/ TSE	OLS
Idle		OLS**	OLS	OLS	OLS
Acceleration	High Acceleration	OLS	OLS	OLS	OLS
	Low Acceleration	OLS	OLS	OLS	
Deceleration	High Deceleration	OLS	OLS	OLS	OLS
	Low Deceleration	OLS	OLS	OLS	
Cruise	High Cruise	OLS	OLS	OLS	OLS
	Low Cruise	OLS	OLS	OLS	

* OLS w TSE: Ordinary Least Squares Regression with Time Series Errors
** OLS: Ordinary Least Squares Regression

of approximately 0.003 g/sec, the range of uncertainty in the mean is approximately plus or minus 15 percent. However, in this latter case, compared to that for a prediction of 0.002 g/sec, the absolute range of uncertainty is larger even though the relative range of uncertainty is approximately the same.

Figure 3-20 displays the same data as in Figure 3-20. However, the prediction interval shown in Figure 3-20 differs from that of Figure 3-19. In Figure 3-20, the prediction interval is a 95 percent range of variability in the observed data that is not explained by the model predictions. This interval was calculated using the SAS software. Details on estimation of confidence interval for the mean prediction can be found in literature (Neter *et al.*, 1996). The prediction interval should be used as an indication of the precision of the model when making predictions of emissions for individual trips. For a predicted emission rate of 0.002 g/sec, the 95 percent prediction interval for unexplained inter-trip variability is approximately plus or minus 90 percent. This is approximately a six-fold larger interval than that for uncertainty in the mean. Thus, the model is expected to give more precise predictions of fleet average emissions than of individual trip emissions.

The prediction intervals as calculated here have some limitations. Emissions cannot be negative. However, the lower bound of the prediction interval in Figure 3-20 is shown to extend into negative values. The prediction interval is estimated based upon a normality assumption for the residuals of the regression. However, because emissions must be non-negative, it is not likely that the residuals are actually normally distributed for small values of emissions. Therefore, even if the prediction interval as calculated implies negative emission values, a non-negativity constraint should be imposed when interpreting the interval. There is a need for other methods that more correctly address the non-negative nature of emissions data. For example, a log transformation of emissions estimates will enforce non-negativity in model. Such an approach can be explored for parity plots (e.g., log-log plots) in future work. The SAS software used to produce the graphs automatically generated a y-axis that displays negative values. However, all of the data in the graph, and the values of the trend line within the range of the data, are non-negative.

Figures 3-21 and 3-22 show the regression result for CO emissions, including the confidence interval for the mean in the former case and the prediction interval for variability not explained by the model in the latter case. The R^2 value for the trend line between the observed values and the predicted values is 0.44, which is typically larger than the R^2 values for the individual regression equations of each of the modes that comprise the model.

Figures 3-23 and 3-24 presents the comparison of observed versus predicted value for NO emissions, including the confidence interval for the mean in the former case and the prediction interval for variability not explained by the model in the latter case . The R^2 value for the trend line between the observed values and predicted values is 0.43. A similar comparison for CO_2 emissions is shown in Figures 3-25 and 3-26. The R^2 for the regression between the predicted and observed values is 0.8. The maximum R^2 value for individual regression equations for modes occur for cruise mode with a value of 0.33. This indicates that dividing the data into modes explains a substantial part of variability in CO_2 emissions. Furthermore, while the R^2 of the trend lines for CO, NO, and HC are typically approximately 0.4 to 0.45, the much larger R^2 of 0.8 for CO_2 illustrates that it may be possible to obtain precise estimates of CO_2 emissions even though predictions for the other pollutants may be less precise.

3.3.8 Quantification of Unexplained Uncertainty and Variability

In developing a model, it is important to quantify the unexplained variability and the uncertainty in the model predictions. One method for quantifying variability and uncertainty in model predictions was illustrated in the parity plots based upon results obtained using the SAS statistical software. In this section, an alternative approach is presented. In the alternative approach, residuals from each trend line fitted to the parity plots of the observed versus predicted data was obtained. As an indicator of unexplained variability, the coefficient of variation (CV) of residuals was determined by dividing the standard deviation of the residuals by the average value of emissions.

Uncertainty in the model estimates was determined using a bottoms-up approach. The uncertainty in the mean for each mode was estimated based upon the standard error of the mean. The OLS regressions were not considered in developing these uncertainty estimates. The procedure for estimating uncertainty in the mean trip emissions prediction is discussed in detail.

The first step in estimating uncertainty in the average model prediction was to estimate the average emission rates in each mode using data from all of the vehicles and trips, as shown in Equation (3-9).

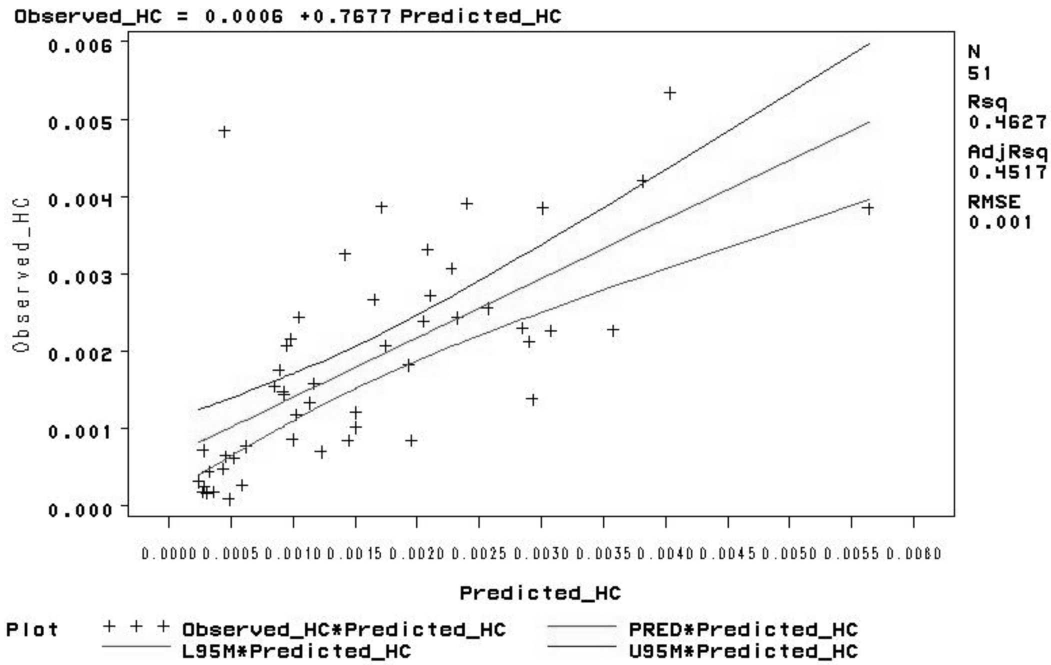


Figure 3-19. Observed versus Predicted Trip Averages for HC Emissions with 95 % Confidence Interval on the Mean Prediction

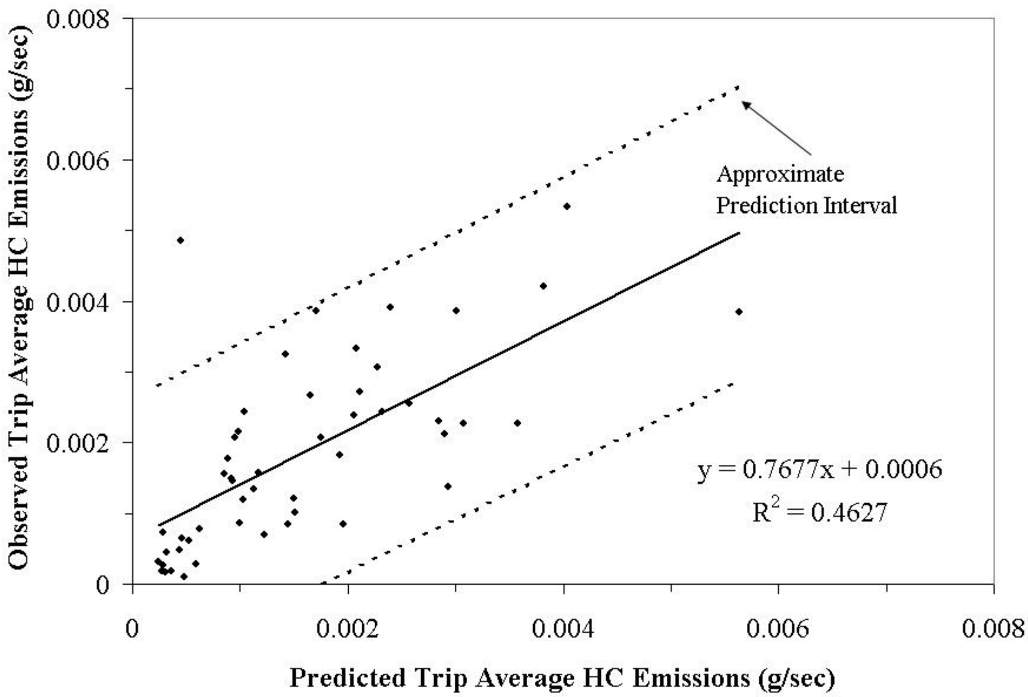


Figure 3-20. Observed versus Predicted Trip Averages for HC Emissions with 95 % Confidence Interval on the Individual Predictions

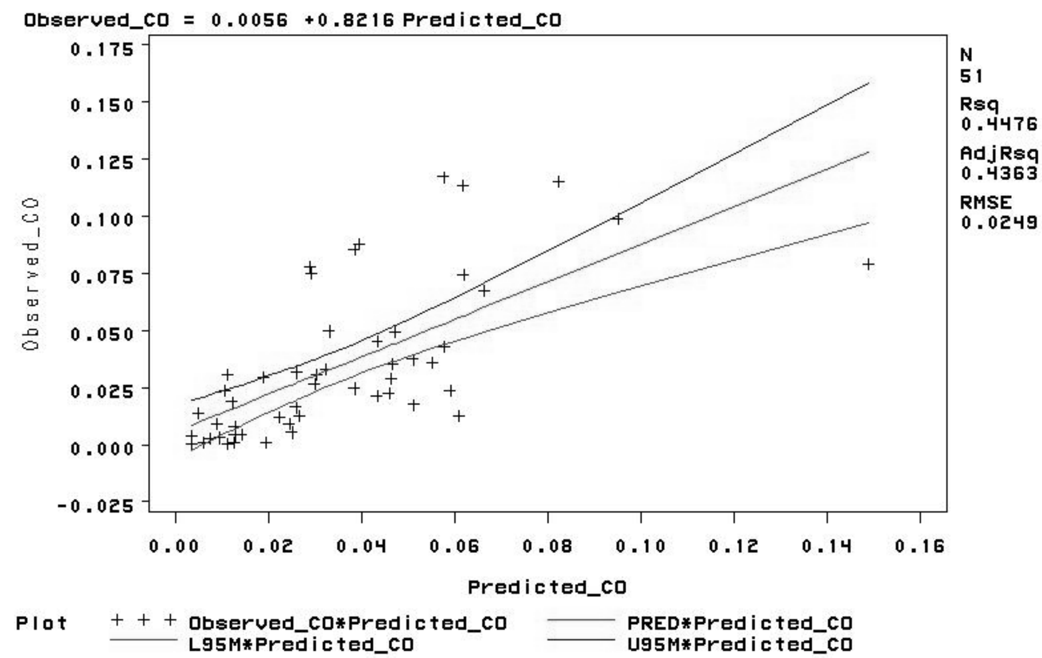


Figure 3-21. Observed versus Predicted Trip Averages for CO Emissions with 95 % Confidence Interval on the Mean Prediction

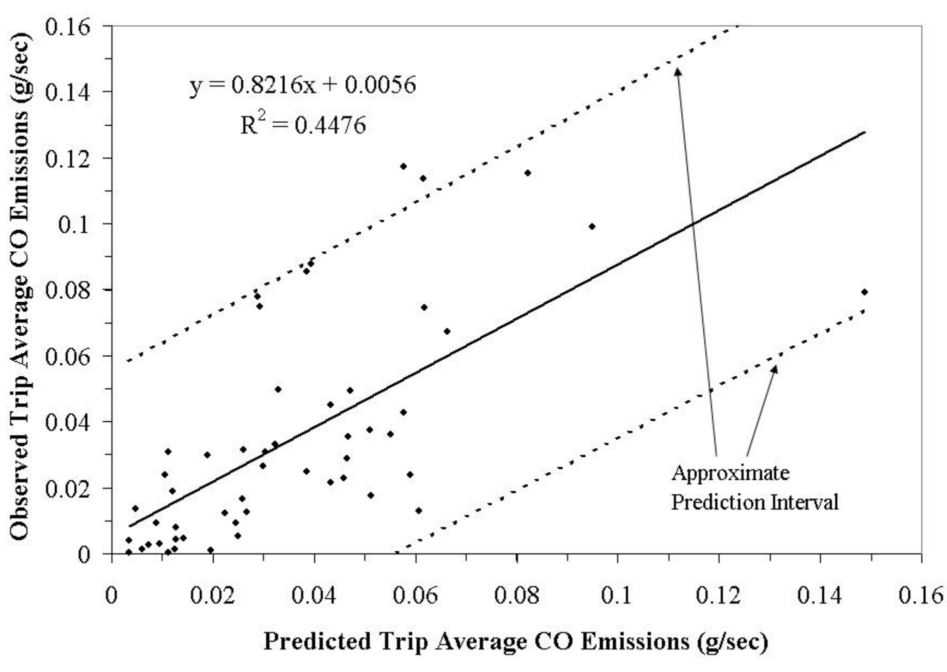


Figure 3-22. Observed versus Predicted Trip Averages for CO Emissions with 95 % Confidence Interval on the Individual Predictions

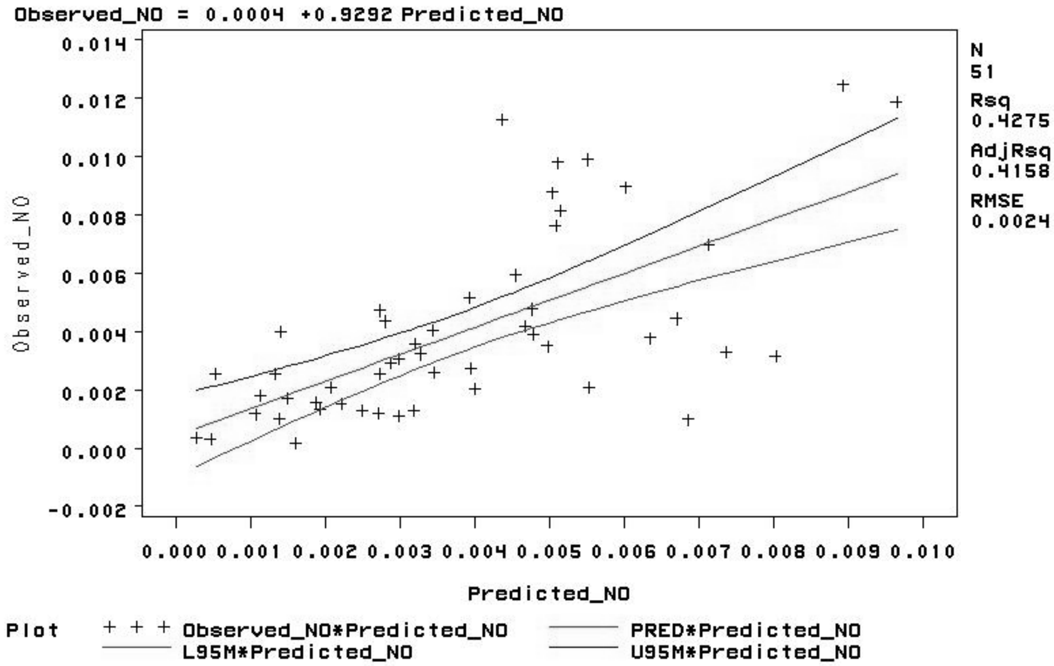


Figure 3-23. Observed versus Predicted Trip Averages for NO Emissions with 95 % Confidence Interval on the Mean Prediction

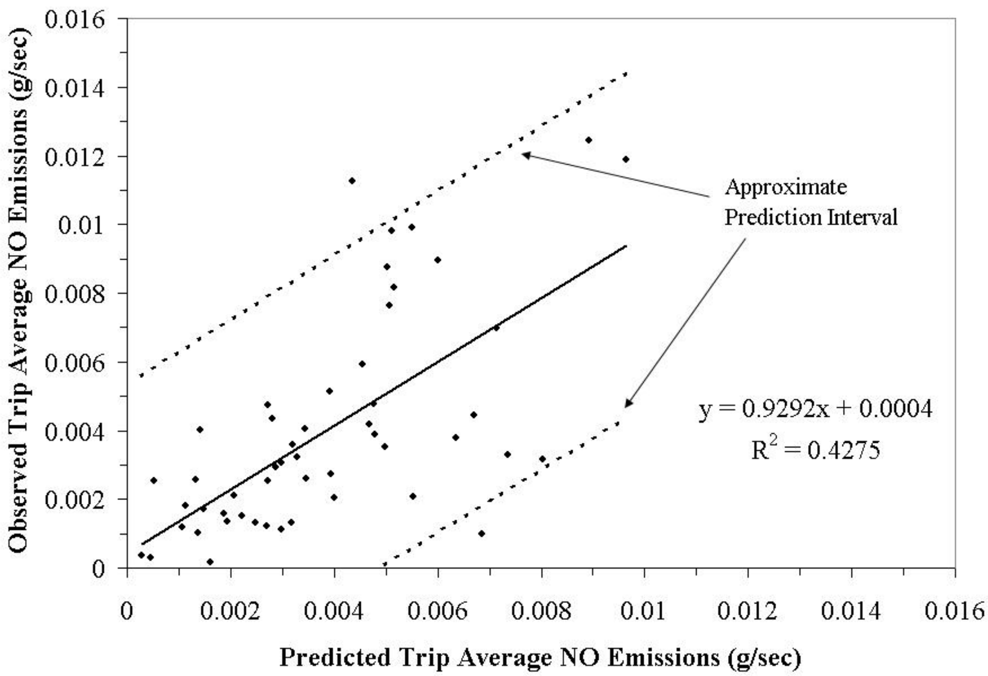


Figure 3-24. Observed versus Predicted Trip Averages for NO Emissions with 95 % Confidence Interval on the Individual Predictions

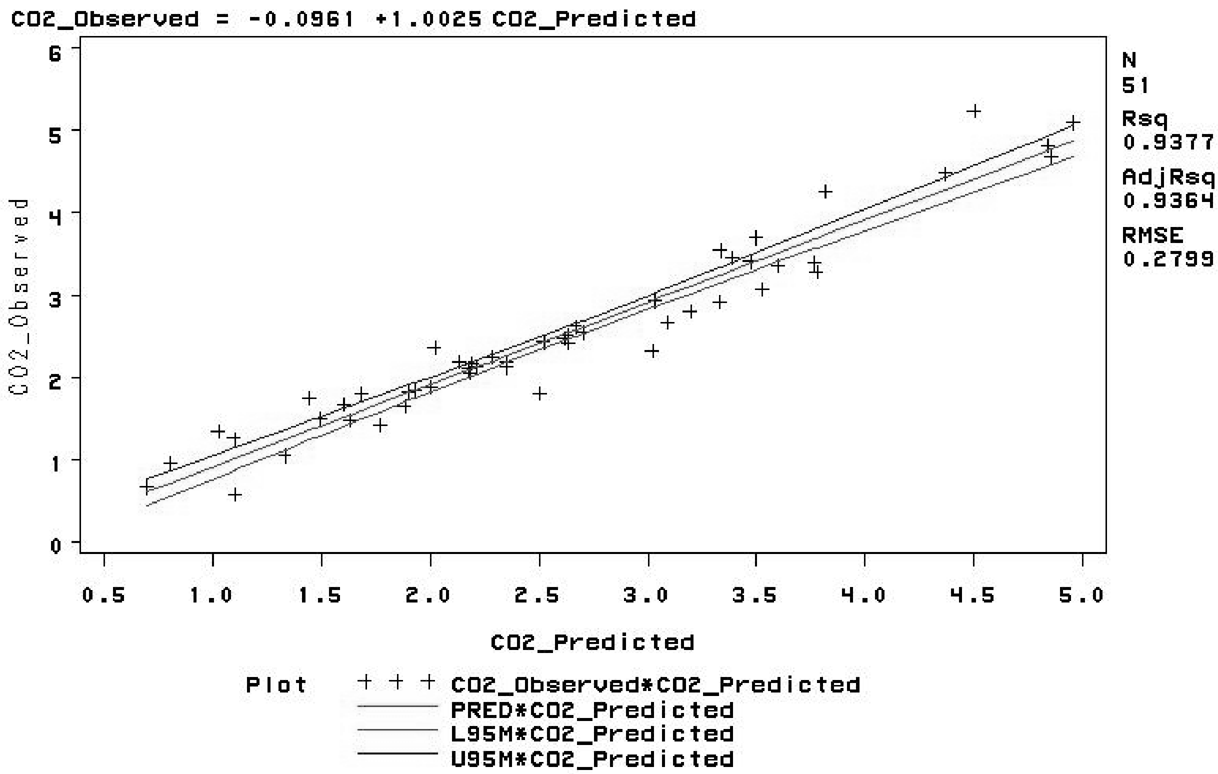


Figure 3-25. Observed versus Predicted Trip Averages for CO_2 Emissions with 95 % Confidence Interval on the Mean Prediction

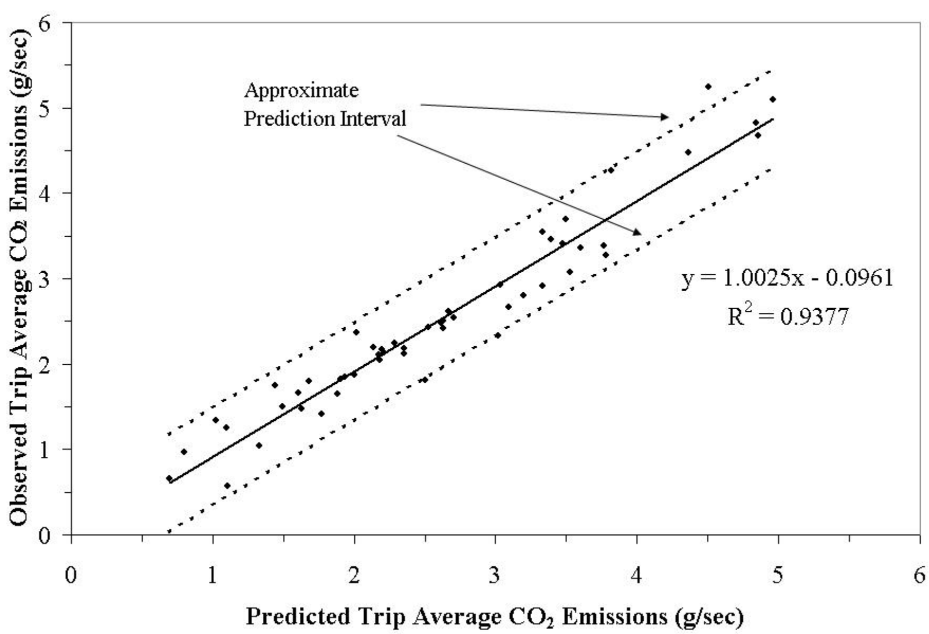


Figure 3-26. Observed versus Predicted Trip Averages for CO_2 Emissions with 95 % Confidence Interval on the Individual Predictions

Table 3-8. Summary for Uncertainty Analysis for the Model and Observed Data

	Uncertainty in the Mean Prediction			**Average Unexplained Variability in the Model**		
Pollutant	*Mean*	*Standard Error of the Mean*	*C.V.*	*Standard Deviation of the Residuals*	*Average of Observed Data*	*C.V.*
HC (g/sec)	0.002	9.01E-05	0.052	0.00097	0.002	0.52
CO (g/sec)	0.032	0.0029	0.092	0.025	0.035	0.71
NO (g/sec)	0.004	0.000302	0.082	0.0024	0.004	0.60
CO_2 (g/sec)	2.465	0.093	0.038	0.28	2.5	0.11

$$\mu_{ij} = \frac{\sum_{k=1}^{n} \mu_{ijk}}{n} \tag{3-9}$$

Where,

μ_{ij} : Average emissions rate for mode i (e.g., idle, acceleration) and pollutant j (e.g., HC, CO) given in g/sec

μ_{ijk} : Average emissions rate for mode i (e.g., idle, acceleration), pollutant j (e.g., HC, CO) and trip k (e.g., trip 1, trip 50) given in g/sec

n : Number of trips (i.e., 51)

The standard variance of the mean for each driving mode for each pollutant was similarly estimated based upon trip data using Equation (3-10):

$$\sigma_{ij}^{\ 2} = \frac{n\sum_{k=1}^{n}(\mu_{ijk})^2 + \left(\sum_{k=1}^{n}\mu_{ijk}\right)^2}{n(n-1)} \tag{3-10}$$

where,

$\sigma_{ij}^{\ 2}$: Standard variance of average emissions rate for mode i (e.g., idle, acceleration) and pollutant j (e.g., HC, CO) given in g/sec

The weights assigned to each of the driving modes for the purpose of calculating the standard variance in total trip emissions were estimated based upon the average time spent in each mode using Equation (3-11):

$$w_{ij} = \frac{\sum_{k=1}^{n} w_{ijk}}{n} \tag{3-11}$$

where,

w_{ij} : Average weight for mode i (e.g., idle, acceleration) and pollutant j (e.g., HC, CO) given as a fraction of time.

w_{ijk} : Average weight for mode i (e.g., idle, acceleration), pollutant j (e.g., HC, CO) and trip k (e.g., Run 1, Run 50) given as a fraction of time.

After getting the average emission rates for each mode for each pollutant, and the corresponding weight, the overall average emission rate for each pollutant was estimated using the properties of mean as given in Casella and Berger (1990) in Equation (3-12):

$$\mu_j = \sum_{i=1}^{4} \left(w_{ij} \times \mu_{ij} \right) \tag{3-12}$$

where

μ_j : Average emissions rate for pollutant j (e.g., HC, CO) given in g/sec

Similarly, the standard variance of the total trip emissions were estimated from the modal emissions standard variances using the properties of variances as given in Casella and Berger (1990) in Equation (3-13):

$$\sigma_j^{\,2} = \sum_{i=1}^{4} \left(w_{ij}^{\,2} \times \sigma_{ij}^{\,2} \right) \tag{3-13}$$

where

$\sigma_j^{\,2}$: Standard variance of average emissions rate for pollutant j (e.g., HC, CO) given in g/sec

In order to estimate the Coefficient of Variation (C.V.), the standard error of the mean is divided by the average value. The standard error of the mean was estimated based upon the square root of the standard variance, as shown in Equation (3-14).

$$C.V._j = \frac{\sqrt{\sigma_j^{\,2}}}{\mu_j} \tag{3-14}$$

where

$C.V._j$: Coefficient of variation estimated for pollutant j (e.g., HC, CO)

Table 3-8 summarizes the analysis of uncertainty in the mean prediction of the model. The uncertainty analysis is relevant to the application of the model to make predictions of fleet average emissions. The results for the coefficient of variation imply that the range of uncertainty in average predictions is approximately plus or minus 10 percent of the mean value for HC emissions. For CO emissions the 95 percent probability range is plus or minus 18 percent of the mean value, and for NO emissions this range is plus or minus 16 percent. The range of uncertainty in average predictions for CO_2 emissions is approximately 7 percent. Thus, the range of uncertainty for the average prediction of an emission rate is typically less than plus or minus 20 percent in all cases. These uncertainty ranges are applicable to predictions near the average of all of the trip emissions. The uncertainty ranges would be wider on an absolute basis for predictions for trip emissions lower or higher than the average trip.

In contrast to an assessment of uncertainty in fleet average emissions, if the model were to be used to make predictions of emissions for an individual trip, then the lack of precision of the model is reflected by the unexplained variability not captured by the model. The results of the analysis of unexplained variability imply that the 95 percent prediction interval for an individual trip is more than approximately plus or minus 100 percent on average for HC, CO, and NO emissions. For CO_2 , this range is plus or minus 22 percent. Thus, there is substantially more imprecision in model predictions when applied to individual trip emissions than fleet average emissions.

3.4 Summary of the Developed Model

This chapter has illustrated the major steps in the development of a modal model of real-world tailpipe emissions using data obtained from on-board measurements.

There are key steps in model development that were not part of the scope of work at NCSU. These include defining a study objective, developing a study design, and executing the study design in all of its elements. The key characteristics of study design are addressed in detail in Chapter 8.

The key steps in model development that were part of this study include the formation of a database from data reported by the on-board emissions contractors (or EPA), data quality assurance and quality control, exploratory analysis of the data, and fitting of a model to the data. The QA/QC activities included searching for common types of errors that can occur when using on-board instruments. In some cases, some data were excluded from the final database in order not to include known or suspected errors in the analysis and model calibration effort. Exploratory analysis included a variety of techniques. The first was development of a summary of the content of the database, including average values and other information. Variability in the emissions data between vehicles and between vehicle-trips was evaluated. Possible explanatory variables were identified. Methods for visualizing the data, such as using multiple scatter plots, were employed to help in identifying patterns in the data. Data were also analyzed spatially using GIS methods. Statistical methods were employed for identifying cold-starts in each trip data set.

Because of the autocorrelation in the data, and the difficulty in working with time series models, an approach based upon binning of the data to reduce the influence of autocorrelation was pursued. The approach involves definition of driving modes for hot stabilized operation based upon criteria applied to the speed trace associated with the trip. The criteria include specific conditions of speed and acceleration, sometimes involving multiple seconds of data. The statistical significance of comparisons of the average emissions for each pollutant among the four hot stabilized modes of idle, acceleration, deceleration, and cruise was assessed. These four driving modes are typically statistically significantly different from each other for a given pollutant with respect to the average emission rates. Therefore, the modal definitions are confirmed to have useful ability to explain differences in vehicle emissions based upon different types of vehicle activity during real-world driving.

HBTR methods were used to determine whether the four driving modes should be subdivided into additional modes. In most cases, criteria for subdividing the modes based upon estimated power demand were found to provide additional capability to capture variation in the observed emissions data. The modal approach represents a mesoscale approach that can be easily aggregated to predict macroscale (e.g., trip average) emissions.

For each modal dataset, OLS regression techniques were applied to illustrate the development of additional explanatory capability with microscale second-by-second data. Because these data were segregated from the original time series into much shorter discontinuous time series, which in turn is expected to reduce the influence of autocorrelation, it was judged acceptable to use regression methods applied to the modal data.

The OLS regression models fit to the modal data offered some additional explanatory capability. These models are illustrative in nature. Some of the coefficients obtained from the analysis, such as for road grade, are not physically intuitive. However, this can be associated with lack of sufficient variability in candidate explanatory variables. The methodology is applicable to larger scale applications to larger databases. In most cases, the relationships obtained with OLS regression were reasonable and useful.

Cold start emissions received attention in this work. Because the average emission rate during cold start is comparable to that of acceleration and large in magnitude compared to other modes, and because cold start can contribute to a substantial fraction of total trip emissions, it was justifiable to devote considerable effort to developing and exploring methods for characterizing cold start emissions. A statistical method for estimating the duration of cold starts was developed, tested, and found to be useful. A statistical relationship regarding soak time and cold start duration was explored. A regression approach with time series errors, which is different than time series applied to predictive variables, was employed as a means for improving the explanatory power the cold start mode.

The performance of the models were evaluated using parity plots and statistical intervals with respect to a trend line. Two types of statistical intervals were developed. One type of interval, which we refer to as a prediction interval, represents the unexplained variability in observed emissions that is not captured by the model. This measure of precision is important to consider when making predictions for emissions for individual trips. The other interval, which we refer to as a confidence interval, represents the 95 percent confidence interval on the mean prediction. This interval is applicable to estimating model precision when making predictions for average emissions over a sufficiently large fleet. The prediction interval is needed in this study when making comparisons between model predictions and observed values in the validation case study described in Chapter 6.

Overall, the techniques applied to develop the illustrative conceptual model were useful in screening the data, creating a data base, exploring the data base, developing the model, characterizing model performance, and quantifying the variability and uncertainty in model predictions. These techniques can be applied to larger data sets than were available in this work for the purpose of developing a nationally representative model of LDGV tailpipe emissions.

4.0 CONCEPTUAL MODELING APPROACH FOR HEAVY DUTY DIESEL VEHICLES

In this section, the conceptual model development approach for Heavy-Duty Diesel Vehicles (HDDV) is presented. On-board data for selected HDDVs were provided by EPA as the basis for developing and demonstrating a methodology for modeling CO, NO_x, HC, and CO_2 emissions. NCSU had no control over study design or data collection pertaining to the HDDV data.

The following section presents data post-processing methods that were required to form an accurate emissions and explanatory variables database. Quality checks were also conducted on data in order to identify and remove any errors from the database. Exploratory analysis of the data is described in Section 4.2. Section 4.3 describes the development of conceptual model. A summary of the development and demonstration of the model is given in Section 4.4.

4.1 Data Post-Processing

In this section, methods for data post-processing are discussed for heavy-duty diesel vehicles (HDDV). This work was important in developing an accurate database, and it included developing protocols for data post-processing, discussion of possible errors in the dataset, and methods for making corrections.

4.1.1 Database Formation

Data for Light-Duty Diesel Vehicles (HDDV) were provided by EPA to NCSU in comma delimited format. These files were converted into Microsoft Excel™ format since Microsoft Excel™ was used as the main environment for data analysis and model development.

A total of 12 files were provided for the purpose of model development. Each file represents data collected with different vehicle. Four of these vehicles are of model years of 1995 and the rest are 1996. All vehicles have the same engine properties. For example, all engines are 8.5 liter. All vehicles have oxidation catalyst. The buses were reported to have been operated on regular routes, but it was also reported that the buses did not board or discharge any passengers during data collection.

Preliminary analysis of individual files indicated that the format of the files was the same for all of the vehicles. Therefore no post-processing was needed for formatting. The data fields included in each file are summarized in Table 4-1.

Each Excel file includes data for one vehicle driven on one trip. Some of the trips have more than 2 hours of data or over 7,200 seconds of data. In order to approximate averaging times that might be more appropriate for air quality modeling or other purposes, data for each vehicle was separated into trips of half an hour. After this processing, there were 54 “trips” for the HDDV database.

Table 4-1. List of Parameters given in HDDV Data Set Provided by EPA

Category	**Parameters**
Vehicle Characteristics	Engine Size; License number; Instrument configuration number
Ambient Conditions	Relative humidity (in both %, grains/lbair units); Ambient temperature (°C); Barometric pressure (in mbar)
Roadway Characteristics	Latitude (degree); Longitude (degree); Altitude (feet); Grade (%)
Vehicle Activities	Coolant Temperature (°F); Engine load (%); Percent throttle (%); Date; Time; Vehicle speed (mph); Engine RPM; A/C (on/off); Fuel Consumption rate (in gallon/sec, grams/sec, and miles/gallon units); Oil temperature (^{0}F); Oil pressure (kPa); Engine pressure (kPA); Exhaust flow (scfm); torque (lb-ft); Brake horse power (bhp)
Vehicle Emission	HC, CO, NO, CO_2 and O_2 emission (in PPM, g/sec, g/kg fuel, g/bhp-hr units)

In the next step of data-processing, variables that might be helpful in explaining variability in vehicle emissions, but that were not provided in the original dataset, were estimated. These variables include acceleration and power demand. Methods explained in Section 3.1.1 were utilized for this purpose.

4.1.2 Data Quality Assurance/Quality Check

For quality assurance purposes, the data set for each vehicle trip was screened to check for errors or possible problems. In developing an experimental design one should consider possible sources of errors for data collection. Since the experimental design in this study was not developed by NCSU, the NCSU study team had not control over these errors. Therefore, in this study, the focus was to check for errors and correct them is possible. The types of errors checked are similar to the ones explained in Section 3.1.2.

Loss of Data: After checking the database for loss of data, it was observed that some trips had cases where HC emissions are missing for more than 100 seconds. For example, Vehicle 1 Trip 1 had missing HC data for 343 seconds. Vehicles 2, 9, and 11 have similar problem. No correction has been done for this problem.

Negative Emissions Values: As explained in Section 3.1.2, sometimes emissions are reported as negative, because of random measurement errors. It was observed that for some trips NO emissions had negative data for the concentration column presented in ppm units. However, the corresponding g/sec column for these data have zero emissions. Therefore there are no negative data as g/sec in the database. Since g/sec data are used for analysis no correction has been done for ppm data.

Synchronization Errors: Data were checked for synchronization errors data. An example of synchronization check is given in Figure 4-1 for Vehicle 1 Trip 1. As seen in Figure 4-1 there is no synchronization error for HDDV data. This is indicated by the sharp rise in CO emissions

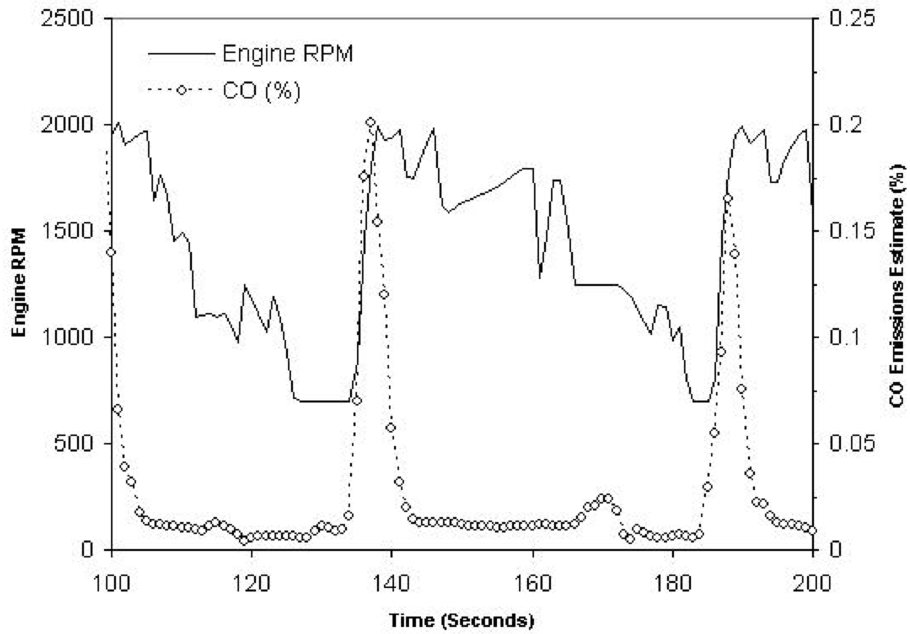


Figure 4-1. Comparison of Engine RPM with CO Emissions for Checking the Presence of Synchronization Error for Vehicle 1 Trip 1

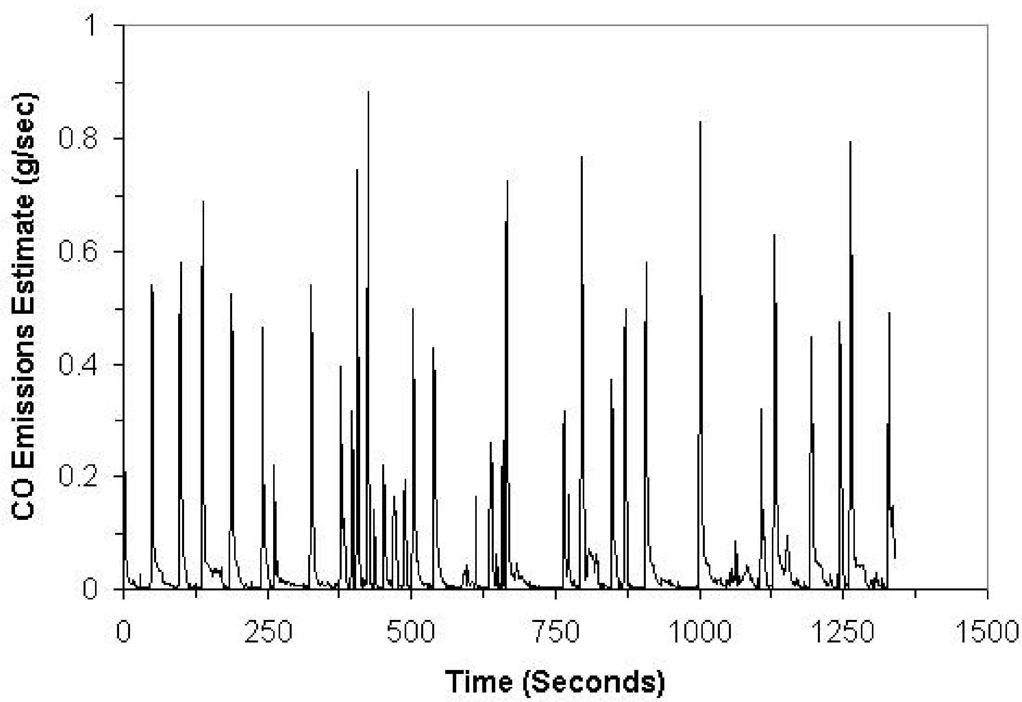


Figure 4-2. Example Check for Drift Error for Vehicle 2 Trip1 for CO Emissions

concurrent with a sharp rise in engine RPM at approximately 135 seconds into the trip and again at approximately 190 seconds into the trip.

Freezing of instrument: The database for HDDV was checked for data freezing. However, no error was identified for this kind of problem.

Drift in data: Another type of possible error is a drift in emissions data. HDDV data were checked for this type of error. Example check for Trip 1 is given in Figure 4-2 for CO emissions.

As seen in Figure 4-2, the minimum CO emissions do not have any upward or downward trend. The average of CO emissions stays approximately the same throughout the trip. Another finding from this analysis is that there is not any cold-start process for HDDV data. There is not any part of the trip in which CO emissions were substantially higher than for the rest of the trip as in the case of LDGV. Therefore, in analysis of HDDV data, CO emissions for the entire trip were treated as generated from a hot-stabilized process.

4.2 Exploratory Analysis

After database formation and screening the data for errors, an exploratory analysis was conducted to better understand the variability of vehicle emissions and the basic trends between explanatory parameters and vehicle emissions for HDDV data. This exploratory analysis was a necessary step before developing any relationships between vehicle emissions and explanatory variables.

This section first presents summary of the data provided for emissions and engine related parameters. Then variability in the emissions data is presented. Scatter plots were utilized for data visualization purposes. Finally, the findings of the exploratory analysis are summarized.

4.2.1 Data Summary

After the post-processing procedure was completed, 54 valid trips were obtained for 12 different buses. An example of the summary of the emissions and activity data as well as environmental and roadway characteristics is given for all vehicles in Table 4-2. Table 4-2 presents a summary of combined data for vehicles.

The data in Table 4-2 were divided into several categories. These categories were: vehicle characteristics; parameters related to vehicle operation; environmental characteristics; and roadway characteristics.

There are 12 vehicles as shown in Table 4-2. The duration of data collection ranged from 5,283 seconds to 10,347 seconds. The slowest average speed occurred for Vehicle 13, with an average speed of 13 mph, whereas the fastest average speed occurred for Vehicle 11 with an average of 23.6 mph. Ambient weather conditions during these trips were similar. The average temperature ranged between 17 ^{o}C and 26 ^{o}C and the average humidity varied between 24 percent and 53 percent. Changes in operation conditions, as well as changes in environmental conditions and roadway conditions, resulted in differences in average emissions. For HC emissions, the highest average emission rate is more than 12.7 times higher than the lowest average emission rate. This ratio is smaller for other pollutants: 3.2 for CO; 1.36 for CO_2; and 2.8 for NO. These results

Table 4-2. Summary of Data for HDDV Database

Bus No	1	2	4	5	6	7	8	9	10	11	14	15
Bus Characteristics												
License	382	384	386	383	381	380	379	377	363	361	372	364
Engine Displacement	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5	8.5
Vehicle Operation												
Average Speed (mph)	19.9	18.2	17.3	18.2	16.3	13.0	15.1	12.1	13.8	23.6	21.4	17.7
Average Engine Load (%)	37.4	29.9	31.1	32.6	31.0	33.5	39.8	35.4	31.5	38.2	39.2	36.3
Average RPM	1219	1133	1164	1118	1146	1093	1182	1127	1138	1241	1171	1194
Average Calculated Engine Power (bhp)	85.21	64.15	62.93	67.19	65.61	72.90	84.75	77.34	64.34	83.35	72.31	77.02
Average Torque (ftlbs)	294	231	231	244	231	247	298	262	236	303	288	274
Average Throttle (%)	4	3	3	3	3	3	3	3	3	4	3	3
Average Coolant Temperature (F)	176	179	180	180	190	188	183	182	181	147	165	186
Average Fuel (g/sec)	3.382	2.538	2.511	2.658	2.790	2.986	3.208	2.980	2.468	2.993	2.975	2.861
Average HC (g/sec)	0.0015	0.0019	0.0015	0.0018	0.0006	0.0011	0.0018	0.0006	0.0003	0.0013	0.0024	0.0034
Average CO (g/sec)	0.0528	0.0362	0.0470	0.0262	0.0342	0.0524	0.0307	0.0283	0.0217	0.0181	0.0166	0.0206
Average CO2 (g/sec)	10.9199	8.2025	8.0378	8.6010	9.0960	9.8224	10.5254	9.7097	7.9950	9.6236	9.4992	9.2206
AverageNO (g/sec)	0.1749	0.1296	0.1247	0.1349	0.1028	0.1077	0.1086	0.0769	0.0628	0.1702	0.1058	0.1410
Environmental Characteristics												
Average Ambient Temperature (C)	22	18	20	21	22	24	24	26	26	17	21	21
Average Ambient Pressure (mbar)	995	993	986	984	988	973	974	973	966	971	982	985
Average Humidity (%)	25	24	35	40	38	51	53	47	58	31	29	31
Roadway Characteristics												
Average Latitude (degree)	42.250	42.245	42.249	42.228	42.274	42.250	42.259	42.253	42.280	42.304	42.260	42.235
Average Longitude (degree)	-83.662	-83.755	-82.685	-83.762	-83.728	-83.719	-83.706	-83.698	-83.752	-83.929	-83.691	-83.648
Average Altitude (feet)	257.5	268.3	241.1	271.0	271.3	279.7	236.1	264.2	270.8	263.0	201.3	244.1
Time of Day	9:21AM	14:30AM	8:53AM	1:21 PM	3:24 PM	3:26 PM	7:09 PM	12:27 PM	5:34 PM	7:58 AM	8:03 AM	1:07 PM
Day of Week	Wed	Wed	Fri	Fri	Mon	Tue	Tue	Wed	Wed	Thur	Fri	Fri
Number of Seconds of Data	3140	8461	10347	7951	7295	8023	7888	8091	8069	5644	5283	5688

indicate that there is some variability in the data. The next section will present this issue in more detail.

4.2.2 Variability in Emissions Data

In this section, data are presented to illustrate the variability in observed data. For this purpose, trip-average emissions rates were utilized. First inter-vehicle variability is presented. In estimating inter-vehicle variability average emission rates were estimated for each vehicle using the trip-based averages. Since for each vehicle the data were divided into multiple time periods based upon an example averaging time of 30 minutes, confidence intervals for the mean were estimated based upon this averaging time. For some vehicles, confidence intervals were wider due to fact that the number of trips is small. For example for Vehicle 1 there were only two trips, whereas there were six trips for Vehicle 4. Figure 4-3 presents inter-vehicle variability for CO emissions. Inter-vehicle variability for other pollutants are given in Appendix A. For most of the vehicles, average CO emissions are not statistically significantly different from each other since the confidence intervals are very wide due to the small number of trips. However, some vehicles are emitting more than others. For example, the average CO emission rate for Vehicle 7 is statistically significantly higher than the average CO emission rate for Vehicles 2, 5, 6, 8, 9, 10, 11, 14, and 15. It seems from Figure 4-3 that there are three different clusters of average CO emissions. Vehicles 10 trough 15 seems to emit the lowest average CO emissions. Vehicles 5, 6, 8, and 9 seem to be moderate emitters, whereas Vehicles 1, 2, 4, and 7 seem to have the highest emissions on a relative basis. However, this trend is not present for other pollutants.

Inter-trip variability was also analyzed for HDDV data. The purpose of this analysis was to characterize the range of variability in trip average emissions among all of the vehicles, to determine whether the data set is relatively homogenous, and to gain insight into whether all of the vehicles can be treated as one group for purposes of analysis and model development. The

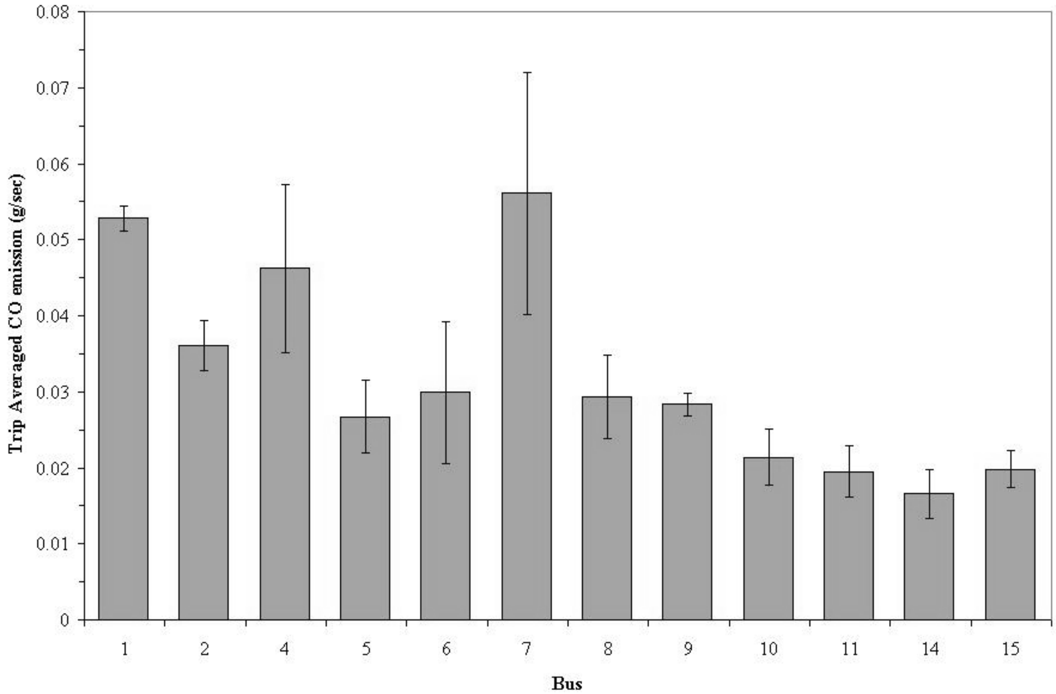


Figure 4-3. Trip-Based Mean CO Emission Rates for Heavy-Duty Diesel Vehicles

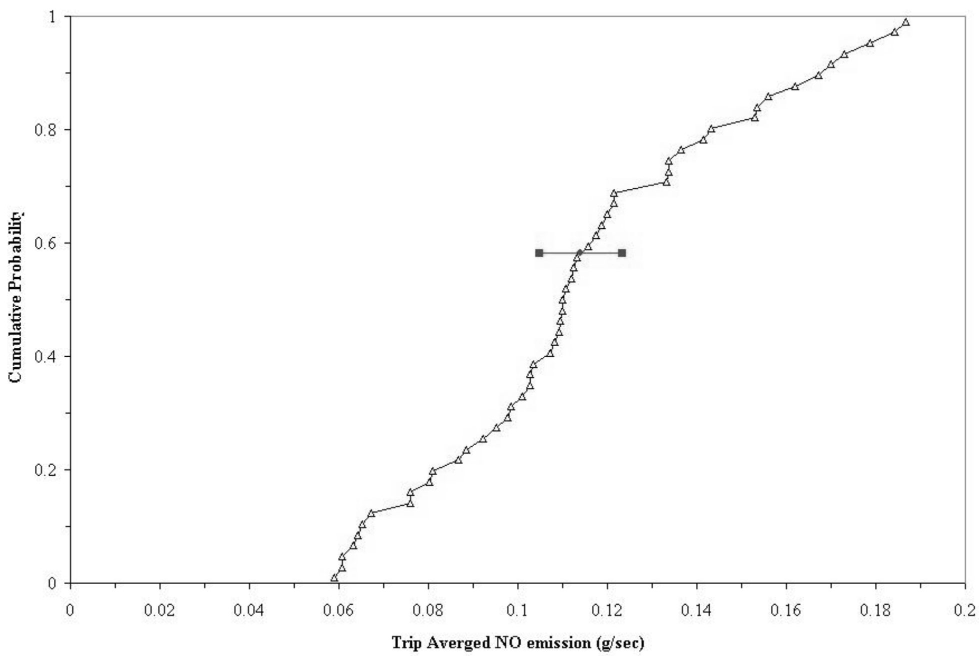


Figure 4-4. HC Inter-Trip Variability and Mean Estimate for Heavy-Duty Diesel Vehicles

trip average NO emission rate was 0.114 g/sec for 54 trips (averaging periods) conducted with 12 different vehicles. The 95 percent confidence interval for the mean value ranges from 0.105 g/sec to 0.123 g/sec, or a range of approximately plus or minus 7 percent. Approximately 90 percent of the values are below 0.17 g/sec. Most of the emissions estimates are within a range of an order-of-magnitude (e.g., ranging from 0.06 to 0.18 g/sec over a 95 percent probability range). In Figure 4-4, the cumulative distribution function of the data is approximately a straight line for several portions of the data which indicates that these data are approximately piecewise uniformly distributed. Although there is some skewness in the distribution as suggested by the upper tail, there are no data points that are obvious outliers. Thus, there are no obvious "high-emitter" cases in this data set. Therefore, this data set is deemed to be sufficiently homogeneous that all of the vehicles within it can and should be treated as a single group for purposes of analysis and model development. It should be noted that there are some vehicles that have as much variability among trips as is observed in the overall dataset.

Similar results were obtained for CO, HC and CO_2 emissions. Most of the emissions estimates are within a range of an order-of-magnitude for all of these pollutants. For CO, emissions range from 0.014 to 0.059 g/sec over a 95 percent probability range. For CO_2, this range is between 5.3 to 11.9 g/sec. Emissions for HC ranges from 0.0002 to 0.003 g/sec over a 95 percent probability range. Probability distributions for CO, CO_2, and NO are given in Appendix A.

4.2.3 Identification of Explanatory Variables

In this section, factors influencing vehicle emissions are summarized as cited in the literature. There are mainly four groups of parameters that affect vehicle emissions as indicated by Guensler (1993). These groups are: (i) vehicle parameters; (ii) fuel parameters; (iii) vehicle operating conditions; and (iv) vehicle operating environment.

Vehicle Parameters

Vehicle parameters are related to vehicle technology and include vehicle class (i.e., weight, engine size, horse power), model year, vehicle mileage, emission control system. Studies have shown that vehicle class and weight are significantly related to vehicle emissions. For example, vehicle emissions increase as the vehicle weight increases (Clark *et al.*, 2002). The effect of other vehicle parameters, such as type of exhaust after treatment and vehicle age, were investigated in several other research projects (Hawker *et al.*, 1998; Clark *et al.*, 2000; Yanowitz *et al.*, 2000).

Fuel Parameters

Fuel differences might affect heavy-duty engine emissions significantly (NRC, 2000). As reported by Clark *et al*., (2002), fuel differences might account for 25 percent changes in NO_X emissions.

Vehicle Operating Conditions

Vehicle applications and duty cycles can have an effect on emissions as noted by Clark *et al.* (2002). The primary difference between different operations is the change in average speed and events requiring full engine power. Recent study by Clark *et al.* (2002) notes that changes in duty might have of an effect of ten percent increase in NO_x emissions.

For HDDV, equivalence ratio is one of the parameters that affects emissions the most. The brake mean effective pressure increases with equivalence ratio, so higher equivalence ratio corresponds to higher engine power output (Flagan and Seinfeld, 1988). CO and PM emissions drop sharply with increasing equivalence ratio, whereas HC and NO emissions drop sharply as equivalence ratio is increased above about 0.2, reaching relatively low levels at an equivalence ratio of about 0.4 (Degobert ,1995). Driver behavior and vehicle speed are two parameters that have significant effect on vehicle emissions since they have an effect on the power required from the engine (Clark *et al.*, 2002).

Vehicle Operating Conditions

Vehicle operating conditions include the environmental conditions under which the vehicle is operated, such as humidity, ambient temperature, and road grade.

There is little known about the effect of ambient conditions on HDDV emissions. EPA is currently conducting studies to answer this question (NRC, 2000).

Another parameter that can have an effect on vehicle emissions is road grade. Road grade affects vehicle emissions by impacting the load on the engine. As stated by Clark *et al*. (2002), road grade can increase NO_X emissions from HDDV by 250 percent.

Summary

In this section, variables influencing vehicle emissions were summarized. The explanatory variables available for model development represent many but not all of the key influences on emissions identified in the literature review. One of the constraints of this study is that the explanatory variables that are available for model validation purposes are only a subset of the explanatory variables available for model development. Therefore, the conceptual model will not include variables that are not available in the prediction dataset. The focus of this study was on using explanatory variables that are available in the prediction dataset or derived variables that can be estimated from the available ones, such as acceleration and power demand.

4.2.4 Data Visualization

In order to find relationships among the variables, data visualization was conducted for the database. For this purpose scatter matrices were prepared using S-Plus. In this section an example will be given for visualizing the relation between possible explanatory variables and NO emissions for Vehicle 1, as shown in Figure 4-5.

Explanatory variables plotted in this figure are: Vehicle Speed (mph); Vehicle Acceleration (mph/sec); Ambient Temperature (^{0}F); Humidity (grains/lb air); Altitude (feet); Grade (percent); Power Demand (mi^2/h^2.sec). HC emissions are reported in grams/second. For this figure, second-by-second data collected with Vehicle 2 are combined from five different trips making a total of 8462 data points.

The bottom row in Figure 4-5 gives the relation between NO emissions (i.e., y-axis) and explanatory variables. For example, the cell on the bottom left represents a scatter plot of NO

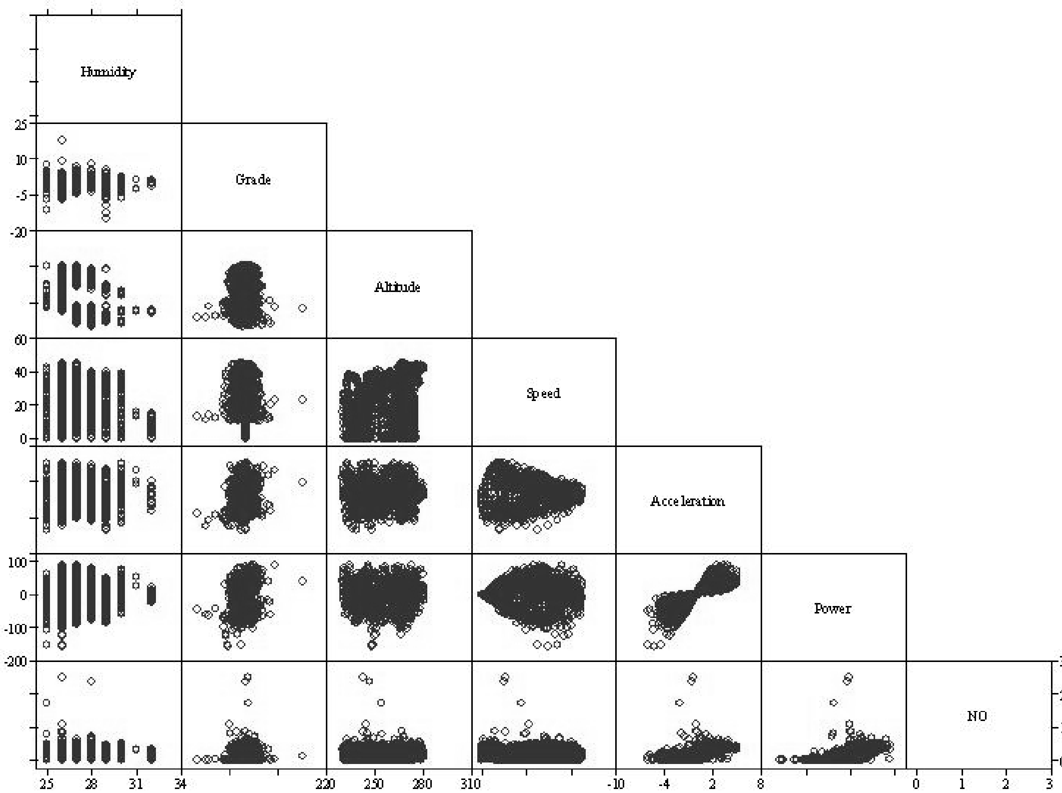


Figure 4-5. Example Scatter Matrix for NO Emissions for Data Collected with Vehicle 1

emissions versus humidity. As can be seen in the figure, the relationship between NO emissions and humidity is noisy. NO emissions tend to increase when road grade is positive and close to zero. The relationship between NO emissions and altitude is very noisy. The same is true for the relationship between speed and NO emissions. There is a positive increase in NO emissions as acceleration increases. NO emissions are low for negative power demand estimates. NO emissions tend to go up as power demand increases, but the largest NO emissions occur at less than the maximum power demand levels. This relation indicates the possible explanatory power of power demand for NO emissions.

There is a substantial amount of variability in emissions data and there is not any explanatory variable that directly explain a large portion of this variability. As in the case for LDGV data, several variables can explain some part of the variability. This means that one needs to look at a combination of explanatory variables in order to explain variability in emissions. For this purpose, both engineering and statistical techniques need to be applied.

4.2.5 Summary of Exploratory Analysis

In this section relationship between possible explanatory variables and emissions were investigated. This is a necessary step before any of the modeling efforts. The insights obtained from this section is utilized to build model as explained in the next section.

4.3 Model Development

The objective of this section is presented along with the requirements of the study. A summary of the model is given with comparison of observed versus predicted data using the model. Finally, a discussion of unexplained variability and uncertainty is given.

4.3.1 Objectives

In this study one of the objectives is to develop conceptual models for heavy-duty diesel vehicles for CO, HC, NO and CO_2 emissions using on-board emissions data provided by the U.S. Environmental Protection Agency. Developed models will be applied to a "validation" dataset and predictions for these datasets will be obtained. As discussed In Section 4.2.3, explanatory variables that were provided in the “validation” dataset will be fewer than the explanatory variables provided in the “modeling” dataset. Therefore, modeling attempts should take this aspect into account to develop models based upon variables available for prediction purposes.

Variables available in the “validation” dataset are: vehicle speed (mph); time/date; a/c (on/off); temperature (^oF); humidity (grains/lb air); ambient pressure (in Hg); latitude (deg); longitude (deg); and grade (percent). These variables and variables that can be estimated from these, such as power demand, are utilized in developing model for HDDV data.

Considerations for autocorrelation in the data provided that were given for LDGV data are also applicable for HDDV data, since these data are also time series. Therefore, one needs to be careful when working with classical statistical models, such as OLS regression, with these data.

For HDDV data, an approach similar to the LDGV modeling method given in Section 3.3.1 is taken. OLS regressions were fit to data at the end nodes of regression trees that were formed from modal analysis. The next section explains the modal analysis conducted for these data. Improvements to modal definitions were made. Results are given for OLS regressions fit to the data with specific modes.

4.3.2 Data Segregation Using Modal Analysis Approach

For modal analysis, mode definitions similar to those for the LDGV data, as given in Section 3.3.3, were utilized. Since there is no cold-start for HDDV data, there are four modes: idle; acceleration; deceleration; cruise. A program was written in Microsoft Visual Basic that determined the driving mode for second-by-second data and estimated the average value of emissions for each of the driving modes. The program also calculated the total emissions for the trip (averaging time period).

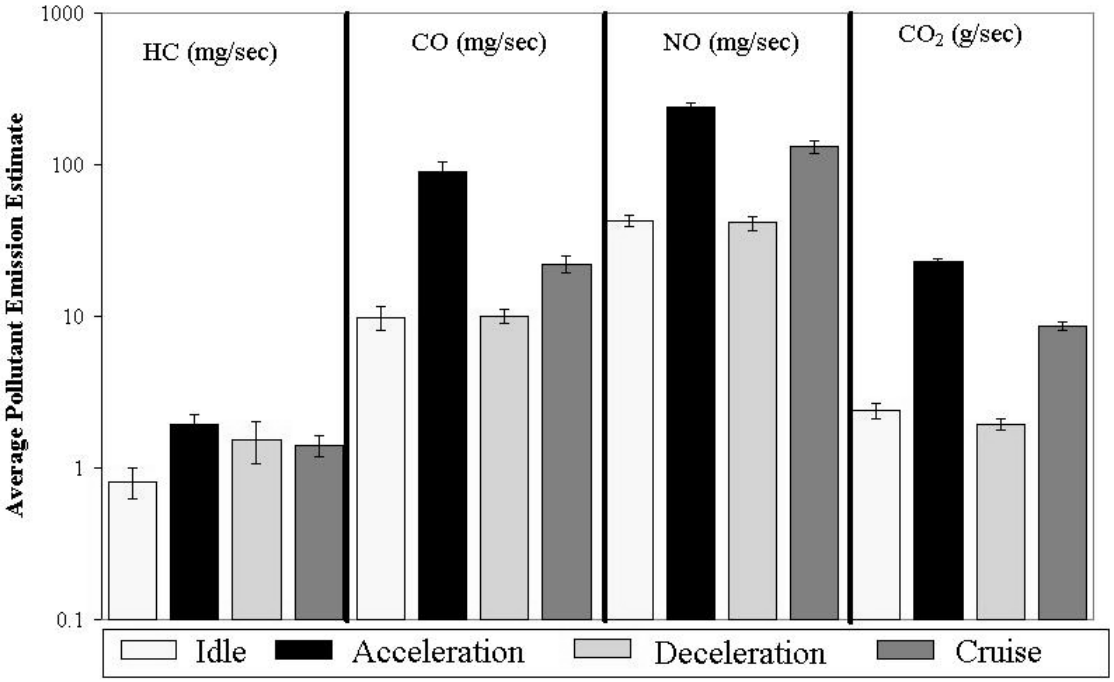


Figure 4-6. Average Modal Emission Rates for All Trips for HDDV

Table 4-3. Result of Pairwise Comparison for Modal Average Estimates in terms of p-value

P-Values for Pairwise T-test				
	Modes	*Acceleration*	*Deceleration*	*Cruise*
HC	*Idle*	0.000	0.006	0.000
	Acceleration		0.146	0.004
	Deceleration			0.617
CO	*Idle*	0.000	0.895	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000
NO	*Idle*	0.000	0.590	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000
CO_2	*Idle*	0.000	0.008	0.000
	Acceleration		0.000	0.000
	Deceleration			0.000

In order to see whether modal analysis has an explanatory power or not, average modal emission rates were estimated for each trip. Then the average of these estimates was calculated for all of the trips. Figure 4-6 presents a comparison of average modal emission rates for different pollutants. The comparison includes 95 percent confidence intervals on the mean emission rates.

The average emissions during the acceleration mode were significantly higher than for any other driving mode for all of the pollutants, except for HC. Conversely, the average emission rate during idling was the lowest of the four modes for all four pollutants. The average cruising emission rate was typically higher than the average deceleration emission rate, except for HC emissions. In order to check whether the average modal emission rates were statistically significantly different from each other, pairwise t-tests were estimated. Results of the t-tests are presented in Table 4-3 in terms of p-values. The cases where the p-value is less than 0.05 indicates that a particular pair has statistically significant differences in the average estimates. For example, the t-test between idle and acceleration modes for HC emissions produced a p-value of 0, indicating that average HC emissions are different between two modes. Out of 24 possible pairwise comparisons, only four of them gave p-values higher than 0.05, indicating that average emissions rates for these pairs are statistically not different from each other. Two of these cases occurred for HC emissions, between the deceleration and acceleration pair, and between the deceleration and cruise pair. The other two occurred between the idle and deceleration modes for both CO and NO emissions.

The modal emissions analysis results suggest that the *a priori* modal definitions assumed here are reasonable. These modal definitions do allow some explanation of differences in emissions based upon driving mode, as revealed by the fact that, in most cases, the average modal emission rates differ from each other. However, for HC, there is relatively little variability among the four modes. As described in Section 2.2.1, HC emissions are expected to be relatively constant, on average, in contrast to the other pollutants.

4.3.3 Improving Driving Mode Definitions

The modal definitions given in this study have a power to explain variability in emissions since average emission rates for different modes are found to be statistically significantly different from each other. In this study, further improvements for modal definitions were obtained using the HTBR method as explained in Section 3.3.4. For this purpose, explanatory variables related to vehicle operation and vehicle characteristics such as vehicle speed, acceleration, power demand, road grade and vehicle model year were utilized.

After analyzing the results from HTBR analysis, it was determined that acceleration equal to 2 mph/sec should be used as a cutoff point for acceleration mode for CO emissions. For other pollutants no reasonable cutoff variable was found that provided any useful improvement.

In order to see whether the newly identified modes have potential benefit in explaining variability in CO emissions, the average modal emission rates for the new modes were estimated and are compared in Figure 4-7. The highest average CO emission rate occurs for the high acceleration mode. The next highest average emission rate is for the low acceleration mode. The cruise mode has the third highest average emission rate. The 95 percent confidence intervals on the mean modal emissions are also shown in Figure 4-7. Since the confidence intervals for the mean are not overlapping, except for the idle and cruise modes, it can be concluded that by dividing the acceleration mode into two parts, the modal analysis is improved.

Another important aspect of modal analysis is the distribution of time and total emissions with respect to modes. For this purpose, the distribution of time and emissions were estimated for each averaging time period. The average of these distributions was estimated. Figure 4-8 presents a bar chart with the result of this analysis.

In addition to developing modes that are statistically significantly different from each other, another consideration in model development is to create modes that are useful in explaining a

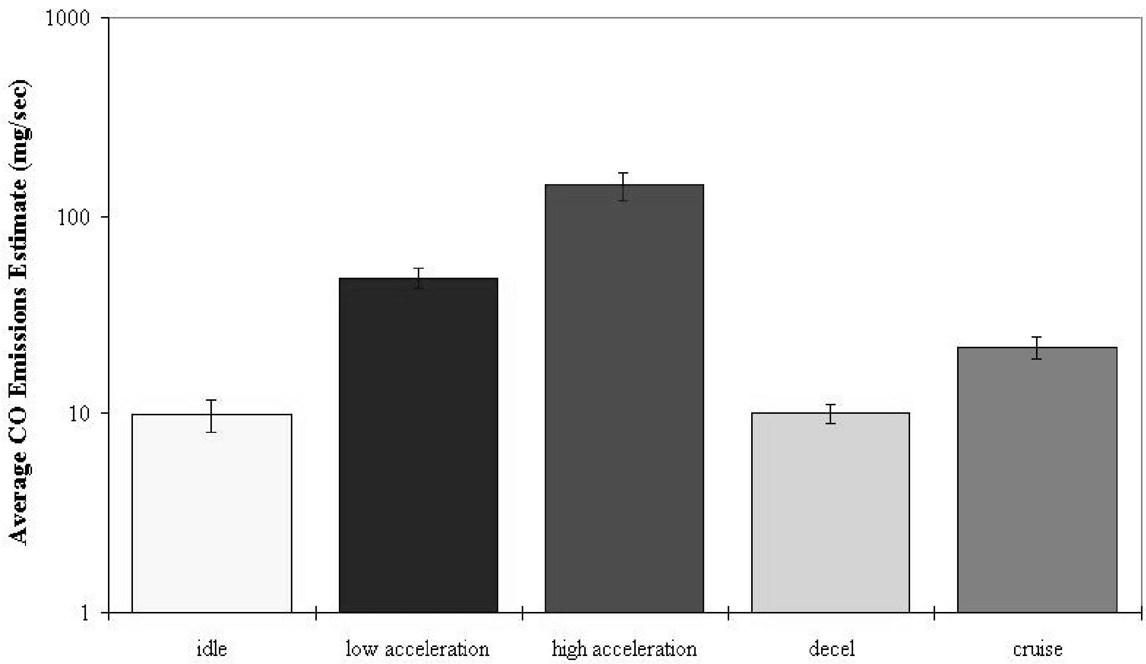


Figure 4-7. Improved Modal Emission Rate for All Trips for CO

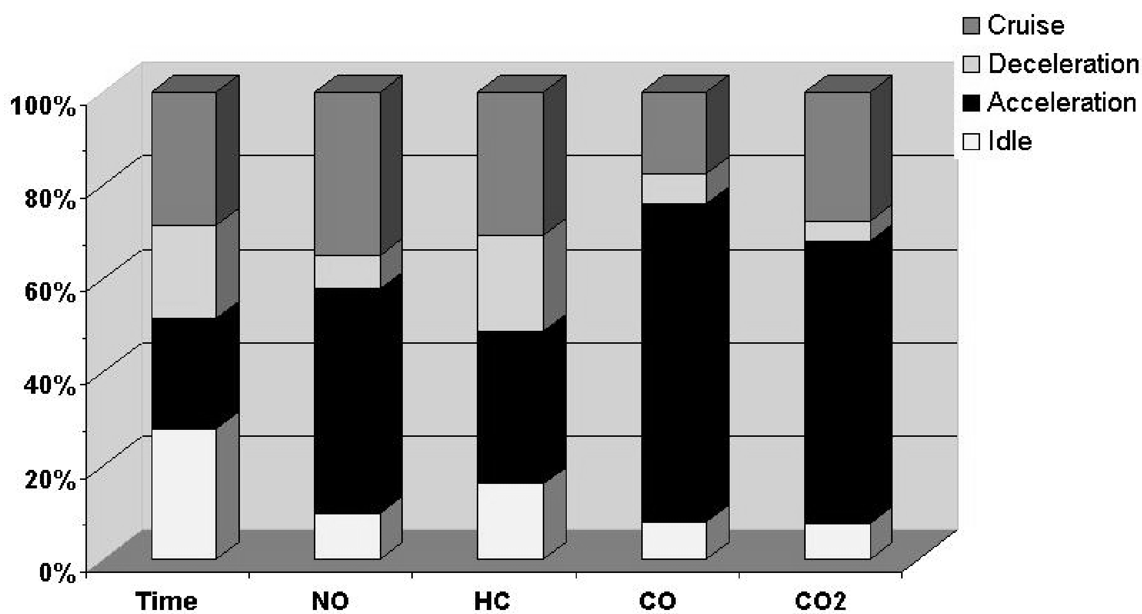


Figure 4-8. Average Distribution of Time and Emissions with respect to Modes

substantial contribution to total trip emissions. Figure 4-8 illustrates the distribution of time spend in each of the four original modes, and the corresponding percentage contribution of each mode to total trip emissions for each of four pollutants. As observed in Figure 4-8, the trip time is approximately equally divided among the four principle driving modes. However, the total emissions are not equally divided among the modes. The acceleration mode comprises a larger proportion of total emissions compared to its proportion of trip time. For example, for CO, acceleration contributes approximately 60 percent of the total emissions for the trip even though it represents only approximately 20 percent of the trip time, on average. Acceleration contributes more than 40 percent of the total average NO emissions, almost 60 percent of total CO_2 emissions, and approximately 30 percent of total HC emissions. In contrast, the idle mode comprises more than 20 percent of the duration of the trip but less than 10 percent of NO, CO, and CO_2 emissions, and approximately 15 percent of the HC emissions. The deceleration mode also contributes a smaller share to total emissions compared to its share of time in the trip. The cruising mode contributes approximately its time-based share to total emissions, but the specific contribution varies. For example, cruising contributes approximately 35 percent to total NO emissions, 30 percent to HC emissions, and 30 percent to CO_2 emissions, but only 20 percent to HC emissions. Overall, the key implication of Figure 4-8 is that the acceleration mode is the single most important of the four modes because it makes the largest contribution to total emissions. Cruise is the second most important mode from this perspective. Deceleration and idle are of comparable importance, and combined contribute less to total emissions for NO, CO, and CO_2 than either of the other modes alone, with the exception of HC emissions.

4.3.4 Fitting OLS Regressions

After developing modal definitions, OLS regressions were fit for each mode using explanatory variables. Reasons for selecting explanatory variables were explained in Section 4.2.3. These explanatory variables are: model year; humidity, speed; acceleration; temperature; altitude; grade; pressure; and power. Second and third powers of speed and acceleration were also included in the regression analysis.

In fitting regression to the data, a stepwise regression technique was applied in SAS as explained in Section 3.3.5. The result from SAS is a statistically significant model with statistically significant parameters. The coefficients of the regression equations for NO_x emissions obtained from this analysis are given in Table 4-4. For HC emissions, the OLS regression did not result in a model that can sufficiently explain variability in emissions. More detailed discussion on modeling of HC emissions is given in Section 4.3.6. Coefficients for the OLS regressions for CO and CO_2 are given in Appendix B.

As seen in Table 4-4, some of the coefficients are zero. This means that those variables were not selected in the regression fits. R^2 values for each regression equation are given. The lowest R^2 value is 0.02, for the idle mode, and the highest one is 0.31 for the cruise mode. These R^2 values are low to moderate. However, given that only a selected set of explanatory variables are available for inclusion in the regression models, it is not surprising that there is a large portion of variability in the data within each mode that remains unexplained. Furthermore, it must be kept in mind that these models are only for bins of data, and that the process of binning the data also accounts for a portion of the variability in the on-board emissions data.

Table 4-4. Results of Regression Fit for NO Emissions for HDDV

Variable	Idle	Acceleration	Deceleration	Cruise
Intercept	691.6	-690.9	1309.5	-412.1
Model Year	-0.3500	0.3530	-0.6807	0.2117
Humidity	0	-0.0152	0.0601	-0.0139
Speed	0	-0.0684	-0.2135	-0.0862
Speed^2	0	0.0039	0.0037	0.0039
Speed^3	0	0	0	0
Accel	0	0.2094	0.1317	1.3932
Accel^2	0	-0.0003	0.0085	-0.3599
Accel^3	0	0	0	-0.5161
Temperature	0.0217	-0.0609	-0.1134	-0.0725
Altitude	0.0006	-0.0005	0	-0.0003
Grade	0	-0.0474	-0.0758	-0.0458
Pressure	0.0029	-0.0139	0.0478	-0.0109
Power Demand	0	0	0.0214	0.0062
R-square	0.02	0.20	0.28	0.31
Correction Factor	1.3	0.3	1.9	1.4

As seen in Table 4-4, model year is selected as a significant parameter for all of the modes for NO_x. However, the coefficient of model year differs among the modes. For the idle mode the coefficient for model year is -0.35 whereas it is 0.35 for acceleration mode. For the deceleration mode it is -0.68 and for the cruise mode it is 0.21. These numbers suggest that increasing model year decreases emission for idling and deceleration modes whereas it increases emissions for acceleration and cruise modes. This result might be due to differences in vehicle design, or model year might be functioning as surrogate for a variable that is not available in this study.

4.3.5 Comparison of Observed Data with Predictions

In order to determine whether the overall model performs well, trip-average emissions estimations from the model were compared to observed data. The model used for each pollutant is summarized in Table 4-5. For example, OLS regressions were used for modeling HC emissions in each driving mode. For CO emissions, separate OLS regressions were used for low and high acceleration modes, whereas for the other pollutants all accelerations were combined into one mode, with one associated OLS regression.

The models for each of the four pollutants were used to predict emissions for the calibration data set based upon the values of the explanatory variables reported in the calibration dataset. The performance of the models was evaluated by comparing model predictions and actual observations for trip average emission rates based upon the calibration data set. In Chapter 6, the models were applied to make predictions for a validation data set that was different from the calibration data set.

Table 4-5. Summary of Model Developed for Each Pollutant for LDGV

<table>
<tr><th>Driving Modes</th><th>HC</th><th>CO</th><th>NO</th><th>CO_2</th></tr>
<tr><td>Idle</td><td>OLS*</td><td>OLS</td><td>OLS</td><td>OLS</td></tr>
<tr><td>High Acceleration</td><td rowspan="2">OLS</td><td>OLS</td><td rowspan="2">OLS</td><td rowspan="2">OLS</td></tr>
<tr><td>Low Acceleration</td><td>OLS</td></tr>
<tr><td>Deceleration</td><td>OLS</td><td>OLS</td><td>OLS</td><td>OLS</td></tr>
<tr><td>Cruise</td><td>OLS</td><td>OLS</td><td>OLS</td><td>OLS</td></tr>
</table>

* OLS: Ordinary Least Squares Regression

A parity plot for CO emissions is given in Figure 4-9 with 95 percent confidence interval on the mean prediction value. Figure 4-10 presents a similar graph with a 95 percent prediction interval on the individual predictions. The theory for estimation of confidence intervals for the mean and for individual predictions can be found elsewhere (Neter *et al.*, 1996).

As seen in Figure 4-9, the trend line between the observed and predicted trip-average CO emissions has a better R^2 value than the regression equations for individual modes. An R^2 of 0.55 indicates that the combined model can explain 55 percent of the variability in average trip emissions for CO, whereas the highest R^2 value achieved for individual modes was 0.31 for the cruise mode as given in Table 4-4. As seen in Figure 4-9, there is one point in the plot that has a prediction 0f .04 g/sec compared to observed value of 0.09. The R^2 value can increase up to 0.62 if this is data point is ignored. However, there is no basis for discarding this particular data point. In the last row of Table 4-4, the correction factor for each regression is reported. Details of the correction procedure are given in Section 3.3.5.

The performance of the model can be evaluated in terms of precision and accuracy. The R^2 value is an indication of precision. Higher R^2 values imply a higher degree of precision, and less unexplained variability in model predictions, than lower R^2 values. The slope of the trend line for the observed versus predicted values is an indication of accuracy. A slope of one indicates an accurate prediction, in that the average prediction of the model corresponds to an average observation. The slope of the trend line for CO is 1.11, which is close to one. It should also be observed that the range of variability in average emissions for the averaging time selected and for the available database is not very large. The lowest trip average value is approximately 0.01 g/sec, and the second highest value is approximately 0.06 g/sec. The highest value of 0.09 g/sec is not within the main cluster of data, although there is also no basis for discarding it. Thus, the range of variation in observed emissions is less than an order of magnitude, and in most cases it is approximately one half order-of-magnitude. The model predicts, on average, a variation from 0.015 g/sec to 0.05 g/sec, which is approximately a factor of three variation and is not substantially less than the variation within the main cluster of data. Therefore, from perspectives of the R^2, slope of the trend line, and variability captured by the model, it appears that this model is performing reasonably well.

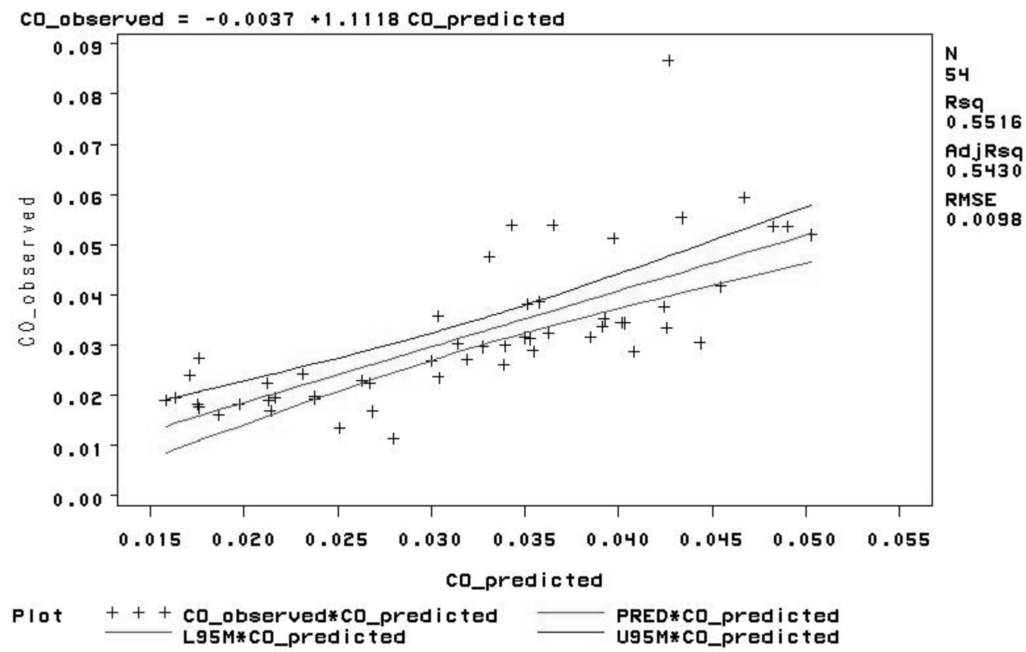


Figure 4-9. Observed versus Predicted Trip Averages for CO Emissions with 95 Percent Confidence Interval on the Mean Prediction

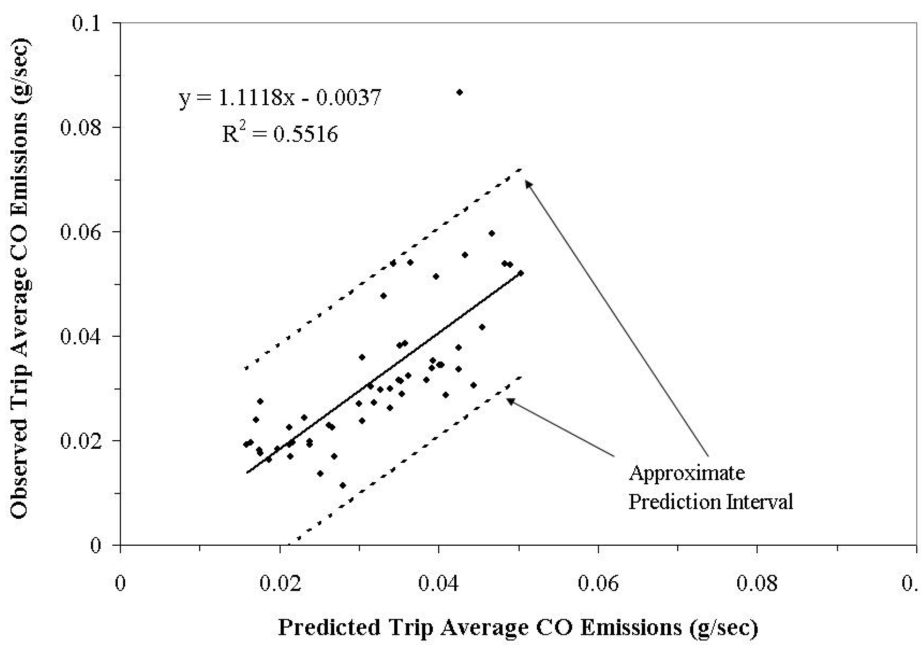


Figure 4-10. Observed versus Predicted Trip Averages for CO Emissions with 95 Percent Confidence Interval on the Individual Predictions

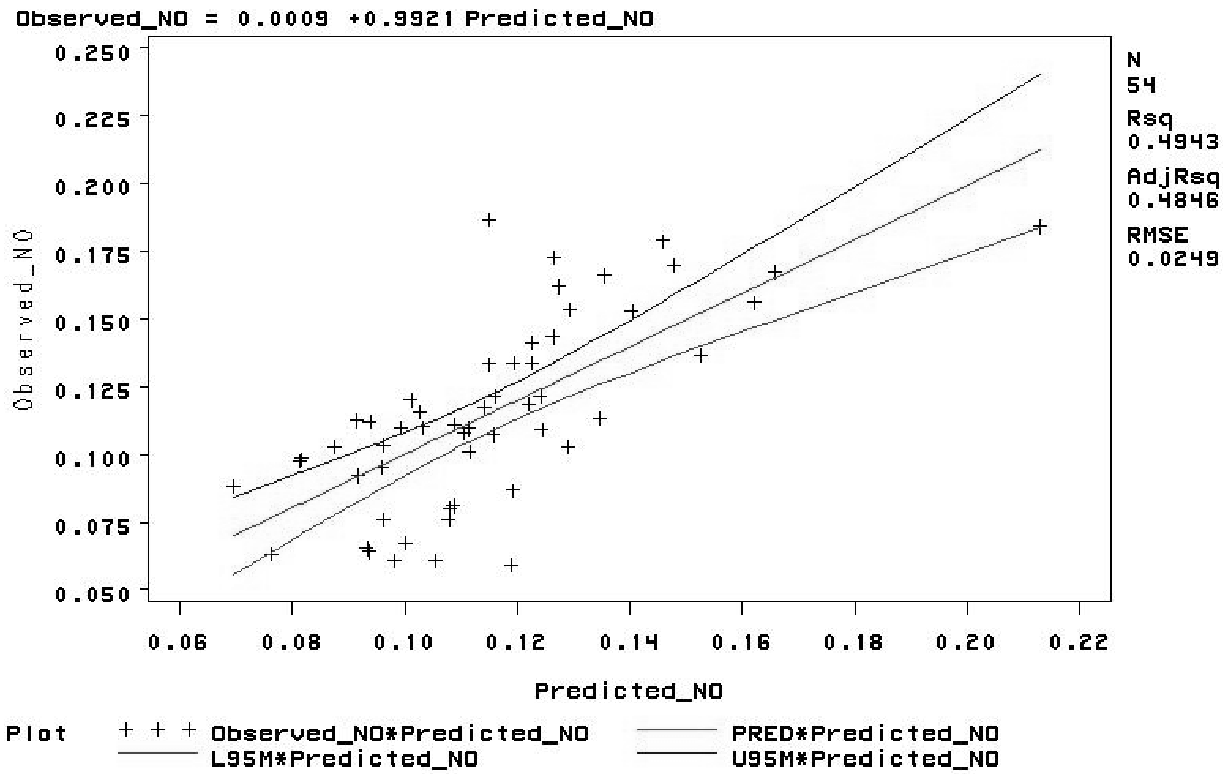


Figure 4-11. Observed versus Predicted Trip Averages for NO Emissions with 95 Percent Confidence Interval on the Mean Prediction

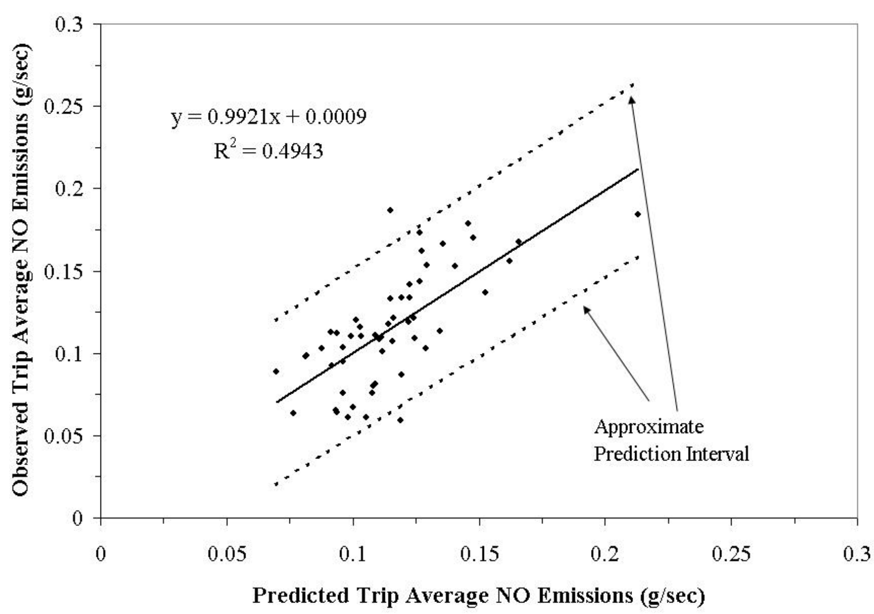


Figure 4-12. Observed versus Predicted Trip Averages for NO Emissions with 95 Percent Confidence Interval on the Individual Predictions

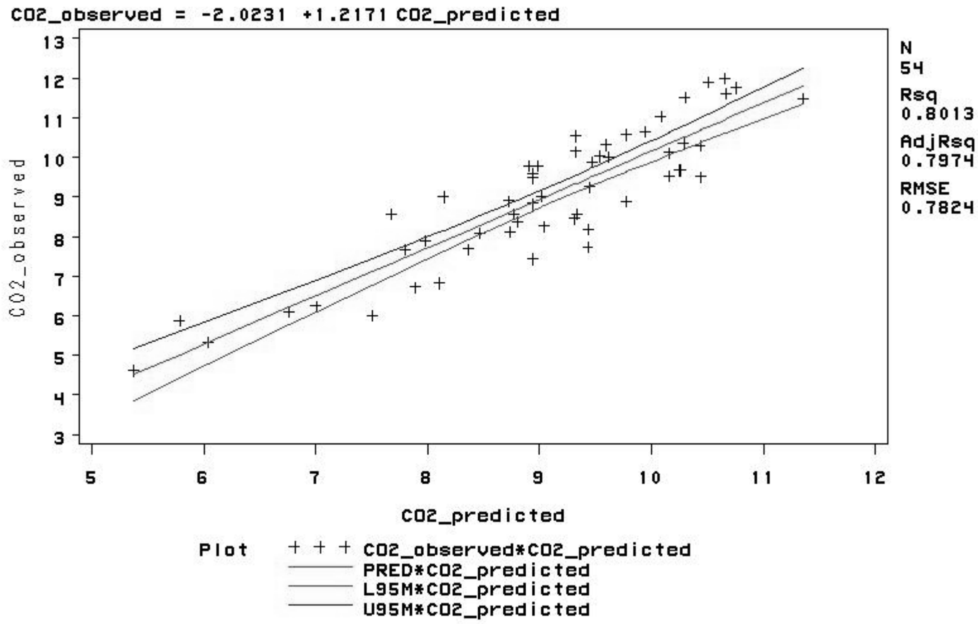


Figure 4-13. Observed versus Predicted Trip Averages for CO_2 Emissions with 95 Percent Confidence Interval on the Mean Prediction

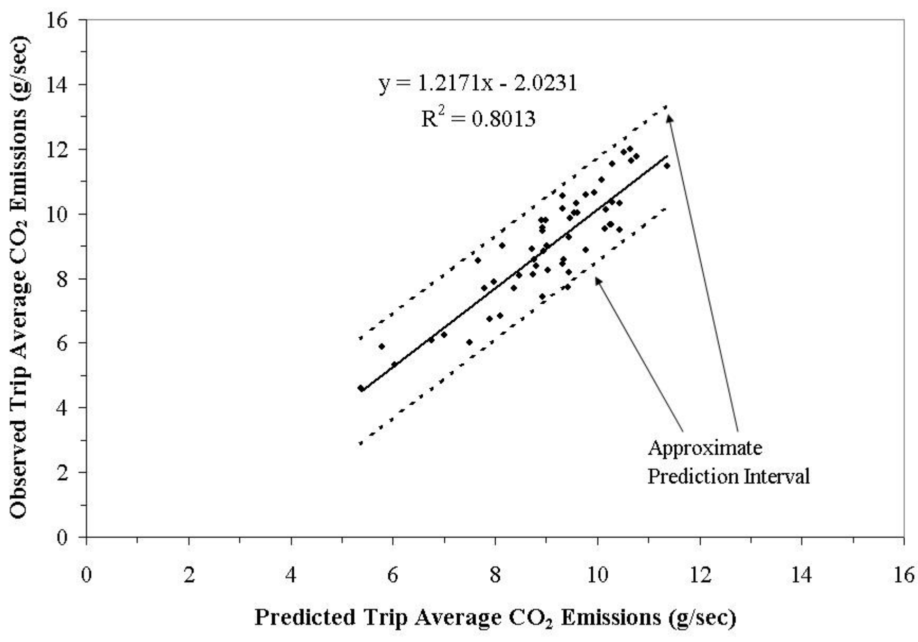


Figure 4-14. Observed versus Predicted Trip Averages for CO_2 Emissions with 95 Percent Confidence Interval on the Individual Predictions

Figures 4-11 and 4-12 show the relationship between the observed and predicted trip-average for NO emissions. As in the case for CO emissions, the overall R^2 value is better than the R^2 values for regression equations for the individual modes. The R^2 value of 0.49 indicates that the combined model can explain 49 percent of the variability in average trip emissions for NO, whereas the maximumR^2 value for individual modes was for cruise mode with an R^2 of 0.31.

The comparison of model predictions and observed values for CO_2 emissions is given in Figures 4-13 and 4-14. The R^2 for the trend line between the predicted and observed values is 0.8, which indicates that the model explains 80 percent of the variability in trip-based averages. The maximum R^2 value for the individual regression equations for the modes occurred for the cruise mode, with a value of 0.33. The much higher R^2 value for the combined model indicates that dividing the data into modes explains some part of variability in CO_2 emissions. The model tends to overpredict CO_2 at the low end of emission rates, as indicated by the negative intercept of the trend line. Thus there appear to be some biases in this model. However, the slope and intercept of the trend line can be used to correct for biases when making predictions.

4.3.6 Model Developed for HC Data

Fitting OLS regressions for HC data for each mode did not result in a model with much explanatory power. For this reason, a detailed investigation was conducted to find an explanatory variable that would work for HC emissions. In the literature, there has not been much research reported for HC emissions from HDDV, since these emissions are quite low. It is known that one of the variables that affects HC emissions is the equivalence ratio. It has been reported that HC emissions drop sharply as the equivalence ratio is increased above about 0.2, and that emissions slightly increase when the equivalence ratio is higher than 0.7 (Flagan and Seinfeld, 1986).

In order to see the relationship between equivalence ratio and HC emissions, the equivalence ratio for HDDV was estimated using air intake rate and fuel intake rate. In the data provided to NCSU by the EPA, air intake rate was not given. Therefore, air intake was estimated using mass balance equations. Equations for these estimates are given in Appendix B. As an illustration of the method, the results of equivalence ratio estimation for Vehicle 1 Trip 1 are given in Figure 4-15. There are 1,141 data points, each representing one second of data.

The relationship between the estimated Equivalence Ratio and HC emissions is noisy. There seems to be a weak upward trend among the lower bound of emissions versus equivalence ratio. However, the highest HC emissions occur for low equivalence ratios. As an alternative, HC emissions were normalized by brake horse power and the normalized emissions were plotted versus equivalence ratio in Figure 4-16. There is a clear relationship between equivalence ratio and normalized HC emissions. The highest HC emission occurred at low values of equivalence ratio, between equivalence ratios equal to zero and 0.4. This finding coincides with the theory as reported in literature by Flagan and Seinfeld (1986). Therefore, one can in principle estimate HC emissions normalized to brake horsepower using equivalence ratio.

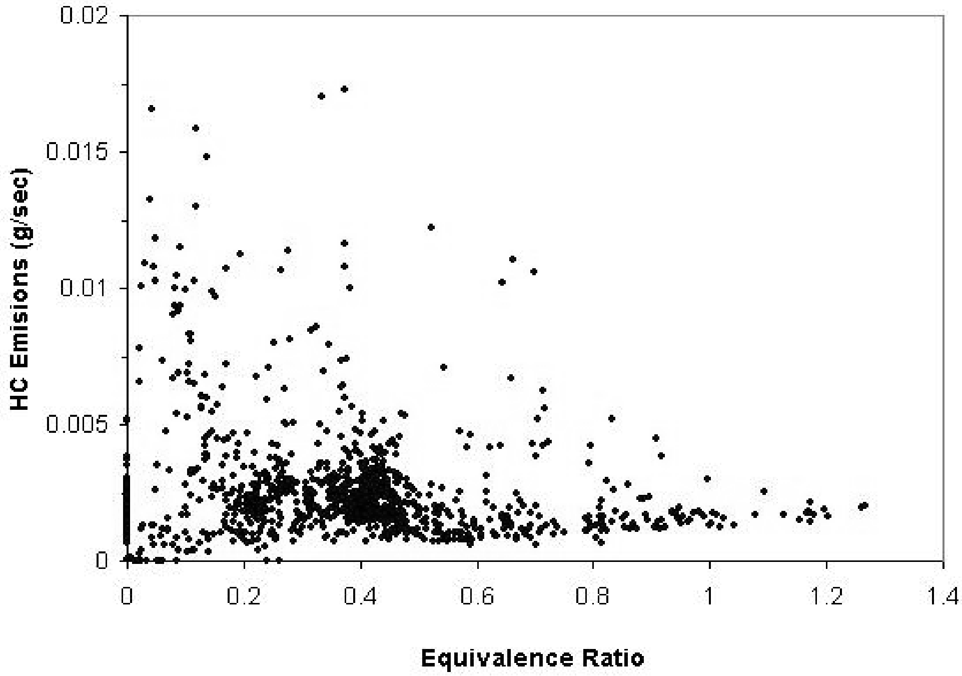


Figure 4-15 Relationship between Equivalence Ratio and HC Emissions (g/sec)

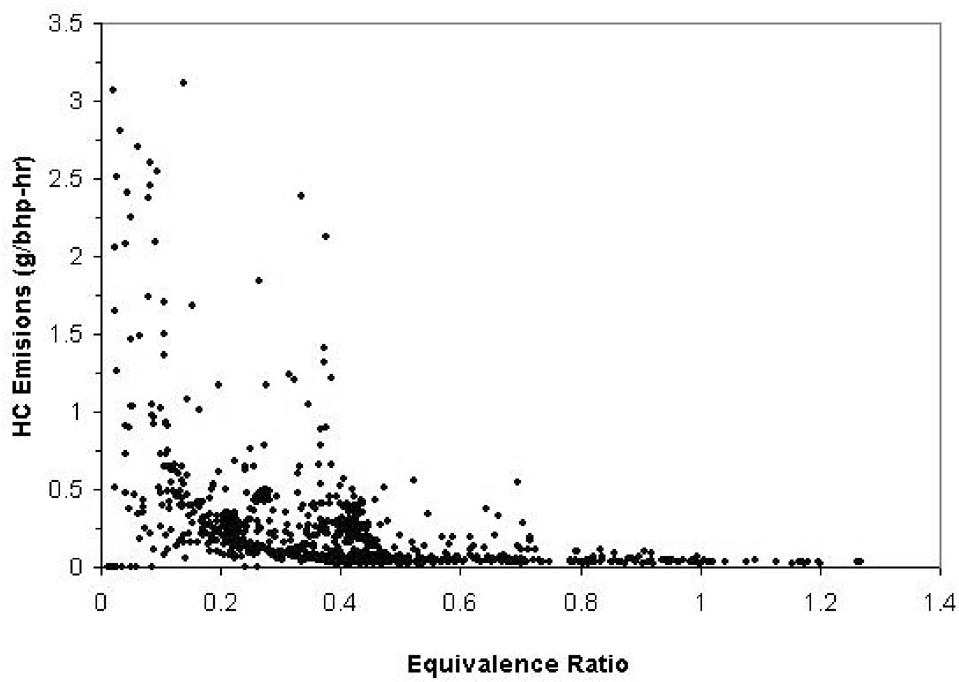


Figure 4-16 Relationship between Equivalence Ratio and HC Emissions (g/bhp-hr)

In order to estimate equivalence ratio one needs to have information on fuel flow and air intake. These parameters were not provided in the "validation" dataset. Second-by-second brake horsepower was not provided either. Therefore it was not possible to estimate HC emissions using this approach in the validation study. Other explanatory variables such as power demand and acceleration were analyzed with respect to their explanatory power for HC emissions. However, none of these parameters were found to be useful. Therefore it was decided to use modal analysis as the model for HC emissions for HDDV data. Comparison between the observed and the predicted HC emission for HDDV using only modal analysis is given in Figure 4-17.

The predictive capability of the model for HC emissions is very weak. The prediction of the model ranges only from 0.0012 g/sec to 0.0016, whereas observed values range from 0.00015 to 0.0038 g/sec. The R^2 value is very low and can explain less than one percent of the variability in the data. This model is not much better than simply using an average HC emissions estimate for all of the trips based upon the observed data. However, as noted above, HDDV HCC emissions are considered to be low, and even the high end of the observed range represents a low emission rate.

The relatively poor performance of the modal-based model for HC is not an inherent limitation of the modal modeling approach. Instead, it is a result of the lack of availability of a suitable explanatory variable for model development purposes. For example, a modal definition based upon equivalence ratio would be more useful for HC than one based upon speed and acceleration. The modal approach works very well for the other three pollutants. HC is unique among the four pollutants in being relatively insensitive to the set of explanatory variables that are available in the validation data set.

4.3.7 Quantification of Unexplained Variability and Uncertainty

In developing a model it is important to quantify the unexplained variability and uncertainty. In order to characterize unexplained variability, the residuals from each trend line fitted to the observed and predicted data are obtained. The coefficient of variation (C.V.) of the residuals was determined by the method given in Section 3.3.6.

Uncertainty in model predictions for mean emissions was determined by estimating the average emissions and the standard variance of emissions for individual modes for each trip. The trip averages and trip standard variances were estimated using weighted averages as explained in Section 3.3.6. Results of the variability and uncertainty estimation are given in Table 4-6.

The uncertainty analysis is relevant to the application of the model to make predictions of fleet average emissions. The results for the coefficient of variation imply that the range of uncertainty in average predictions is approximately plus or minus 10 percent of the mean value for HC and CO emissions, plus or minus 5 percent of the mean value for NO emissions, and plus or minus 3 percent of the mean value for CO_2 emissions. Thus, the 95 percent confidence interval for the mean prediction is less than approximately plus or minus 10 percent in all cases. The uncertainty in the mean for HC emissions, for which it was difficult to develop a useful model based upon the available explanatory variables, was comparable to that for the other pollutants. Thus, it appears to be the case that a detailed model is not necessary for HC, because the precision of the model prediction is comparable to that for the other pollutants.

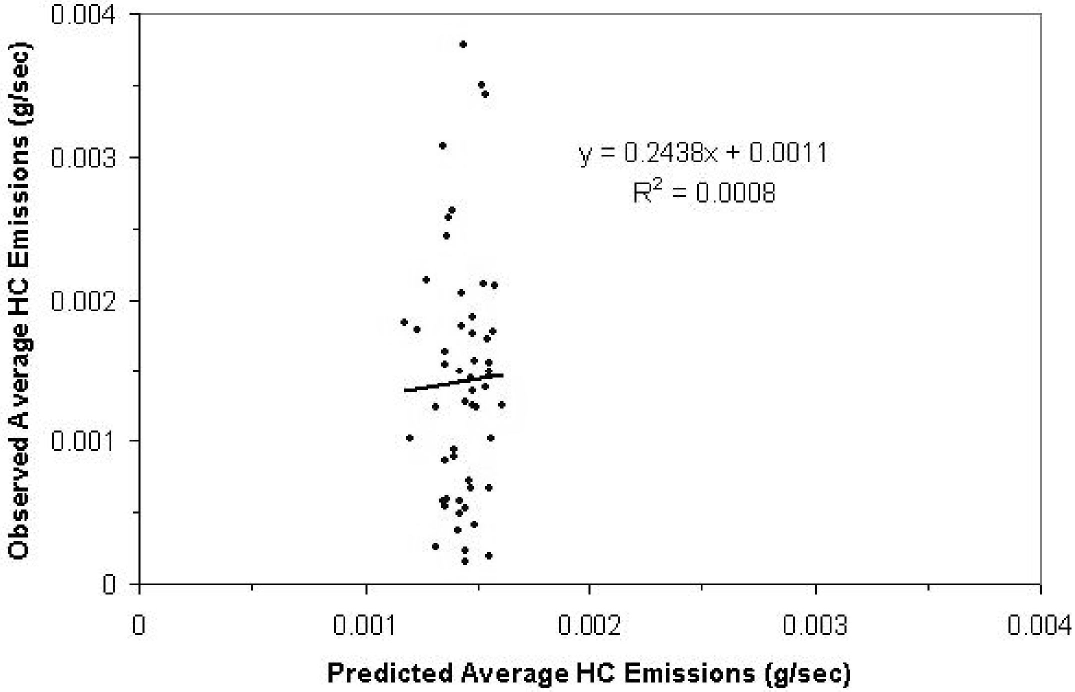


Figure 4-17. Observed versus Predicted Trip Averages for HC Emissions

Table 4-6. Summary for Uncertainty Analysis for the Model and Observed Data

	Uncertainty in the Mean Prediction			**Variability in the Model**		
Poll.	*Mean*	*StDev (Mean)*	*C.V.*	*S. E. of the Residuals*	*Average of Observed Data*	*C.V.*
HC (g/sec)	0.001	7.2E-05	0.052	0.0007	0.002	0.33
CO (g/sec)	0.032	0.0017	0.051	0.0097	0.032	0.30
NO (g/sec)	0.11	0.0029	0.026	0.025	0.11	0.21
CO_2 (g/sec)	8.9	0.14	0.016	0.77	9.01	0.09

In contrast, if the model were to be used to make predictions of emissions for an individual trip, then the lack of precision of the model is reflected by the unexplained variability for individual trips not captured by the model. The results of the analysis of unexplained variability imply that the 95 percent prediction interval for an average individual trip is approximately plus or minus 66 percent for HC emissions, plus or minus 60 percent for CO emissions, plus or minus 42 percent for NO emissions, and plus or minus 18 percent for CO_2 emissions. Thus, the range of uncertainty for prediction of emissions of an individual trip is much larger than the range of uncertainty for prediction of average emissions for a fleet.

4.4 Summary of the Model

This chapter has illustrated the major steps in the development of a modal model of real-world tailpipe emissions for HDDV using data obtained from on-board measurements.

Similar to LDGV there are key steps in model development that were not part of the scope of work at NCSU. These include defining a study objective, developing a study design, and executing the study design in all of its elements. The key characteristics of study design are addressed in detail in Chapter 8.

The key steps in model development that were part of this study include the formation of a database from data reported by the on-board emissions contractors (or EPA), data quality assurance and quality control, exploratory analysis of the data, and fitting of a model to the data. The QA/QC activities including searching for common types of errors that can occur when using on-board instruments. In some cases, some data were excluded from the final database in order not to include known or suspected errors in the analysis and model calibration effort.

Exploratory analysis included a variety of techniques. The first was development of a summary of the content of the database, including average values and other information. Variability in the emissions data between vehicles and between vehicle-trips was evaluated. Possible explanatory variables were identified. Methods for visualizing the data, such as using multiple scatter plots, were employed to help in identifying patterns in the data.

Because of the autocorrelation in the data, and the difficulty in working with time series models, an approach based upon binning of the data to reduce the influence of autocorrelation was pursued. The approach involves definition of driving modes based upon criteria applied to the speed trace associated with the trip. The criteria include specific conditions of speed and acceleration, sometimes involving multiple seconds of data, that are used to segregate the database. The statistical significance of comparisons of the average emissions for each pollutant among the four modes of idle, acceleration, deceleration, and cruise was assessed. These four driving modes are typically statistically significantly different from each other for a given pollutant with respect to the average emission rates. Therefore, the modal definitions are confirmed to have useful ability to explain differences in vehicle emissions based upon different types of vehicle activity during real-world driving.

HBTR methods were used to determine whether the four driving modes should be subdivided into additional modes. In one case, acceleration mode, criteria for subdividing the modes based upon acceleration were found to provide additional capability to capture variation in the observed emissions data. The modal approach represents a mesoscale approach that can be easily aggregated to predict macroscale (e.g., trip average) emissions.

For each modal dataset, OLS regression techniques were applied to illustrate the development of additional explanatory capability with microscale second-by-second data. Because these data were segregated from the original time series into much shorter discontinuous time series, which in turn is expected to reduce the influence of autocorrelation, it was judged acceptable to use regression methods applied to the modal data.

The OLS regression models fit to the modal data offered some additional explanatory capability. These models are illustrative in nature. Some of the coefficients obtained from the analysis, such as for road grade, are not physically intuitive. However, this can be associated with lack of sufficient variability in candidate explanatory variables. The methodology is applicable to larger scale applications to larger databases. In most cases, the relationships obtained with OLS regression were reasonable and useful. For HC emissions HTBR and OLS analysis did not give an efficient model. Therefore, modal analysis was used as the basic model for HC emissions.

The performance of the models was evaluated using parity plots and statistical intervals with respect to a trend line. Two types of statistical intervals were developed. One type of interval, which we refer to as a prediction interval, represents the unexplained variability in observed emissions that is not captured by the model. This measure of precision is important to consider when making predictions for emissions for individual trips. The other interval, which we refer to as a confidence interval, represents the 95 percent confidence interval on the mean prediction. This interval is applicable to estimating model precision when making predictions for average emissions over a sufficiently large fleet. The prediction interval is needed in this study when making comparisons between model predictions and observed values in the validation case study described in Chapter 6.

Overall, the techniques applied to develop the illustrative conceptual model were useful in screening the data, creating a data base, exploring the data base, developing the model, characterizing model performance, and quantifying the variability and uncertainty in model predictions. These techniques can be applied to larger datasets than were available in this work for the purpose of developing a nationally representative model of HDDV tailpipe emissions.

5.0 CONCEPTUAL MODELING APPROACH FOR SELECTED NONROAD VEHICLES

This chapter focuses on the development of conceptual emissions models for selected nonroad vehicles. EPA provided three hours of second-by-second calibration data for each of three vehicles, including a bulldozer, a compactor, and a scraper. From these data, conceptual models were developed for predicting NO_x and CO_2 emissions. Several different methods were explored, including binning the data into modes, supplementing the modal model with OLS regression, multiple regression, and time series analysis. The methods were compared with regarding to explanatory power and ease of implementation.

5.1 Data Post-Processing

In this section, methods for data post-processing are discussed for nonroad vehicles. This work is important in developing an accurate database.

5.1.1 Database Formation

Data for nonroad vehicles were provided in a tab delimited format. These files were converted into Microsoft Excel™ format since Microsoft Excel™ was used as the main environment for data analysis and model development.

Three files were provided for the purpose of model development. Each file represents data collected with a different vehicle. All of the vehicles were diesel fuelled and the engines were manufactured by Caterpillar. All of these vehicles were six cylinder vehicles with fuel-injection. Preliminary analysis of individual files indicated that the format was the same for all vehicles. Therefore, no post-processing was needed for formatting.

The data fields in each file included: date of data collection; time of data collection; relative humidity (%); ambient temperature (^{0}C); exhaust temperature (^{0}C); mass air flow temperature (^{0}C); barometric pressure (kPa); engine RPM; mass air flow (scfm) SATP (kPa); exhaust flow (scfm); fuel flow (kg/h); NO_X emissions (in ppm and g/hr units); CO_2 emissions (in percent and kg/h units); NO_X/Fuel ratio.

Data for each vehicle were used to create an Excel file for one vehicle driven on one trip. Each of the files has three hours of data. For the purposes of model development using modal and regression approaches, the three hours of data for each vehicle were used without subdividing the data into trips. It was found that file for bulldozer and the scraper represented a continuous trip, whereas data for compactor represented three trips. The first trip for the compactor was very short at only five minutes in duration. The second trip for compactor was almost one hour 45 minutes in duration and the third trip was one hour and seven minutes in length.

5.1.2 Data Quality Assurance/Quality Check

For the modal and regression analyses, the nonroad equipment data streams were screened for cases of zero engine RPM and inspected for cases of zero NO_x emissions. For the bulldozer, there were 309 records (seconds of data) with zero engine RPM. Since these records imply either no vehicle activity, and/or a data collection problem, these records were deleted in creating a screened data base. No cases of zero NO_x emissions were observed after the zero engine RPM records were deleted. For the compactor, five records were deleted that contained zero values for RPM, and 258 records were deleted that contained zero values for NO_x. For the scraper, 4 records were deleted that contained zero values for engine RPM, and 103 records were deleted that contained zero values for NO_x.

5.2 Exploratory Analysis

After database formation and screening the data for errors an exploratory analysis was conducted to better understand the variability of vehicle emissions and the basic trends between explanatory parameters and vehicle emissions for nonroad data. This section first presents summary of the data provided for emissions and engine related parameters. Variability in the emissions data are presented. Scatter plots were utilized for data visualization purpose. The identified explanatory variables used for model development are listed. A summary of the exploratory analysis is presented.

5.2.1 Data Summary

A summary of the emissions and activity data as well as environmental and roadway characteristics is given for all vehicles in Table 5-1.

The data in Table 5-1 are divided into several categories. These categories are: vehicle characteristics; parameters related to vehicle operation; and environmental characteristics.

Duration of trips for individual vehicles ranged from 380 seconds to 10,800 seconds. The average engine RPM varies among the equipment and between trips. The minimum average engine RPM occurred for Compactor Trip 1, with an average of 685 whereas the highest average RPM occurred for Compactor Trip 3, with an average of 2,526. Ambient weather conditions were different for the different vehicles. For the Bulldozer, the average temperature was 29 ^{0}C, whereas it was less than 10 ^{0}C for trips conducted with the compactor. Average relative humidity was ranged between 48 percent to 71 percent. For CO_2 emissions, the highest average emission rate was more than four times higher than lowest average emission rate. This ratio was approximately 15 for NO_x emissions.

Inter-trip variability analysis was not conducted for the nonroad data because the number of trips was limited. However, emission estimates for different trips of the compactor imply that inter-trip variability can be very high. For example, the average NO_x emissions from Trip 2 were approximately three times higher than the NO_x emissions from Trip 1. Similarly, the average CO_2 emissions from Trip 3 were approximately 4.5 times higher than the CO_2 emissions from Trip 1. Inter-vehicle variability is also substantial for the nonroad data. As given in Table 5-1, the average NO_x emissions rate for the bulldozer was almost three times higher than the NO_x emission rate from the scraper and seven times higher than the average of the three trips for the compactor. For CO_2 emissions, the differences were less pronounced. For example, the CO_2 emission rate from the bulldozer was approximately 1.5 times higher than for the.

Table 5-1. Summary of Data for the Nonroad Database.

	Bulldozer	Scraper	Compactor Trip 1	Compactor Trip 2	Compactor Trip 3
Vehicle Characteristics					
Model Year	1990	2001	1980	1980	1980
Rated Power	305	515	170	170	170
Vehicle Operation					
Average RPM	1466	1557	685	2295	2526
Average Exhaust Flow (scfm)	599	427	194	301	346
Average NO_x Emissions (g/hr)	1894	673	128	386	288
Average CO_2 Emissions (kg/hr)	98	67	24	70	107
Environmental Characteristics					
Ambient Temperature (^oC)	29	15	8	6	3
Ambient Pressure (kPa)	61	100	100	98	99
Relative Humidity (%)	67	48	57	64	71
Time of Day	6:30 AM	7:30 AM	18:05 PM	9:15 AM	8:15 AM
# of Seconds of data	10800	10695	380	6405	4015

5.2.2 Identification of Explanatory Variables

The analysis of potential explanatory variables was limited to those variables that would be available in the validation data set. Although other variables were available in the calibration data set, such as mass air flow, fuel rate, and some others, they were not used in model development because they would not be available in the validation data set. Of the five variables that are available in the validation data set, which include exhaust flow, engine RPM, ambient temperature, barometric pressure, and relative humidity, it is clear that exhaust flow and engine RPM are the two variables that are most highly correlated with emissions of both NO_x and CO_2. Therefore, these two variables were the main focus of model development efforts. Because temperature and humidity were highly correlated in the data for all three nonroad pieces of equipment, it was judged that it would not be appropriate to include both in the model development. An arbitrary choice was made to use ambient temperature as the surrogate measure for the simultaneous inversely proportional covariation of temperature and humidity. Barometric pressure was also considered as a possible explanatory variable.

5.2.3 Data Visualization Using Scatter Plots

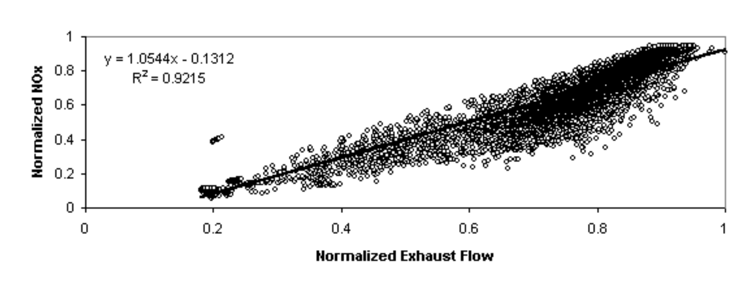
Scatter plots for both NO_x and CO_2 emissions are given with respect to each of five possible explanatory variables for each of the three pieces of nonroad equipment. The five possible explanatory variables are exhaust flow, engine RPM, ambient temperature, barometric pressure, and relative humidity. Exhaust flow is a surrogate for engine load. The emission rate of the two pollutants, the exhaust flow and the engine RPM were normalized with respect to the maximum values of each quantity for each piece of equipment. This was done to simplify the graphical presentation of results. All values of the two pollutants, exhaust flow, and engine RPM are shown as between zero and one in the scatter plots and parity plots.

For all three pieces of equipment, the emission rate of both pollutants is highly correlated with the exhaust flow rate. For illustrative purposes, trend lines are shown in each scatter plot, along with an R^2 value. Because the data are autocorrelated, the R^2 value obtained based upon ordinary least squares (OLS) regression is presented not as a quantitative indication of a linear relationship but as a qualitative indicator.

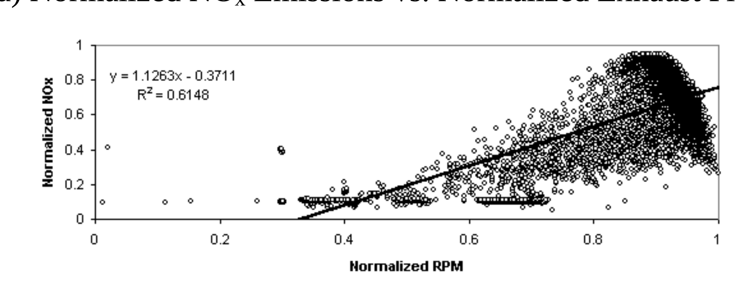
As a typical case, consider the scatter plots for the bulldozer for normalized NO_x emissions versus each of the five candidate explanatory variables shown in Figure 5-1. Scatter plots are useful, but have some limitations. In particular, when there are many data points with similar values, it is difficult to interpret the density of the data in a particular region of the graph. However, in spite of this limitation of scatter plots, some general inferences can be made about the relationship between NO_x emissions and each of the explanatory variables. NO_x emissions are a function, at least in part, of exhaust flow rate, as illustrated in Figure 5-1(a). There is almost a linear trend in average NO_x emissions for a given exhaust flow and the normalized exhaust flow rate. However, there is also substantial variability in NO_x emissions for any single point estimate of normalized exhaust flow.

Figure 5-1(b) illustrates that there is also a relationship between NO_x emissions and engine RPM. However, this relationship is complex. On average, NO_x emissions increase with an increase in engine RPM. However, at high RPM, there appears to be a domain in which average NO_x emissions may actually decrease with an increase in engine RPM. In fact, although not shown here, inspection of other scatter plots during data analysis reveals that the maximum exhaust flow rate does not occur at the maximum RPM, but at approximately 90 percent of the maximum RPM. Figure 5-1(b) indicates that the highest values of NO_x emissions occur at approximately 90 percent of maximum RPM. Figure 5-1(a) indicates that the highest values of NO_x emissions occur at or near the maximum exhaust flow. Therefore, it is reasonable to conclude that the maximum emissions are associated with the highest exhaust flow rates and with engine RPM at approximately 90 percent of the maximum value. The comparison of Figures 5-1(a) and 5-1(b) suggest that most of the observed variability in NO_x emissions is likely to be explained by a combination of exhaust flow and engine RPM.

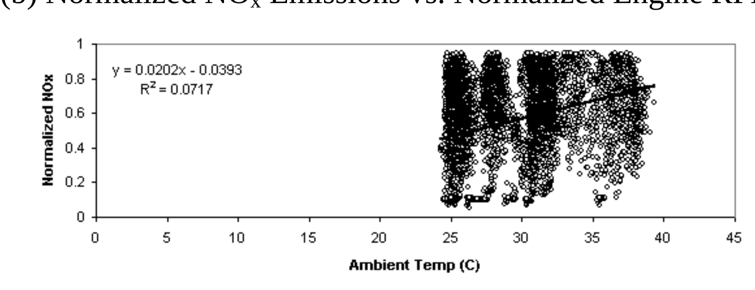
There appear to be relationships between NOx and both ambient temperature and relative humidity. However, although not shown here, the exploratory analysis also revealed that ambient temperature and relative humidity were highly correlated with each other for this particular dataset. For example, at a temperature of approximately 25 ^{o}C, the relative humidity was 85 percent. At a temperature of approximately 33 ^{o}C, the relative humidity was 38 percent. During the data collection, it is apparent that there was a steady increase in temperature and a corresponding steady decrease in the relative humidity. A significant portion of the decrease in relative humidity can be attributed to an increase in the capacity of the atmosphere to hold water vapor as the temperature increases. For example, if the relative humidity is 85 percent at 25 ^{o}C, the atmosphere can hold approximately 0.016 lb of moisture per lb of dry air. At a temperature of 33 oC, and with the same amount of moisture per dry air, the relative humidity is only approximately 52 percent. With an observed humidity of only 38 percent at 33 ^{o}C, it is likely that some moisture was removed from the air during the time that the ambient temperature was increasing. Because the observed temperature and humidity are closely related to each other, they cannot both be used in a statistical analysis to develop an explanatory model of emissions.



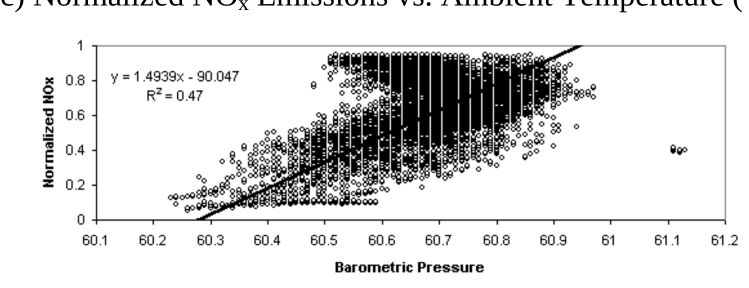
(a) Normalized NO_x Emissions vs. Normalized Exhaust Flow



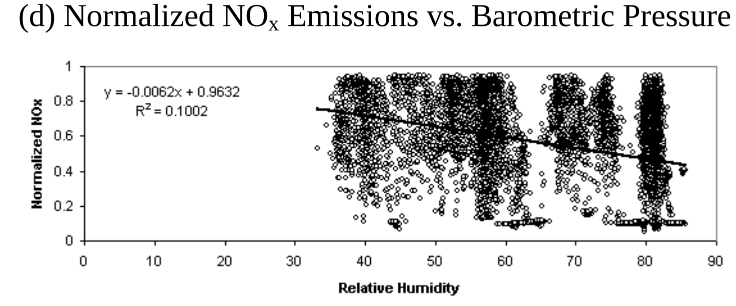
(b) Normalized NO_x Emissions vs. Normalized Engine RPM



(c) Normalized NO_x Emissions vs. Ambient Temperature (^oC)

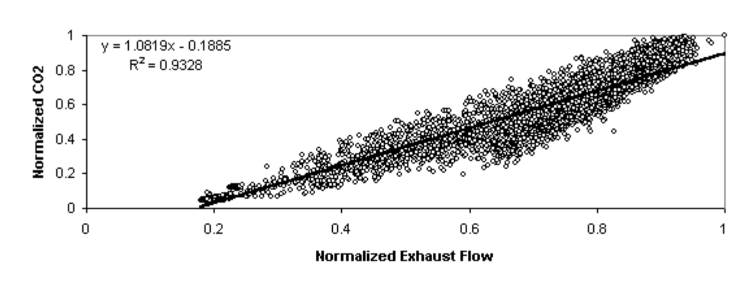


(d) Normalized NO_x Emissions vs. Barometric Pressure

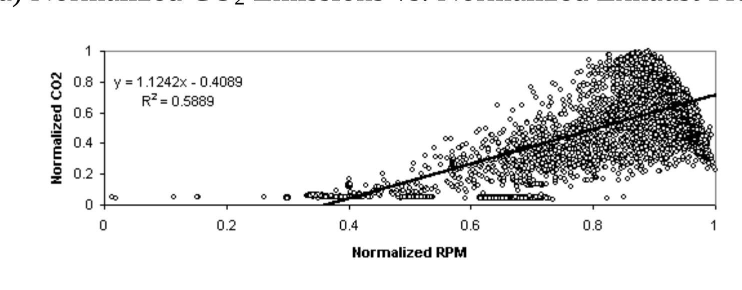


(e) Normalized NO_x Emissions vs. Relative Humidity

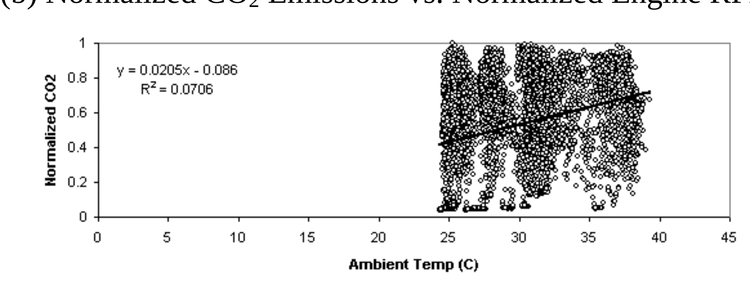
Figure 5-1. Scatter Plots of Normalized Second-by-Second NO_x Emissions versus Candidate Explanatory Variables for Bulldozer, with Trend Lines Indicated



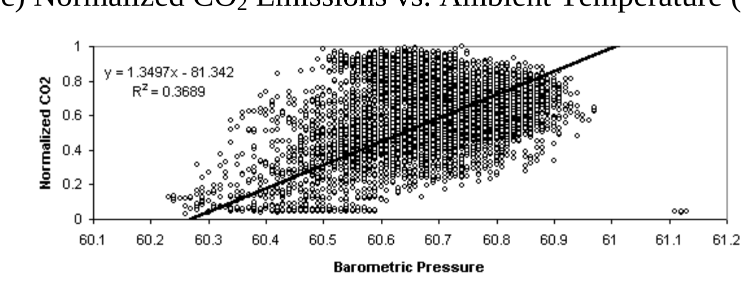
(a) Normalized CO_2 Emissions vs. Normalized Exhaust Flow



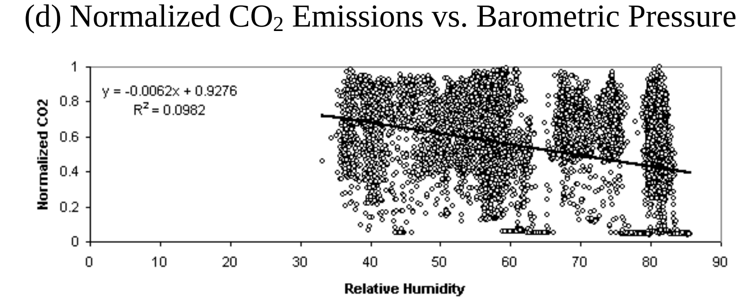
(b) Normalized CO_2 Emissions vs. Normalized Engine RPM



(c) Normalized CO_2 Emissions vs. Ambient Temperature (^{o}C)



(d) Normalized CO_2 Emissions vs. Barometric Pressure



(e) Normalized CO_2 Emissions vs. Relative Humidity

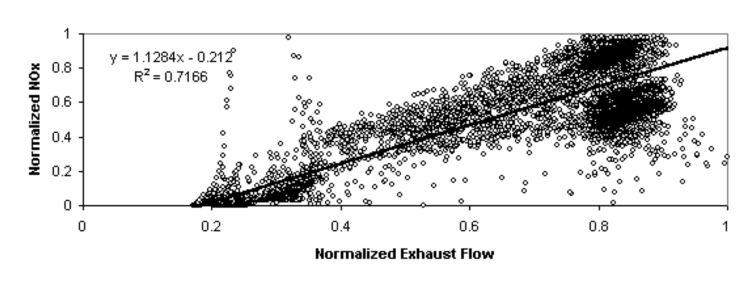
Figure 5-2. Scatter Plots of Normalized Second-by-Second CO_2 Emissions versus Candidate Explanatory Variables for Bulldozer, with Trend Lines Indicated

With the caveat that ambient temperature and relative humidity are highly correlated in the bulldozer data set, the relationship of NO_x emissions with respect to each one appears to be intuitively reasonable. If all else were constant, NO_x emissions would be expected to decrease with an increase in humidity levels, or to increases with an increase in temperature. However, because temperature and humidity are changing in inverse proportion, it is not possible to determine whether the change in average NO_x emissions is influenced more by temperature or by humidity in this case.

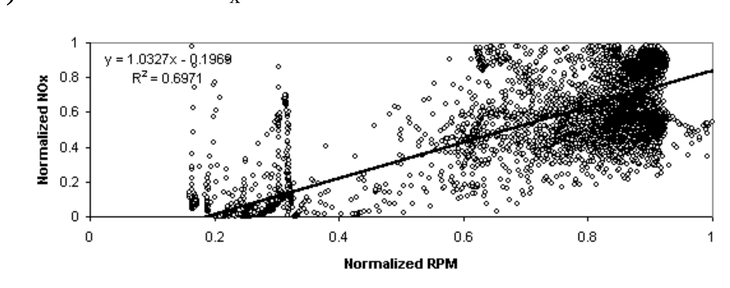
Figure 5-1(d) illustrates that NO_x emissions appear to be increasing with barometric pressure, on average. All else being constant, it would be expected that NO_X emissions would increase with an increase in barometric pressure if the increase in barometric pressure also influenced the maximum pressure during the combustion process. Therefore, the observed average trend is intuitively reasonable. However, there does appear to be a domain in Figure 5-1(d) for the upper half of the barometric pressure data where NO_x is not a linear function of barometric pressure.

The scatter plots for CO_2 emissions from the bulldozer have similar features to those for NO_x emissions, as evident from a comparison of Figures 5-2 and 5-1. In fact, although not shown here, CO_2 and NO_x emissions are highly correlated with each other. Therefore, it is expected in this case that a similar modeling approach should be appropriate for both of these pollutants. Factors that cause an increase in NO_X emissions, such as higher fuel flow reflected by higher exhaust flow and higher engine RPM, also cause an increase in CO_2 emissions. In fact, CO_2 emissions are a surrogate for fuel flow, since the vast majority of the carbon in the fuel is emitted in the form of CO_2. Although not shown, a scatter plot of CO_2 versus fuel flow based upon the data provided by EPA illustrated that there was an almost perfect linear relationship between the two, with hardly any scatter. Of course, such a result could also be a function of how fuel flow may be estimated by some instruments.

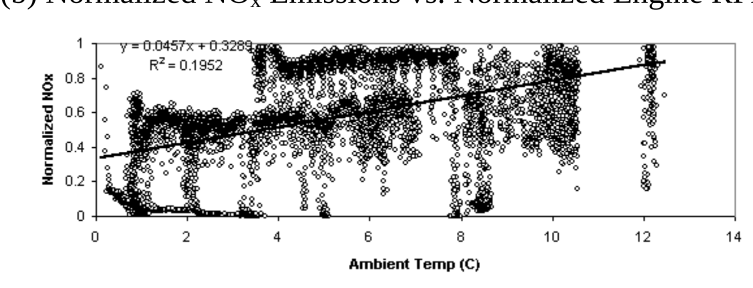
For the most part, the inferences from the scatter plots for NO_x and CO_2 for the compactor, shown in Figures 5-3 and 5-4, respectively, and for NO_x and CO_2 for the scraper, shown in Figures 5-5 and 5-6, respectively, reveal similar trends to those for the bulldozer. There is some variation regarding the degree of explanatory power from one case to another. For example, there is more scatter in the relationship between NO_x emissions and exhaust flow for the compactor compared to that for the bulldozer. However, qualitatively, the results are similar.



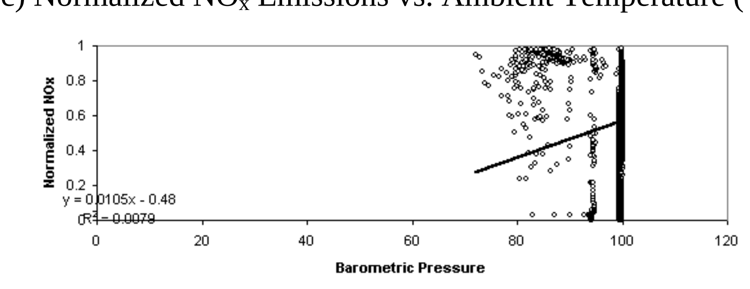
(a) Normalized NO_x Emissions vs. Normalized Exhaust Flow



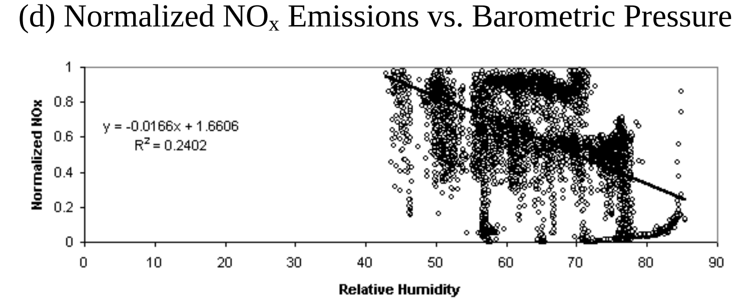
(b) Normalized NO_x Emissions vs. Normalized Engine RPM



(c) Normalized NO_x Emissions vs. Ambient Temperature (^oC)

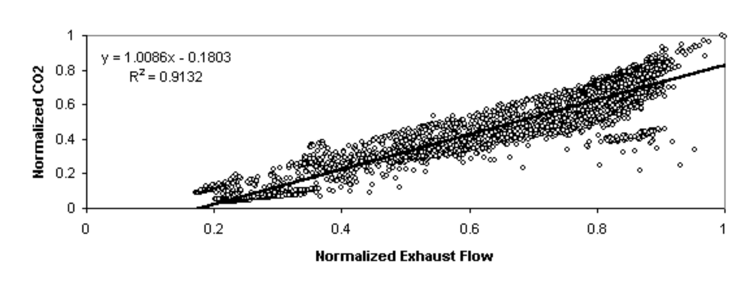


(d) Normalized NO_x Emissions vs. Barometric Pressure

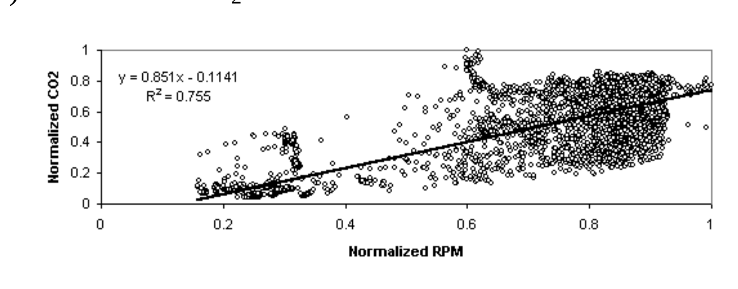


(e) Normalized NO_x Emissions vs. Relative Humidity

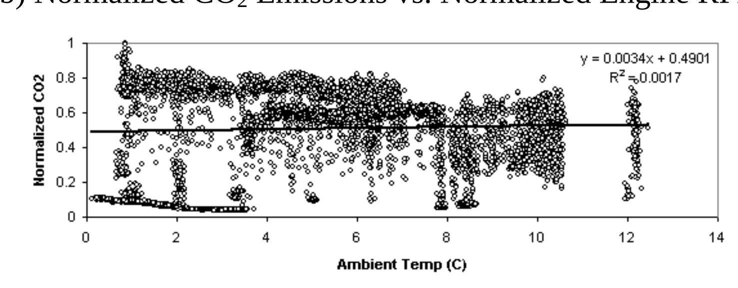
Figure 5-3. Scatter Plots of Normalized Second-by-Second NO_x Emissions versus Candidate Explanatory Variables for Compactor, with Trend Lines Indicated



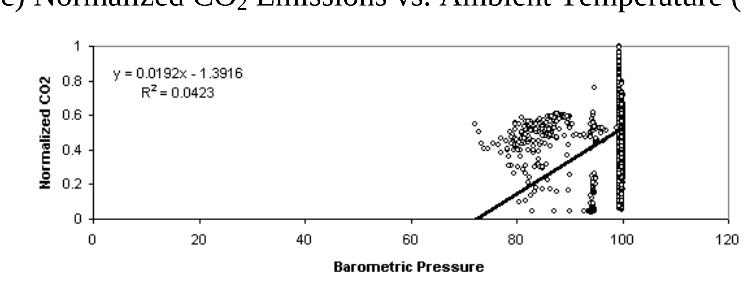
(a) Normalized CO_2 Emissions vs. Normalized Exhaust Flow



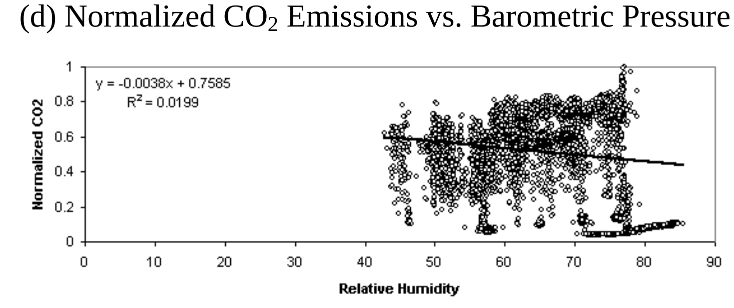
(b) Normalized CO_2 Emissions vs. Normalized Engine RPM



(c) Normalized CO_2 Emissions vs. Ambient Temperature (^oC)

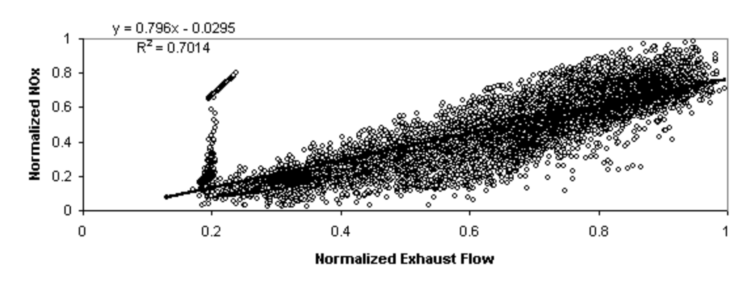


(d) Normalized CO_2 Emissions vs. Barometric Pressure

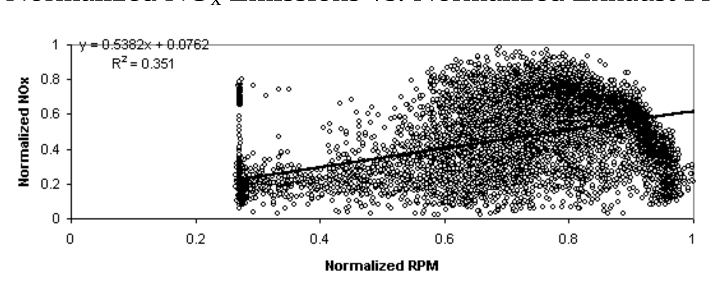


(e) Normalized CO_2 Emissions vs. Relative Humidity

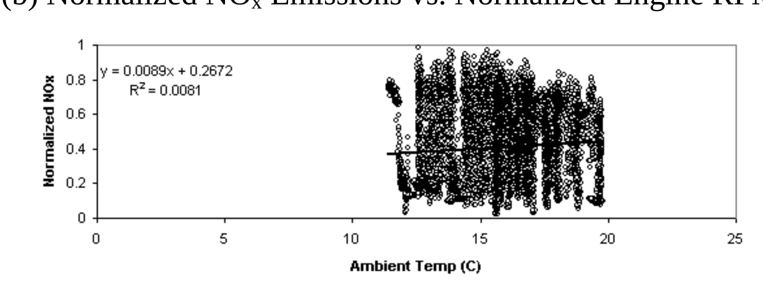
Figure 5-4. Scatter Plots of Normalized Second-by-Second CO_2 Emissions versus Candidate Explanatory Variables for Compactor, with Trend Lines Indicated



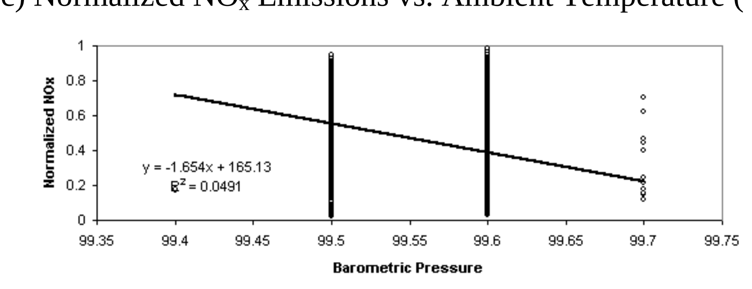
(a) Normalized NO_x Emissions vs. Normalized Exhaust Flow



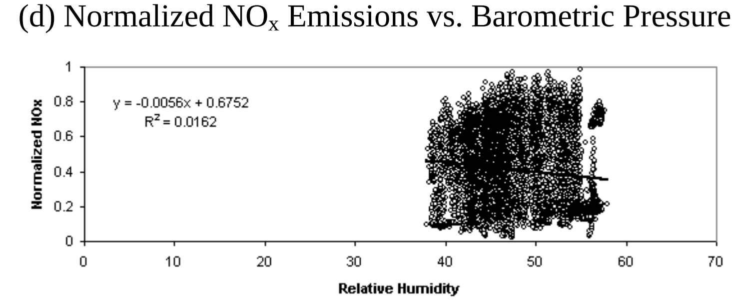
(b) Normalized NO_x Emissions vs. Normalized Engine RPM



(c) Normalized NO_x Emissions vs. Ambient Temperature (^oC)

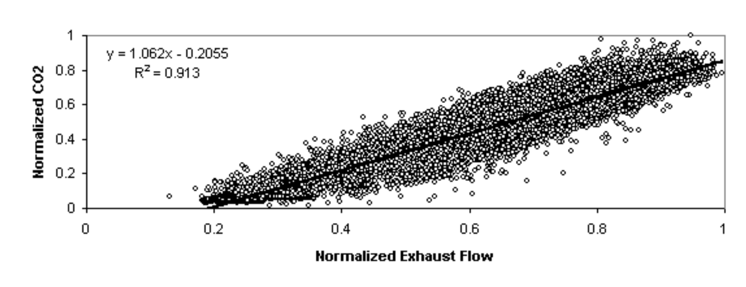


(d) Normalized NO_x Emissions vs. Barometric Pressure

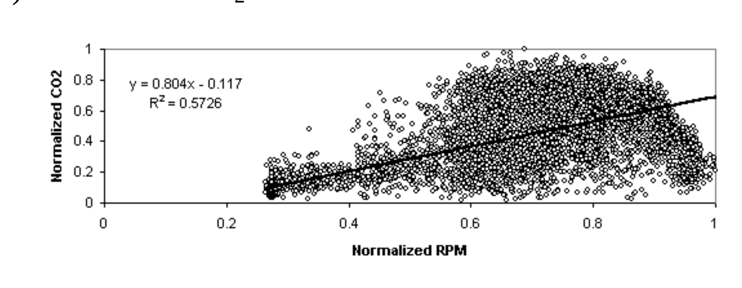


(e) Normalized NO_x Emissions vs. Relative Humidity

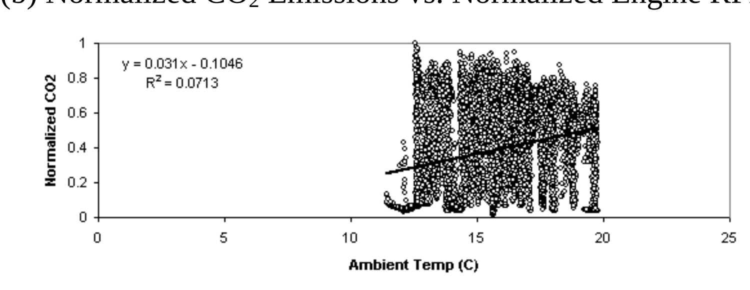
Figure 5-5. Scatter Plots of Normalized Second-by-Second NO_x Emissions versus Candidate Explanatory Variables for Scraper, with Trend Lines Indicated



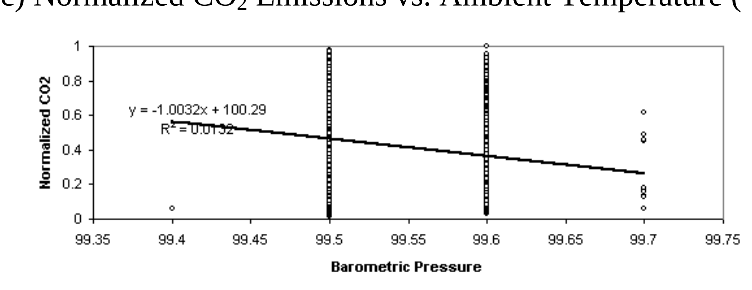
(a) Normalized CO_2 Emissions vs. Normalized Exhaust Flow



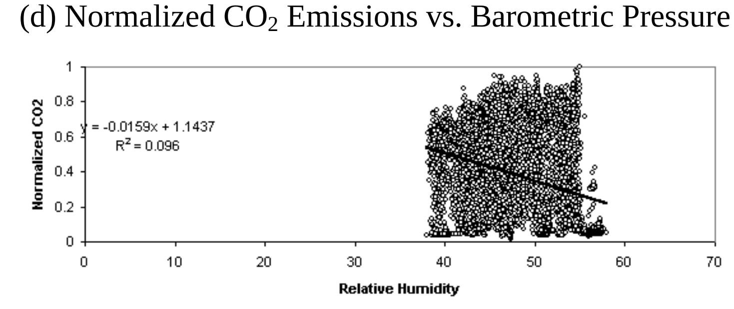
(b) Normalized CO_2 Emissions vs. Normalized Engine RPM



(c) Normalized CO_2 Emissions vs. Ambient Temperature (^oC)



(d) Normalized CO_2 Emissions vs. Barometric Pressure



(e) Normalized CO_2 Emissions vs. Relative Humidity

Figure 5-6. Scatter Plots of Normalized Second-by-Second CO_2 Emissions versus Candidate Explanatory Variables for Scraper, with Trend Lines Indicated

5.3 Model Development

The development of alternative conceptual models for emissions of NO_x and CO_2 from three examples of nonroad equipment is presented in this section. Several methods were explored in order to evaluate the explanatory power of alternative approaches, including modal analysis, regression analysis, and time series analysis.

5.3.1 Objectives

In this study one of the objectives was to develop conceptual models for nonroad vehicles for NO_x and CO_2 emissions using on-board emissions data provided by EPA. The models were later applied to a "validation" data set, as described in Chapter 6, and predictions for these datasets were obtained. Explanatory variables that were provided in the “validation” data set were fewer than the explanatory variables provided in the “modeling” or calibration data set. Therefore, a decision was made to develop models the based only upon variables that were later available for prediction purposes. Variables available in the “validation” dataset are: time/date; temperature (^{0}C); relative humidity (percent); barometric pressure (kPa); engine RPM; and exhaust flow (scfm).

As noted in Chapter 3 for the case of the LDGV data, the second-by-second measurements of vehicle performance and emissions represent time series. Therefore, a component of the work for the nonroad conceptual model development was to quantify the autocorrelation in the data. If there is substantial autocorrelation, then a time series approach might be appropriate for making predictions for individual vehicles based upon one continuous time series of data.. However, as noted in Chapter 3, a time series approach is not expected to be practical for the NGM because it is difficult to develop such models based upon multiple time series for different trips with the same vehicles or for different vehicles. A key question, however, is whether there is a loss of explanatory capability if a time series approach is not used. In order to compare the explanatory capability of a time series approach with other methods, one of the alternative conceptual modeling approaches included for the nonroad cases was a time series approach. In addition, a relatively simple modal approach was employed. As a third alternative, a modal approach combined with OLS regressions for data within each mode was explored. Finally, for comparison purposes only, a multiple OLS regression approach was also explored. These methods are explained in the next sections.

5.3.2 Time Series Approach

In the time series approach, NO_x and CO_2 emissions were modeled using regression with time series errors. Details of this method is given in Section 3.3.6. The reason for using a time series for errors is that the nonroad data are a time series and there is autocorrelation in the data. In order to show the presence of autocorrelation in the data, the autocorrelation coefficients for compactor Trip 2 for NO_x emissions estimated using SAS are given in Figure 5-1. The autocorrelation estimates are significantly different from zero up to lag 11. This indicates that there is autocorrelation in the data. The exponential decrease of the autocorrelation estimates suggests an that autoregressive (AR) process can be fit to NO_x data.

The time series models that were fit to data are summarized in Table 5-2. There are a total of six models, representing two pollutants for each of three vehicles. Four out of the six models are

```
                           Autocorrelations

Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

  0      0.024376        1.00000    |                    |********************|              0
  1      0.021269        0.87254    |                   .|*****************   |       0.025811
  2      0.018732        0.76847    |                  . |***************     |       0.040996
  3      0.015810        0.64861    |                  . |*************       |       0.049674
  4      0.012760        0.52345    |                  . |**********          |       0.055028
  5      0.010115        0.41495    |                  . |********            |       0.058251
  6     0.0081114        0.33276    |                  . |*******             |       0.060188
  7     0.0064554        0.26483    |                  . |*****               |       0.061401
  8     0.0053552        0.21969    |                  . |****                |       0.062158
  9     0.0045766        0.18775    |                 .  |****                |       0.062673
 10     0.0039429        0.16175    |                 .  |***                 |       0.063046
 11     0.0035044        0.14376    |                 .  |***                 |       0.063322
 12     0.0031012        0.12722    |                 .  |***                 |       0.063539
 13     0.0027615        0.11329    |                 .  |**.                 |       0.063709
 14     0.0024546        0.10070    |                 .  |**.                 |       0.063843
 15     0.0021727        0.08913    |                 .  |**.                 |       0.063949
 16     0.0019729        0.08094    |                 .  |**.                 |       0.064031
 17     0.0018180        0.07458    |                 .  |* .                 |       0.064100
 18     0.0016128        0.06616    |                 .  |* .                 |       0.064157
 19     0.0013617        0.05586    |                 .  |* .                 |       0.064203
 20     0.0011243        0.04612    |                 .  |* .                 |       0.064235
 21    0.00090454        0.03711    |                 .  |* .                 |       0.064257
 22    0.00063796        0.02617    |                 .  |* .                 |       0.064272
 23    0.00036546        0.01499    |                 .  |  .                 |       0.064279
 24    0.00013033        0.00535    |                 .  |  .                 |       0.064281

                                  "." marks two standard errors
```

Figure 5-7. Autocorrelation Coefficients Estimates for Compactor Trip 2

Table 5-2. Results of Regression with Time Series Models Fit to Nonroad Data

Vehicle	Pollutant	Model	Explanatory Variables for Regression
Bulldozer	CO_2	AR(4)	ambient temperature, barometric pressure, RPM, Exhaust Flow
	NO_X	AR(4)	Relative Humidity, ambient Temperature, barometric pressure, RPM, Exhaust Flow
Compactor	CO_2	AR(4)	RPM, Exhaust Flow
	NO_X	AR(4)	RPM, Exhaust Flow
Scraper	CO_2	AR(2)	RPM, Exhaust Flow
	NO_X	AR(2)	RPM, Exhaust Flow

based upon an autoregression time series model with a lag of 4 time steps, referred to as an AR(4) model. The other two models are of the AR(2) type. Differences in the autoregressive process for different vehicles might be due to differences in their engine designs or history. Table 5-2 also lists the explanatory variables used in the regression part of the model. All of the variables shown were statistically significant. Coefficients of an example regression equation with time series errors, for NO_x emissions from compactor, are given in Table 5-3. Coefficients of other regression equations are given in Appendix C.

Table 5-3. Coefficients for Regression Equation Fit to Compactor NO_X Data

Parameter	Estimate	Error	Pr > |t|
Intercept	0.00004	0.0008	0.04
AR(1)	0.28	0.026	< 0.001
AR(2)	0.05	0.027	0.049
AR(3)	-0.08	0.027	0.001
AR(4)	-0.15	0.026	< 0.001
RPM	0.00005	8.8E-06	< 0.001
Exhaust Flow	0.003	0.00003	< 0.001

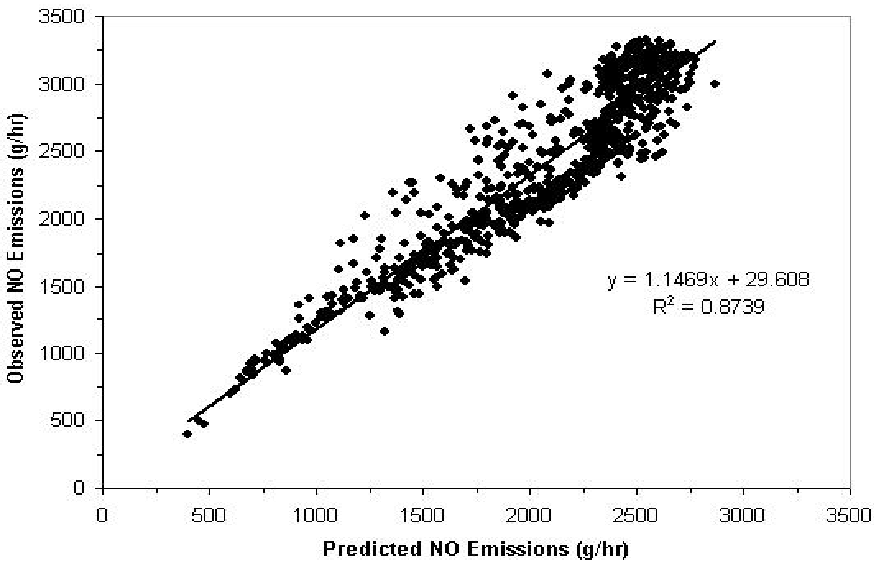


Figure 5-8. Observed NO Emissions versus Predicted using Regression with Time Series Model for Bulldozer Data

In Table 5-3, the parameters for regression equation are given along with the coefficients and p-value showing whether the parameters are significant. All of the parameters have p-values lower than 0.05, indicating that they are significant at a significance level of 0.05. The p-value for AR(2), representing the lag 2 term in the model, is very close to 0.05, and it is kept in the regression equation since coefficients for higher autoregressive parameters are significant. The regression equation for this model is as follows:

$$NO_X = 0.00004 + 0.00005 \times RPM + 0.003 \times Exh + 0.28 \times \varepsilon_{t-1} + 0.05 \times \varepsilon_{t-2} - 0.08 \times \varepsilon_{t-3} - 0.15 \times \varepsilon_{t-4} \quad (5\text{-}1)$$

where:

Exh. = Exhaust Flow (scfm)

ε_k = Error term

Using Equation 5-1, it is possible to estimate NO_x emissions. It should be noted that one needs the first four seconds of emissions data in order to predict emissions for time t. In this study, the first four seconds were estimated using the regression part of the equation, without time series errors. Then the regression with time series was used to get estimates for the fifth and subsequent seconds. In order to evaluate the explanatory power of the model, observed NO_x emissions are plotted versus the model predictions in Figure 5-8. The trend line for the observations versus the predictions has an R^2 of 0.87, indicating that this model can explain 87 percent of the variability in the second-by-second data. The slope of the trend is within 15 percent of one, and the intercept is small compared to the average and span of the data, suggesting that the model can make somewhat accurate estimates of emissions.

5.3.3 Modal and Regression Methods for Model Development

In this section, the application of model and regression modeling methods to the three nonroad data sets is described. As noted in the previous sections, the nonroad second-by-second data are autocorrelated. Therefore, the time series approach is a theoretically appealing method for analyzing and modeling the data. However, an alternative to using time series is to divide the data into categories. When the data are binned into categories, the time series is divided into discontinuous segments, with adjacent segments separated into different bins. The process of binning the data can be a technique for destroying autocorrelation in the data. It is possible that the process of binning autocorrelated data may result in some loss of explanatory power, especially on a second-by-second basis. However, the impact of such a loss of explanatory power on mesoscale or microscale predictions may be small. Thus, we consider a modal or binning approach as an alternative to the time series approach of the previous section.

For each of the three pieces of equipment, the data were binned based upon exhaust flow rate, which was found from the scatter plots in the exploratory analysis to be the variable most highly associated with a change in average NO_x and CO_2 emissions. In deciding upon the endpoints of each bin, consideration was given to several factors. These factors included:

- **Number of bins –** ideally, as few as possible
- **Fraction of total emissions represented by each bin –** ideally, as close to the inverse of the number of bins as possible
- **Trend for average NO_x emissions –** ideally, there should be a well-defined trend (preferably a monotonic increase) in average NO_x emissions with respect to bins for increasing values of exhaust flow rate
- **Coefficient of Variation of Each Bin –** ideally, the coefficient of variation for NO_x emissions, representing the standard deviation of NO_x emissions within a bin divided by the mean NO_x emissions within a bin, should be as small as possible. The modes are more useful in explaining differences in emissions if the values of the CV for adjacent bins are small, indicating that the adjacent bins are clearly different in terms of NO_x emissions.
- **Same approach for CO_2 as for NO_x –** because CO_2 and NO_x are highly correlated for all three pieces of equipment, the same bins were used for both pollutants.

Table 5-4 illustrates the results of the binning process for the bulldozer. A total of 15 bins were defined. The bins were defined with respect to the normalized exhaust flow rate. Approximately 20 percent of the calibration data involved normalized exhaust flows of less than 0.25. However, the contribution to total emissions of this particular mode is only four percent for the calibration data. The average normalized NO_X emission rate is 11 percent of the maximum observed emission rate. The coefficient of variation of 0.25 implies that the standard deviation in this bin is 25 percent of the average value, or approximately 0.03 on a normalized NO_x emissions basis. In fact, this bin appears to be distinct, in terms of NO_x emissions, from the 2nd mode, which has a normalized NO_x emissions average of 0.28 and a coefficient of variation of 0.32. The latter indicates that the standard deviation in the 2nd bin is 0.09 in terms of normalized NO_x emission units. Each successive bin has a higher average NO_x emission rate, and typically the coefficient of variation decreases as the emission rate increases. For the bins with the highest emission rate, the coefficients of variation are less than 10 percent of the mean value. Some of the modes account for more than 10 percent of the total NO_x emissions in the calibration data set, such as Modes 10, 11, and 12.

The modal definitions appear to be effective at accounting for variation in CO_2 emissions. The average CO_2 emission rate in each bin increases monotonically from Modes 1 through 15. The coefficient of variation tends to decrease, in most cases, as the average emission rate increases. Because the total emissions from the vehicle are influenced more by periods of high emission rate than by periods of low emission rate, it is desirable for the model to offer the most precision in estimating the highest emission rate, which this one appears to do for both pollutants. In fact, Modes 7 through 15 have a coefficient of variation of 0.10 or less, which is a good result.

The average emission rates vary from 0.11 to 0.95, on a normalized basis, for NO_X and from 0.05 to 0.94, on a normalized basis, for CO_2. Therefore, it appears that variability in average emissions among the modes is a factor of 8.6 for NO_x and a factor of almost 19 for CO_2. This is a substantial range of variation and indicates that the modal approach offers some ability to discriminate among different emission rates. More importantly, the average emission rates when comparing Modes 1 and 15 are clearly significantly different from a statistical perspective. For example, for NO_x emissions, the average value of Mode 15 is approximately 30 standard deviations from the average of Mode 1, using the standard deviation of either Mode 1 or Mode 15 as the basis for the comparison. This is a statistically significant difference.

Tables 5-5 and 5-6 show the results of the modal models for the compactor and the scraper, respectively. For illustrative purposes, two slightly different objectives were used in developing these two models. For the compactor, the objective was to define the bins in terms of arbitrary but equally wide, with respect to exhaust flow rate, bins, with less attention paid to the fraction of total emissions represented by each bin. The result is that there are some bins that represent a large fraction of the total emissions. For example, Modes 5 and 6 together account for over one half of the total NO_x emissions. For the scraper, the objective was to define modes that explained approximately equal proportions of the total emissions. Therefore, with the exception of Mode 10, each mode accounts for approximately 10 to 15 percent of the total emissions, with no single mode accounting for more than 15 percent of the total NO_x emissions. The mode with the lowest emission rate accounts for 39 percent of the operating time.

Both the bulldozer and the scraper have monotonic increases in both NO_x and CO_2 emission as exhaust flow increases. However, the scraper has a peak in average NO_x emissions associated

Table 5-4. Summary of Modal Emission Model for Bulldozer

Mode	Normalized Exhaust Flow Rate	Fraction of Time in Mode	Fraction of Emissions in Mode	Normalized NO_x Emissions		Normalized CO_2 Emissions	
				Average	CV	Average	CV
1	0-0.25	0.20	0.04	0.11	0.25	0.05	0.25
2	0.25 - 0.50	0.05	0.03	0.28	0.32	0.25	0.36
3	0.50 - 0.60	0.03	0.02	0.41	0.19	0.39	0.20
4	0.60 - 0.70	0.08	0.08	0.50	0.18	0.46	0.19
5	0.70 - 0.725	0.05	0.05	0.57	0.13	0.51	0.13
6	0.725 - 0.75	0.08	0.09	0.60	0.11	0.54	0.11
7	0.75 - 0.775	0.07	0.08	0.63	0.12	0.58	0.10
8	0.775 - 0.80	0.06	0.07	0.67	0.13	0.64	0.10
9	0.80 - 0.825	0.06	0.08	0.72	0.11	0.68	0.08
10	0.825 - 0.85	0.08	0.11	0.78	0.09	0.74	0.07
11	0.85 - 0.875	0.09	0.13	0.82	0.07	0.79	0.06
12	0.875 - 0.90	0.08	0.12	0.87	0.07	0.85	0.06
13	0.90 - 0.925	0.04	0.07	0.90	0.06	0.89	0.05
14	0.925 - 0.95	0.01	0.02	0.92	0.04	0.92	0.04
15	0.95 - 1.00	0.00	0.01	0.95	0.03	0.94	0.04

CV = Coefficient of variation (standard deviation divided by the mean)

Table 5-5. Summary of Modal Emission Model for Compactor

Mode	Normalized Exhaust Flow Rate	Fraction of Time in Mode	Fraction of Emissions in Mode	Normalized NO_x Emissions		Normalized CO_2 Emissions	
				Average	CV	Average	CV
1	0.50	0.23	0.05	0.12	1.85	0.11	0.73
2	0.70	0.08	0.07	0.53	0.24	0.41	0.19
3	0.75	0.03	0.03	0.67	0.21	0.52	0.13
4	0.80	0.08	0.10	0.75	0.23	0.57	0.12
5	0.83	0.18	0.24	0.78	0.24	0.62	0.11
6	0.85	0.26	0.33	0.75	0.25	0.66	0.11
7	0.88	0.10	0.12	0.68	0.26	0.72	0.11
8	0.90	0.04	0.04	0.64	0.22	0.76	0.12
9	1.00	0.01	0.01	0.62	0.39	0.81	0.15

CV = Coefficient of variation (standard deviation divided by the mean)

Table 5-6. Summary of Modal Emission Model for Scraper

Mode	Normalized Exhaust Flow Rate	Fraction of Time in Mode	Fraction of Emissions in Mode	Normalized NO_x Emissions		Normalized CO_2 Emissions	
				Average	CV	Average	CV
1	0.41	0.39	0.10	0.08	0.76	0.20	0.69
2	0.57	0.11	0.10	0.31	0.34	0.30	0.33
3	0.65	0.08	0.11	0.44	0.26	0.41	0.32
4	0.72	0.09	0.14	0.51	0.21	0.48	0.24
5	0.76	0.07	0.12	0.59	0.17	0.56	0.20
6	0.80	0.06	0.11	0.65	0.15	0.62	0.18
7	0.85	0.07	0.13	0.69	0.13	0.66	0.16
8	0.89	0.07	0.15	0.72	0.09	0.71	0.12
9	0.93	0.05	0.12	0.76	0.08	0.73	0.11
10	1.00	0.02	0.04	0.80	0.07	0.76	0.10

CV = Coefficient of variation (standard deviation divided by the mean) with Mode 5, which represents exhaust flow of 0.80 to 0.825 of the maximum value in the database. Thus, the emissions behavior of the compactor is different in this respect compared to the other two pieces of equipment. However, although the average NO_x emissions reach a peak at Mode 5, the average CO_2 emissions increase monotonically as exhaust flow increases from Mode 1 through Mode 9. In fact, average CO_2 emissions increase monotonically with exhaust flow in all three cases.

The modal models for each piece of equipment offer some explanatory power. However, it is possible to attempt to improve the modal models by incorporating functional relationships between emissions and one or more explanatory variables within the data for each mode. A simple approach to doing this was explored in these examples based upon the use of ordinary least squares (OLS) regression for one explanatory variable at a time for the data in each bin. These models are referred to as "Modes with OLS".

As an example, consider NO_x emissions for the bulldozer. The results of the OLS regression analysis of each individual possible explanatory variable are shown in Table 5-7. For each bin of modal data, a linear regression with intercept b and slope m was fit to the data to attempt to explain the variability in NO_x emissions as a function of either engine RPM, exhaust flow, ambient temperature, barometric pressure or humidity along. The R^2 values reported in the table indicate whether the linear model offered any explanatory power. In this particular case, the explanatory power of engine RPM and exhaust flow is almost negligible for almost all of the modes. Of course, the binning of the data took into account a significant portion of the explanatory power of exhaust flow with respect to emissions. The data within each bin is relatively homogeneous with respect to exhaust flow. Therefore, it is expected that the explanatory power of exhaust flow as a predictive variable in OLS would be very small. There appears to be a weak depending of emissions within each bin on ambient temperature or humidity, such as for Modes 5 and 12. There is also a weak dependence of emissions on barometric pressure.

For CO_2, the results are somewhat different, as illustrated by a comparison of Table 5-8 to Table 5-7. Engine RPM has an R^2 value of 0.5 or more for Modes 11 and 12 in Table 5-8. Exhaust flow has very low R^2 values as expected. Ambient temperature, relative humidity, and barometric pressure have R^2 values exceeding 0.4 in some cases.

In inspecting the results for the compactor and the scraper, it appears that engine RPM has useful explanatory power in several cases. For example, for the compactor, Table 5-9 shows results for NO_x emissions and Table 5-10 shows results for CO_2 emissions. For the higher emission modes, such as Mode 8 and Mode 9, engine RPM has an R^2 of greater than 0.3 in one case for both NO_x and CO_2. Table 5-11 shows results for NO_x emissions and Table 5-12 shows results for CO_2 emissions for the scraper. This case shows the strongest dependence of the emissions data within each mode on engine RPM. For NO_x, the R^2 values exceed 0.5 for eight of the modes, and for CO_2 the R^2 values exceed 0.3 for eight of the modes.

To simplify the model development process, it was decided to choose only one supplemental

Table 5-7. Summary of OLS Regression Equations for NO_x Emissions as a Function of an Individual Candidate Explanatory Variable, for the Bulldozer.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	0.12	-0.02	0.02	0.03	0.41	0.03	0.12	0.00	0.00	-14.0	0.23	0.50	0.10	0.00	0.00
2	-0.01	0.41	0.26	-0.13	0.99	0.48	0.22	0.00	0.01	-30.8	0.51	0.69	0.30	0.00	0.00
3	0.26	0.19	0.05	0.11	0.53	0.04	0.30	0.00	0.04	-28.6	0.48	0.56	0.47	0.00	0.04
4	0.44	0.06	0.00	-0.04	0.82	0.06	0.26	0.01	0.15	-37.0	0.62	0.52	0.63	0.00	0.16
5	0.69	-0.13	0.01	-0.77	1.88	0.03	0.25	0.01	0.21	-33.7	0.56	0.42	0.74	0.00	0.23
6	0.48	0.13	0.01	-0.59	1.61	0.03	0.41	0.01	0.10	-28.0	0.47	0.35	0.72	0.00	0.12
7	0.18	0.48	0.07	-0.44	1.40	0.02	0.50	0.00	0.04	-30.0	0.50	0.42	0.71	0.00	0.05
8	0.46	0.23	0.01	-1.07	2.21	0.03	0.63	0.00	0.00	-26.1	0.44	0.28	0.71	0.00	0.01
9	0.61	0.12	0.00	-1.29	2.48	0.05	0.63	0.00	0.02	-16.2	0.28	0.11	0.79	0.00	0.04
10	0.42	0.39	0.02	-0.90	2.01	0.04	0.61	0.01	0.09	0.73	0.00	0.00	0.90	0.00	0.13
11	1.12	-0.32	0.01	-1.00	2.11	0.06	0.64	0.01	0.14	9.67	-0.15	0.04	0.95	0.00	0.19
12	1.29	-0.47	0.02	-0.66	1.72	0.04	0.68	0.01	0.18	12.6	-0.19	0.09	0.99	0.00	0.22
13	0.97	-0.08	0.00	0.39	0.55	0.01	0.68	0.01	0.17	15.0	-0.23	0.13	1.02	0.00	0.20
14	0.67	0.29	0.01	0.15	0.82	0.02	0.86	0.00	0.02	5.20	-0.07	0.02	0.97	0.00	0.02
15	1.33	-0.42	0.04	0.81	0.15	0.00	0.76	0.01	0.02	0.64	0.01	0.00	1.03	0.00	0.00

b = intercept, m = slope, R^2 = coefficient of determination

Table 5-8. Summary of OLS Regression Equations for CO_2 Emissions as a Function of an Individual Candidate Explanatory Variable, for the Bulldozer.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	0.06	-0.02	0.05	-0.09	0.71	0.38	0.03	0.00	0.02	-0.09	0.00	0.00	0.07	0.00	0.04
2	0.05	0.29	0.12	-0.18	1.06	0.51	0.35	0.00	0.02	-23.7	0.40	0.38	0.19	0.00	0.02
3	0.46	-0.08	0.01	-0.02	0.75	0.07	0.46	0.00	0.01	-12.9	0.22	0.11	0.36	0.00	0.01
4	0.81	-0.38	0.12	0.10	0.54	0.03	0.43	0.00	0.00	-20.3	0.34	0.16	0.48	0.00	0.00
5	1.21	-0.75	0.29	0.11	0.55	0.00	0.35	0.01	0.08	-10.6	0.18	0.06	0.59	0.00	0.08
6	1.17	-0.67	0.21	-0.72	1.71	0.04	0.37	0.01	0.10	1.54	-0.02	0.00	0.64	0.00	0.12
7	1.03	-0.48	0.11	-1.04	2.13	0.07	0.40	0.01	0.15	4.87	-0.07	0.01	0.70	0.00	0.17
8	1.35	-0.77	0.20	-1.13	2.24	0.06	0.46	0.01	0.16	9.50	-0.15	0.06	0.75	0.00	0.19
9	1.48	-0.86	0.20	-1.05	2.14	0.08	0.54	0.01	0.12	10.38	-0.16	0.08	0.78	0.00	0.15
10	1.54	-0.87	0.17	-1.06	2.14	0.09	0.54	0.01	0.24	19.97	-0.32	0.29	0.86	0.00	0.29
11	2.41	-1.77	0.55	-1.46	2.61	0.14	0.55	0.01	0.37	25.38	-0.41	0.48	0.94	0.00	0.41
12	2.63	-1.97	0.53	-1.37	2.51	0.12	0.57	0.01	0.45	24.99	-0.40	0.51	1.00	0.00	0.49
13	2.50	-1.79	0.37	-0.62	1.66	0.06	0.62	0.01	0.34	26.19	-0.42	0.56	1.04	0.00	0.40
14	1.99	-1.19	0.21	0.72	0.22	0.00	0.67	0.01	0.29	22.36	-0.35	0.53	1.09	0.00	0.32
15	2.74	-2.00	0.42	-0.27	1.26	0.15	0.87	0.00	0.00	27.61	-0.44	0.48	1.93	-0.01	0.17

b = intercept, m = slope, R^2 = coefficient of determination

Table 5-9. Summary of OLS Regression Equations for NO_x Emissions as a Function of an Individual Candidate Explanatory Variable, for the Compactor.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	-0.06	0.54	0.19	-0.34	1.57	0.28	0.04	0.02	0.09	-1.14	0.01	0.02	0.58	-0.01	0.09
2	0.28	0.30	0.06	-0.12	1.07	0.24	0.40	0.02	0.16	1.38	-0.01	0.07	0.86	-0.01	0.13
3	0.72	-0.07	0.00	-1.61	3.13	0.11	0.54	0.02	0.13	1.72	-0.01	0.15	0.99	-0.01	0.10
4	0.66	0.11	0.00	-0.69	1.85	0.02	0.67	0.01	0.06	2.18	-0.01	0.19	1.01	0.00	0.04
5	0.50	0.32	0.02	1.04	-0.33	0.00	0.62	0.03	0.19	2.27	-0.02	0.15	1.39	-0.01	0.16
6	0.35	0.46	0.03	1.85	-1.31	0.00	0.52	0.05	0.37	2.13	-0.01	0.06	1.79	-0.02	0.32
7	0.39	0.34	0.03	3.89	-3.73	0.02	0.48	0.04	0.35	2.24	-0.02	0.06	1.57	-0.01	0.30
8	0.34	0.36	0.11	0.09	0.62	0.00	0.48	0.03	0.48	-81	0.82	0.70	1.37	-0.01	0.46
9	-0.04	0.86	0.36	5.82	-5.66	0.26	0.37	0.05	0.67	-111	1.12	0.79	1.75	-0.02	0.67

b = intercept, m = slope, R^2 = coefficient of determination

Table 5-10. Summary of OLS Regression Equations for CO_2 Emissions as a Function of an Individual Candidate Explanatory Variable, for the Compactor.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	-0.02	0.39	0.66	-0.13	0.85	0.54	0.10	0.00	0.03	-0.91	0.01	0.10	0.28	0.00	0.07
2	0.18	0.29	0.13	-0.07	0.80	0.34	0.51	-0.01	0.21	0.25	0.00	0.01	0.19	0.00	0.16
3	0.35	0.21	0.08	0.28	0.32	0.01	0.57	-0.01	0.12	0.18	0.00	0.07	0.38	0.00	0.08
4	0.45	0.14	0.04	-0.51	1.37	0.08	0.61	-0.01	0.12	0.20	0.00	0.09	0.42	0.00	0.09
5	0.56	0.07	0.01	-0.81	1.75	0.03	0.69	-0.01	0.30	0.22	0.00	0.07	0.32	0.00	0.26
6	0.54	0.14	0.02	-0.91	1.88	0.03	0.76	-0.02	0.45	0.30	0.00	0.03	0.23	0.01	0.39
7	0.47	0.29	0.13	-1.15	2.17	0.04	0.82	-0.02	0.46	0.33	0.00	0.02	0.28	0.01	0.38
8	0.38	0.46	0.47	-0.51	1.43	0.01	0.86	-0.02	0.46	24.5	-0.24	0.15	0.34	0.01	0.41
9	0.65	0.20	0.07	-0.83	1.78	0.10	0.90	-0.02	0.39	27.9	-0.27	0.18	0.39	0.01	0.35

b = intercept, m = slope, R^2 = coefficient of determination

Table 5-11. Summary of OLS Regression Equations for NO_x Emissions as a Function of an Individual Candidate Explanatory Variable, for the Scraper.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	-0.03	0.35	0.56	-0.09	0.64	0.40	0.04	0.00	0.02	8.96	-0.09	0.00	0.17	0.00	0.03
2	0.32	-0.01	0.00	-0.16	0.97	0.16	0.16	0.01	0.03	3.47	-0.03	0.00	0.51	0.00	0.03
3	0.86	-0.54	0.43	-0.34	1.28	0.07	0.35	0.01	0.01	24.6	-0.24	0.00	0.53	0.00	0.00
4	1.01	-0.61	0.54	-0.33	1.22	0.04	0.49	0.00	0.00	44.1	-0.44	0.02	0.51	0.00	0.00
5	1.14	-0.68	0.61	-0.61	1.62	0.04	0.71	-0.01	0.02	48.0	-0.48	0.03	0.43	0.00	0.02
6	1.25	-0.76	0.65	-0.18	1.07	0.02	0.90	-0.02	0.09	32.8	-0.32	0.01	0.34	0.01	0.07
7	1.33	-0.80	0.60	-0.14	1.00	0.02	1.01	-0.02	0.16	43.8	-0.43	0.03	0.26	0.01	0.14
8	1.43	-0.86	0.61	-0.17	1.03	0.04	0.96	-0.01	0.13	51.0	-0.50	0.05	0.42	0.01	0.12
9	1.60	-1.02	0.58	0.00	0.83	0.03	0.95	-0.01	0.09	40.8	-0.40	0.06	0.52	0.01	0.08
10	1.71	-1.11	0.63	0.45	0.36	0.01	0.88	-0.01	0.02	42.0	-0.41	0.11	0.70	0.00	0.01

b = intercept, m = slope, R^2 = coefficient of determination

Table 5-12. Summary of OLS Regression Equations for CO_2 Emissions as a Function of an Individual Candidate Explanatory Variable, for the Scraper.

Mode	Candidate Explanatory Variables														
	Engine RPM			Exhaust Flow			Amb. Temp.			Bar. Pressure			Rel. Humidity		
	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2	b	m	R^2
1	0.20	-0.02	0.00	0.25	-0.19	0.01	0.48	-0.02	0.16	291	-2.92	0.35	-0.23	0.01	0.14
2	0.40	-0.14	0.07	0.03	0.55	0.06	0.28	0.00	0.00	-8.1	0.08	0.00	0.34	0.00	0.00
3	0.82	-0.52	0.33	-0.41	1.34	0.06	0.33	0.00	0.00	25.5	-0.25	0.00	0.47	0.00	0.00
4	0.91	-0.52	0.34	-0.44	1.34	0.05	0.44	0.00	0.00	46.4	-0.46	0.02	0.50	0.00	0.00
5	1.00	-0.54	0.30	-0.69	1.70	0.03	0.60	0.00	0.00	51.4	-0.51	0.02	0.49	0.00	0.00
6	1.13	-0.64	0.36	-0.26	1.13	0.02	0.86	-0.01	0.06	23.7	-0.23	0.01	0.33	0.01	0.05
7	1.24	-0.72	0.35	-0.31	1.17	0.02	0.97	-0.02	0.10	31.8	-0.31	0.01	0.27	0.01	0.09
8	1.39	-0.83	0.36	-0.11	0.94	0.02	0.98	-0.02	0.11	35.4	-0.35	0.01	0.36	0.01	0.10
9	1.70	-1.17	0.39	0.14	0.65	0.01	1.01	-0.02	0.10	37.8	-0.37	0.03	0.37	0.01	0.09
10	2.02	-1.51	0.54	0.55	0.23	0.00	0.91	-0.01	0.03	53.5	-0.53	0.08	0.60	0.00	0.02

b = intercept, m = slope, R^2 = coefficient of determination

explanatory variable for use in OLS regression for each mode. Based upon a review of results for all three pieces of equipment, a judgment was made to select engine RPM as the supplemental explanatory variable. In principle, multiple regression models could be developed for each mode that would also include barometric pressure and either temperature or humidity. As previously noted, temperature and humidity are highly correlated in these data sets, so both cannot be selected for a model. However, given the highly correlated nature of temperature and humidity, and the inability to separate their effects, it was decided not to include them here.

As an alternative to a modal approach, a multiple OLS regression approach was also explored. It is recognized that this approach is not appropriate from a strictly statistical perspective, given the autocorrelated nature of the data and the lack of binning to destroy autocorrelation. However, an objective was to compare the multiple OLS regression approach with the time series approach to determine if accounting for autocorrelation increased the explanatory power of the model to a significant degree when compared to an approach that does not properly account for autocorrelation. Therefore, the "naïve" application of multiple OLS regression to the autocorrelated nonroad data sets is intended mainly to help identify or understand the potential benefits of a time series approach, but is not recommended as an approach to use in future model development. The results of the multiple OLS regressions are summarized in Tables 5-13, 5-14, and 5-15 for the bulldozer, compactor, and scraper, respectively.

The performance of the modal, modal and OLS, and multiple OLS approaches are evaluated using parity plots of observed emissions versus predicted emissions, as shown in Figures 5-9 through 5-14. Figures 5-9 and 5-10 show results for NO_x and CO_2, respectively, for the bulldozer. Figures 5-11 and 5-12 show results for NO_x and CO_2, respectively, for the compactor. Figures 5-13 and 5-14 show results for NO_x and CO_2, respectively, for the scraper. Each figure displays three panels, with panel (a) showing results for the modal model, panel (b) showing results for the modal model with linear OLS regression based upon engine RPM for each mode, and panel (c) showing results for the multiple OLS regression model.

There are some general features common to all of the figures. A choice was made to plot observed values versus predicted values because we were interested in the question of how to convert predicted values to a correct average observed value if the model predictions were biased. However, in all cases, the trend lines shown in each panel and in each figure have a slope very close to or identically equal to one. The slope of the trend line indicates that the models are accurate in predicting second-by-second emissions. The slope does not indicate whether the model is precise.

The degree of scatter of the observed values above and below the trend line is an indication of the precision (or lack thereof) of the model predictions. However, because the scatter plots are based upon in excess of 10,000 second-by-second data points, it is difficult to judge the density of data values in specific regions of each graph. Therefore, the scatter plots can give a misleading sense of unexplained variability in the predictions. For example, in Figure 5-9(a), the vertical lines represent the predicted emissions for each mode. The predictions appear as if they are vertical lines because the plot symbols are large enough to overlap each other. The highest density of predicted values occurs near the average of the observed values for a given mode.

Table 5-13. Summary of Multiple OLS Regression Equations for NO_x and CO_2 Emissions as a Function of Four Candidate Explanatory Variables, for the Bulldozer.

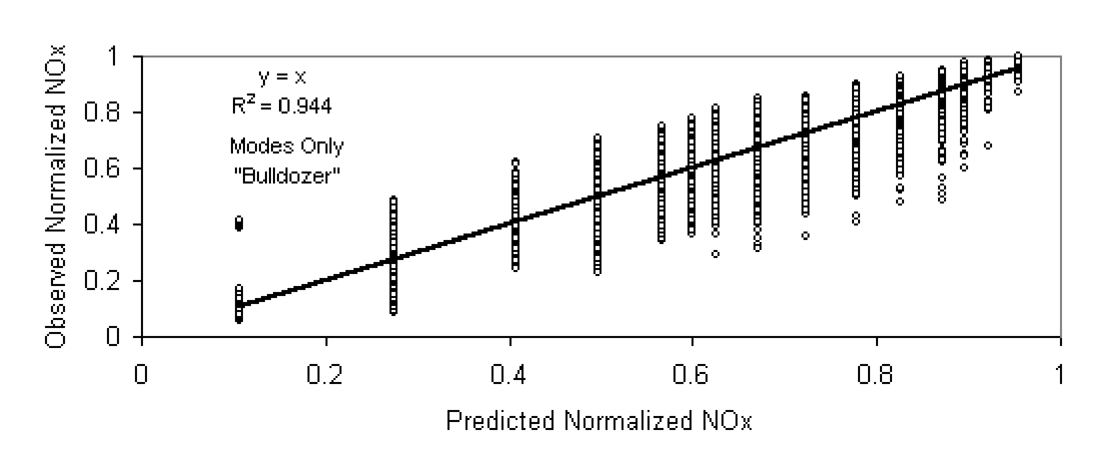
Description	Normalized NO_x Emissions		Normalized CO_2 Emissions	
	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	-15.09	-33	5.16	13
Ambient Temperature	0.01	27	0.00	18
Barometric Pressure	0.25	33	-0.09	-13
Normalized Engine RPM	-0.26	-37	-0.36	-57
Normalized Exhaust Flow	1.13	197	1.34	259
Adjusted R^2	0.937		0.950	
Standard Error	0.071		0.064	
Sample Size	10491		10491	

Table 5-14. Summary of Multiple OLS Regression Equations for NO_x and CO_2 Emissions as a Function of Four Candidate Explanatory Variables, for the Compactor.

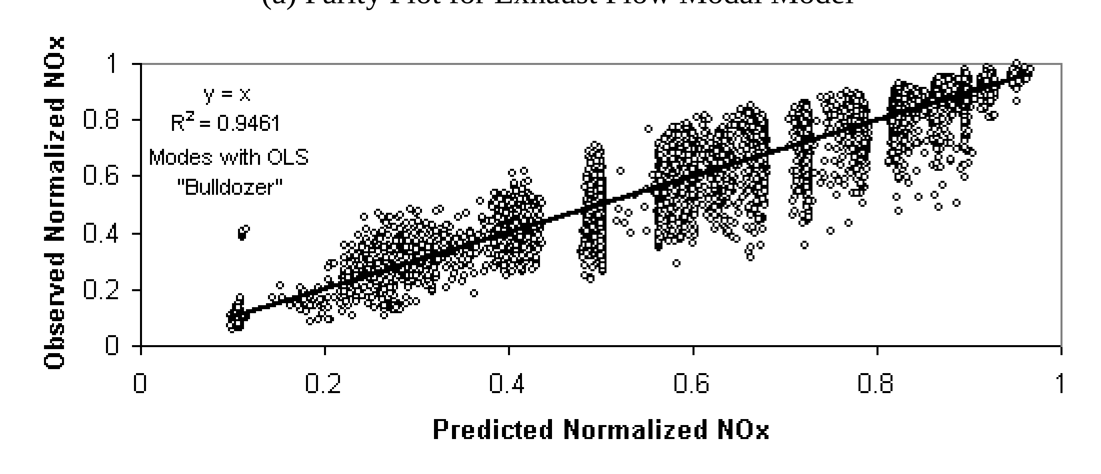
Description	Normalized NO_x Emissions		Normalized CO_2 Emissions	
	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	1.51	37	-0.67	-44
Ambient Temperature	0.03	54	-0.01	-75
Barometric Pressure	-0.02	-45	0.01	35
Normalized Engine RPM	0.28	20	0.17	35
Normalized Exhaust Flow	0.81	57	0.87	166
Adjusted R^2	0.770		0.945	
Standard Error	0.154		0.057	
Sample Size	10537		10537	

Table 5-15. Summary of Multiple OLS Regression Equations for NO_x and CO_2 Emissions as a Function of Four Candidate Explanatory Variables, for the Scraper.

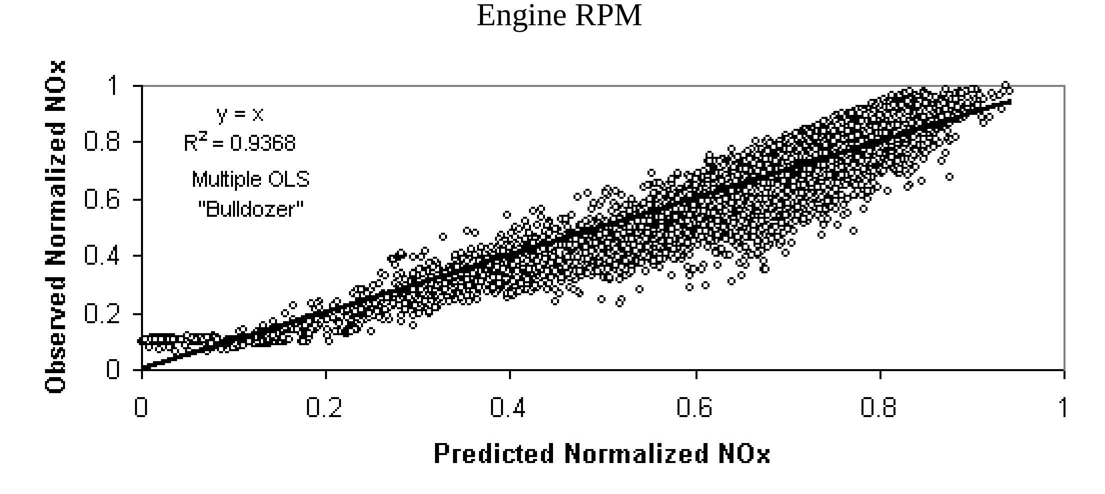
Description	Normalized NO_x Emissions		Normalized CO_2 Emissions	
	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	33.65	14	101.52	29
Ambient Temperature	0.00	5	-0.01	-18
Barometric Pressure	-0.34	-14	-1.02	-29
Normalized Engine RPM	-0.15	-28	-0.27	-33
Normalized Exhaust Flow	1.19	214	1.05	130
Adjusted R^2	0.920		0.770	
Standard Error	0.078		0.113	
Sample Size	10693		10693	



(a) Parity Plot for Exhaust Flow Modal Model

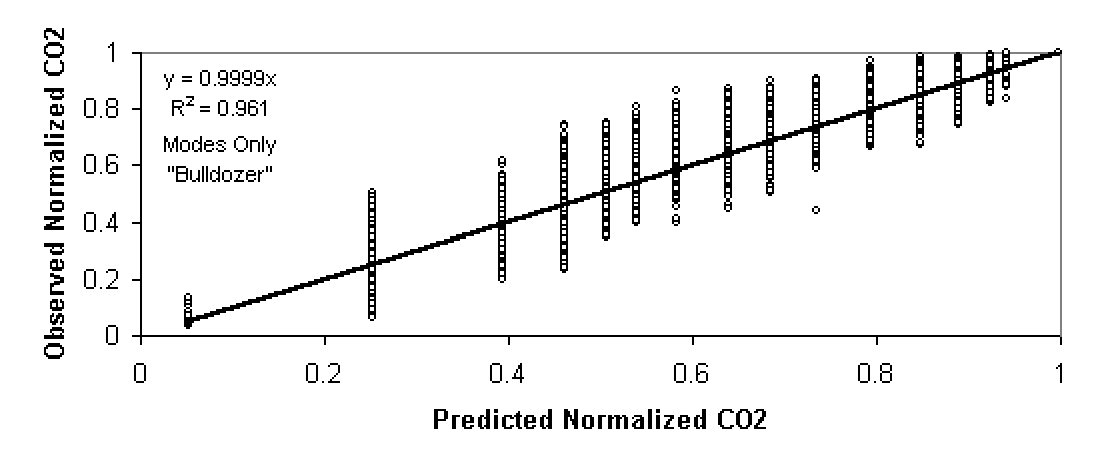


(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM

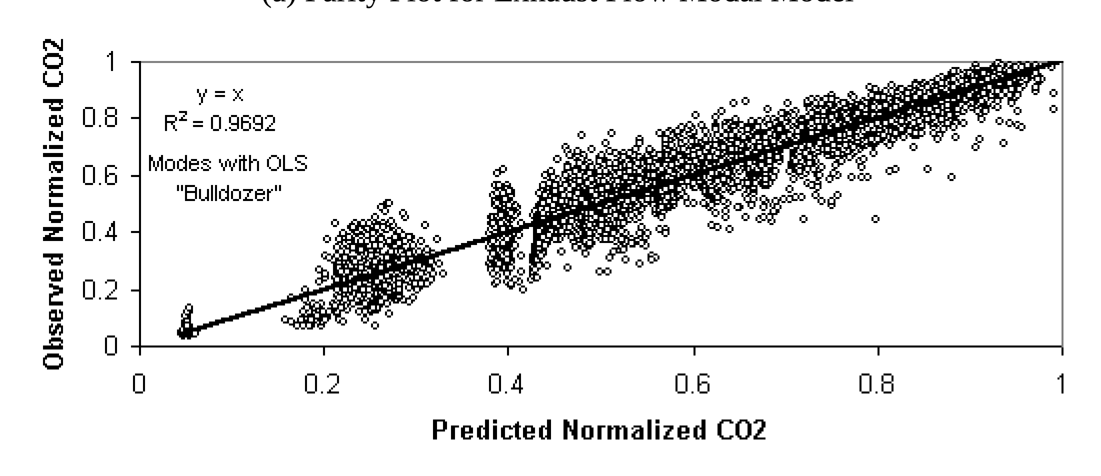


(c) Parity Plot of Multiple OLS Regression Model

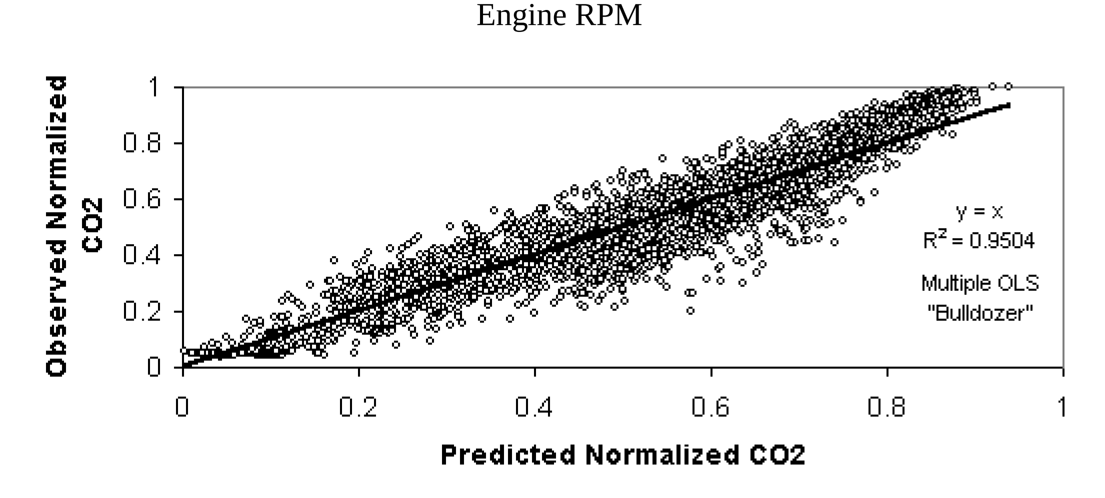
Figure 5-9. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for NO_x Emissions from the Bulldozer.



(a) Parity Plot for Exhaust Flow Modal Model

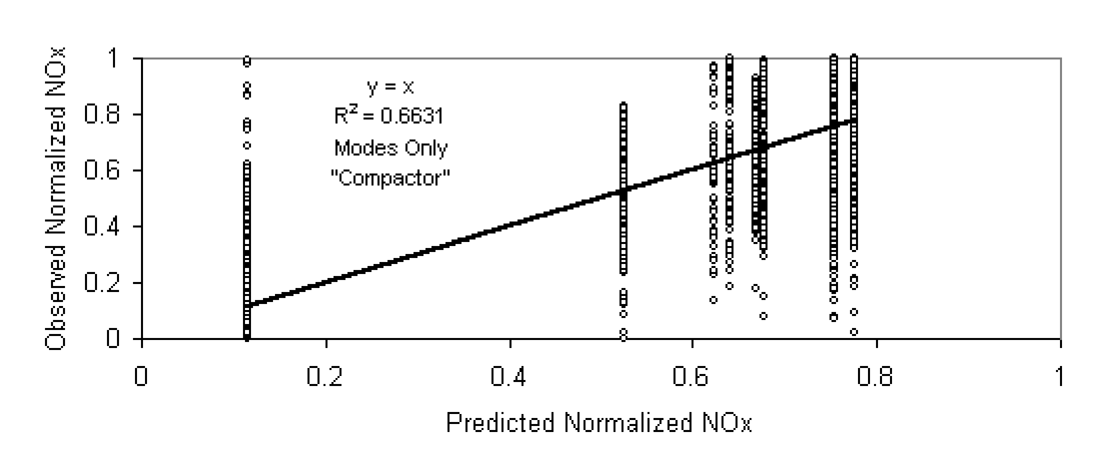


(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM

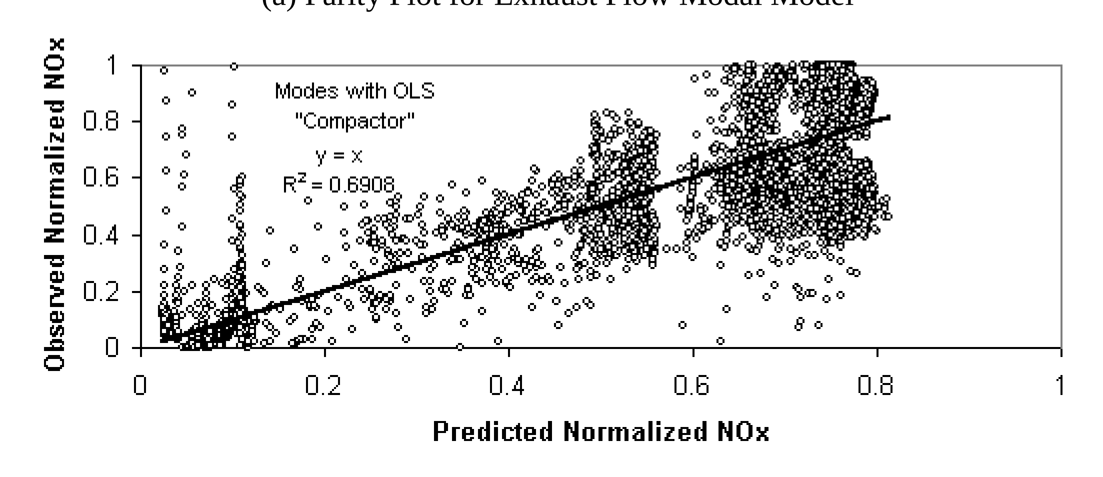


(c) Parity Plot of Multiple OLS Regression Model

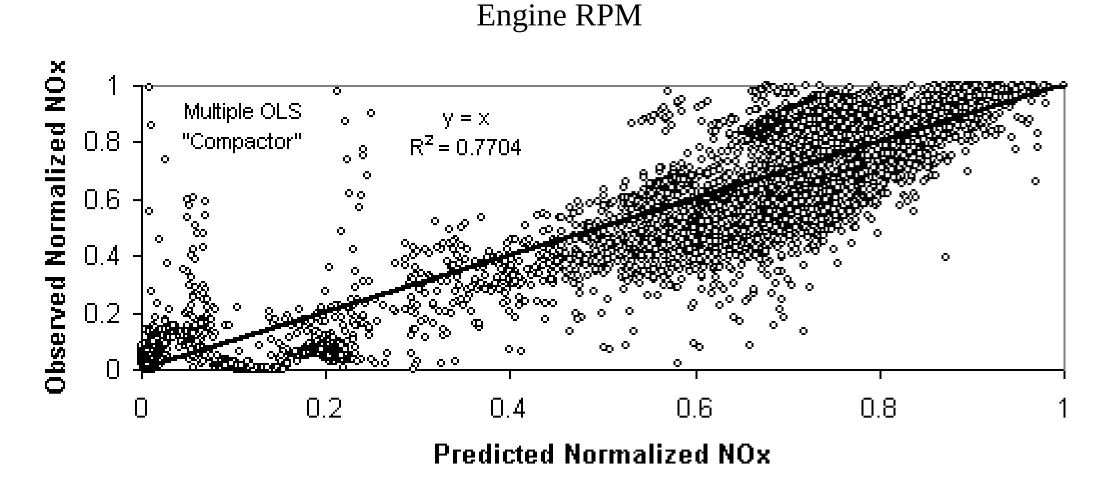
Figure 5-10. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for CO_2 Emissions from the Bulldozer.



(a) Parity Plot for Exhaust Flow Modal Model

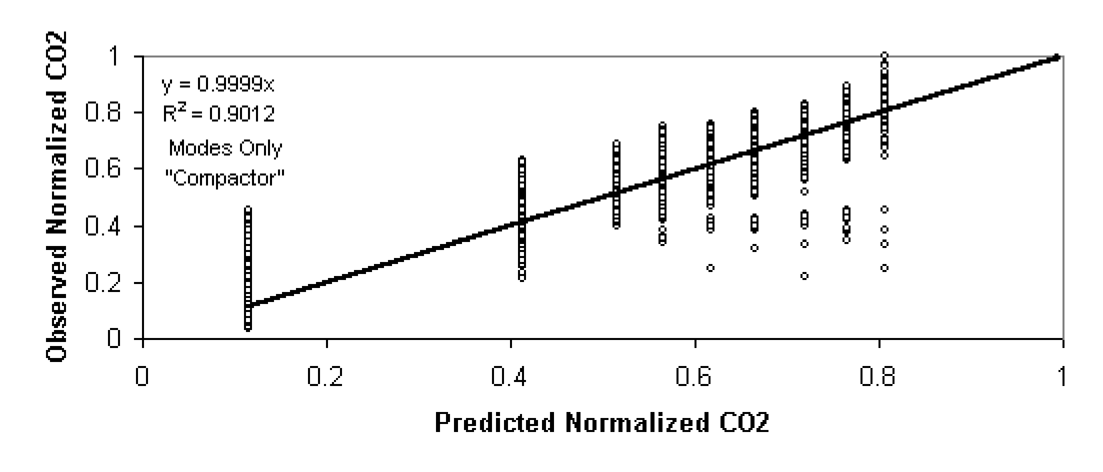


(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM

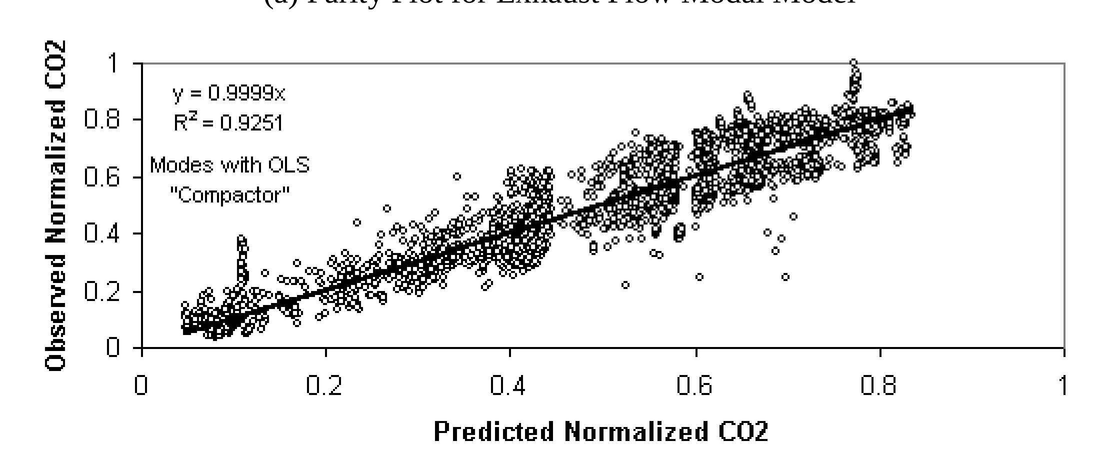


(c) Parity Plot of Multiple OLS Regression Model

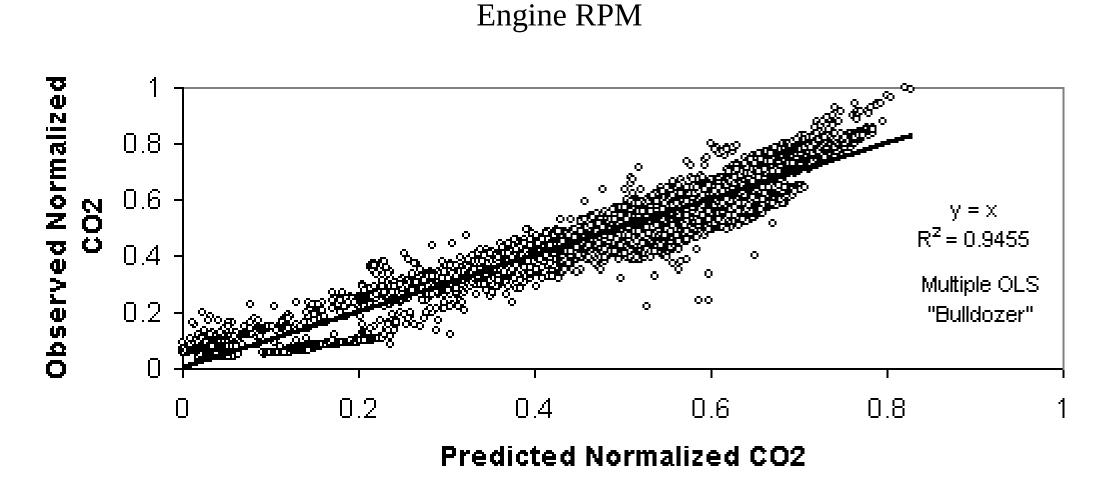
Figure 5-11. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for NO_x Emissions from the Compactor.



(a) Parity Plot for Exhaust Flow Modal Model

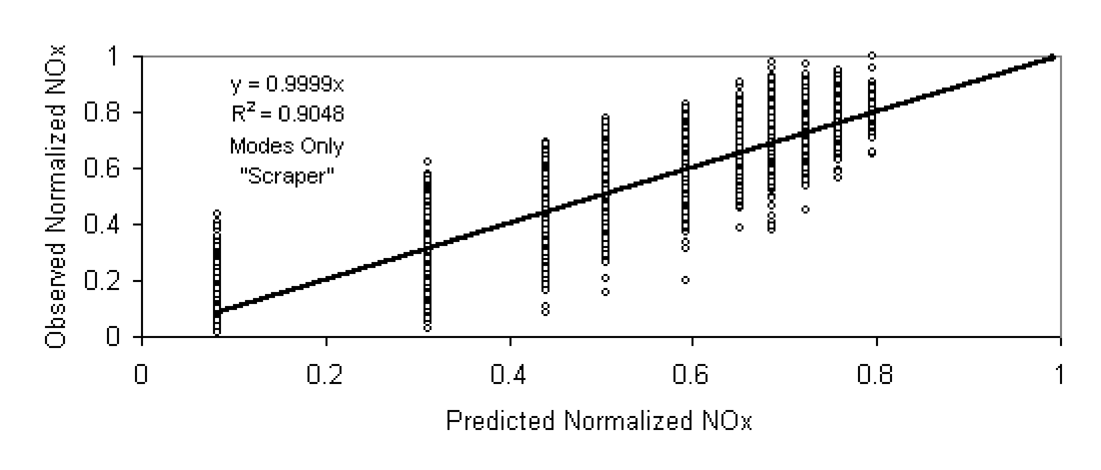


(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM

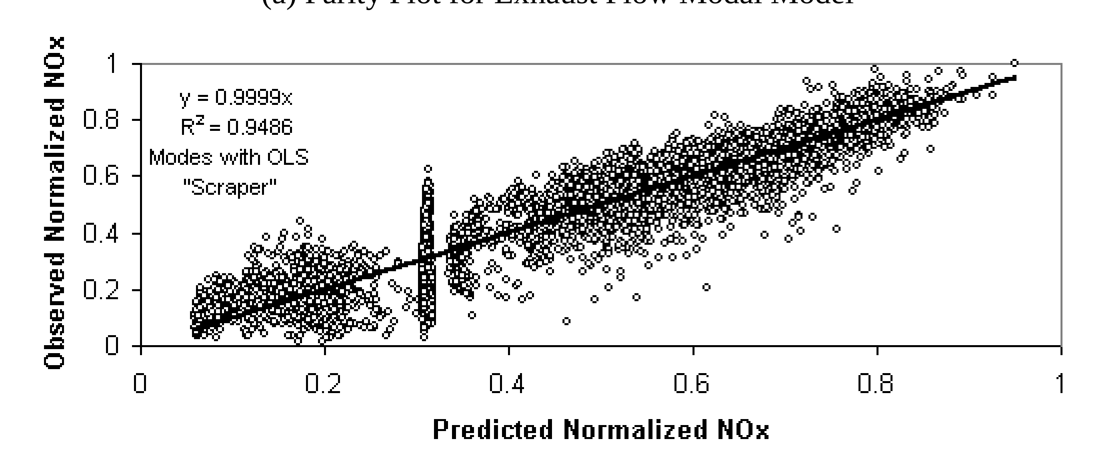


(c) Parity Plot of Multiple OLS Regression Model

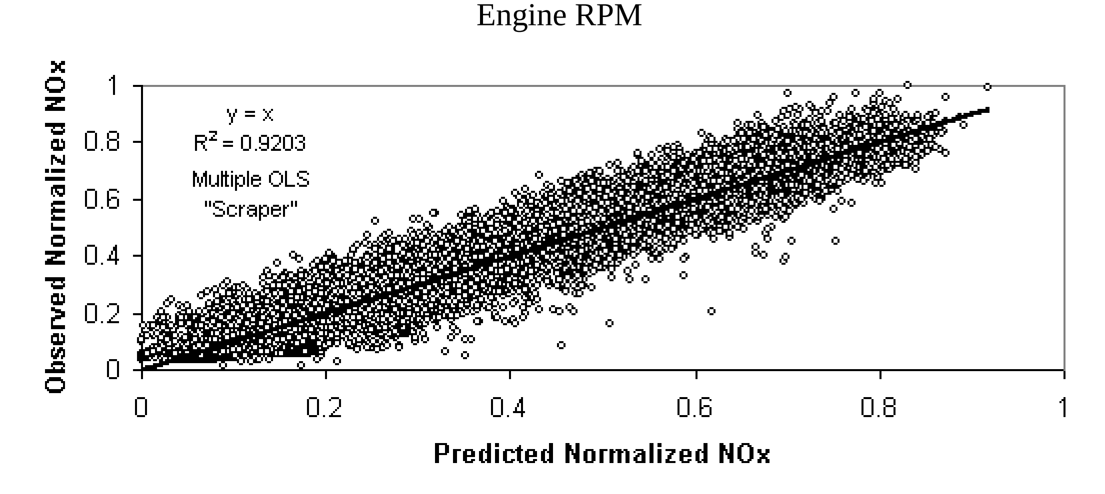
Figure 5-12. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for CO_2 Emissions from the Compactor.



(a) Parity Plot for Exhaust Flow Modal Model

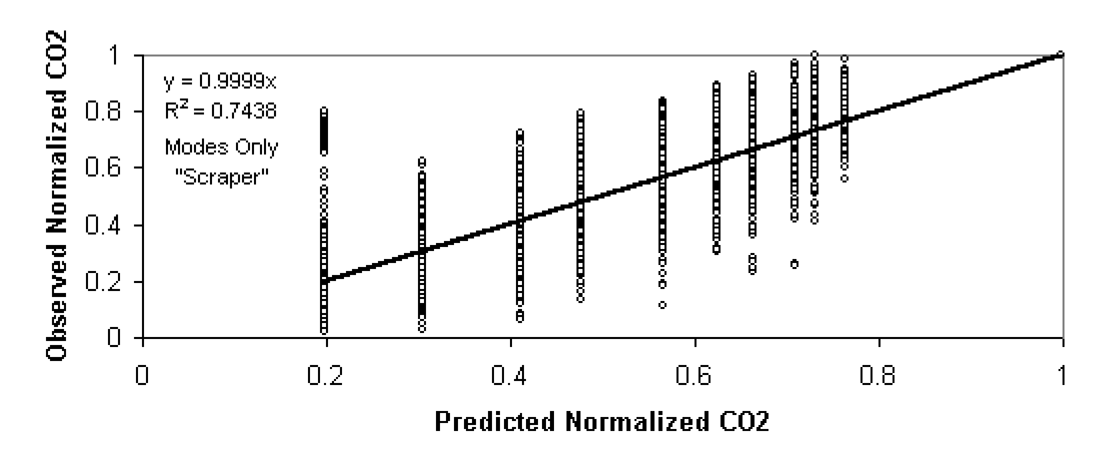


(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM

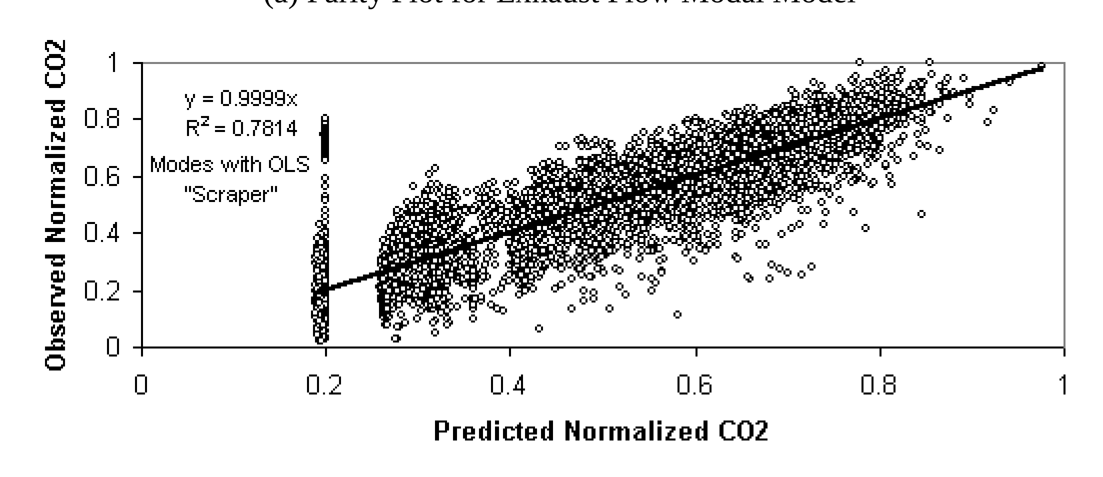


(c) Parity Plot of Multiple OLS Regression Model

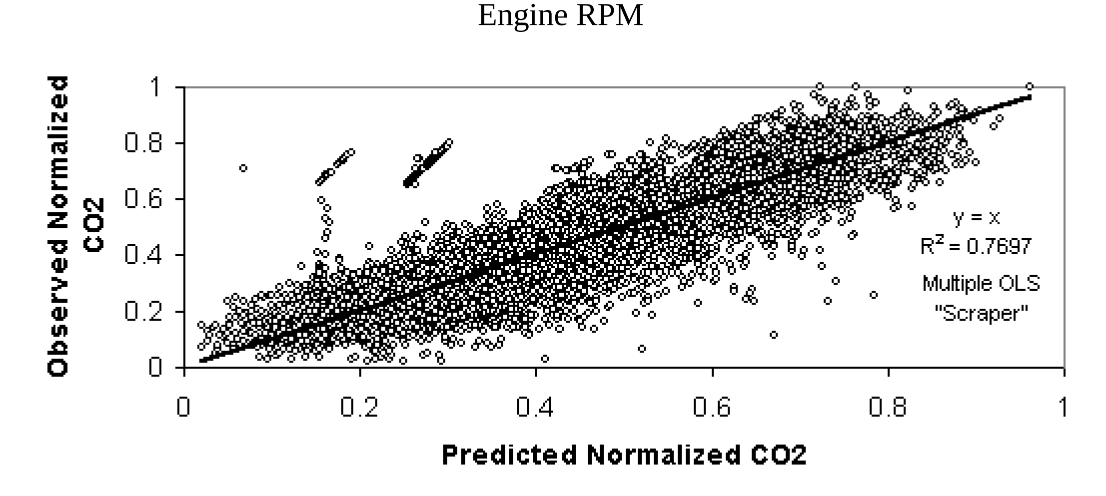
Figure 5-13. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for NO_x Emissions from the Scraper.



(a) Parity Plot for Exhaust Flow Modal Model



(b) Parity Plot for Model with Exhaust Flow-Based Modes and Linear OLS Regression for Engine RPM



(c) Parity Plot of Multiple OLS Regression Model

Figure 5-14. Comparison of Second-by-Second Observations with Three Alternative Model and/or Regression Based Models for CO_2 Emissions from the Scraper.

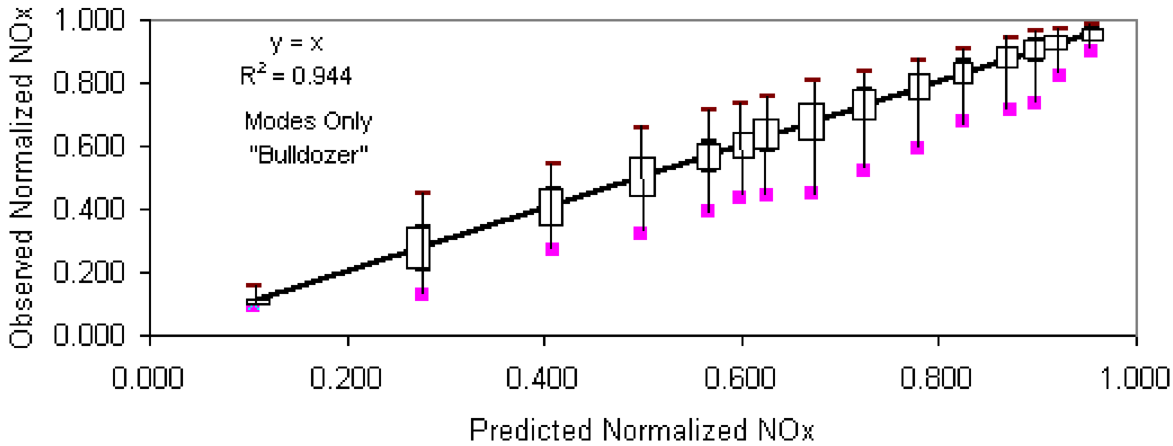


Figure 5-15. Example of the Depiction of Variability in Modal Predictions Using Box and Whiskers (Box represents 50 percent of the predicted values, whiskers represent 95 percent of the predicted values).

Therefore, the highest density of predicted values is typically close to the trend line. However, the scatter plot gives a misleading appearance of a uniform distribution of data with respect to the trend line. As an alternative to the scatter plot in Figure 5-9(a), the same information is displayed using boxes and whiskers in Figure 5-15. The boxes denote the range that encloses 50 percent of the observed values, and the whiskers (vertical lines) denote the range that encloses 95 percent of the observed values. It is clearer from Figure 5-15 than from Figure 5-9(a) that the modal estimates of emissions are clustered close to the trend line, and that the typical values of observed emissions, therefore, are consistent with model predictions.

The degree of scatter of the data with respect to the trend lines in Figure 5-9 is comparable for all three of the models. The R^2 values are very similar for the trend lines in all three cases. The combination of a modal emission model with OLS regressions for engine RPM, depicted in Figure 5-9(b), leads to more variability in the predicted values compared to the 15 discrete predictions observed in Figure 5-9(a). However, there is not a significant increase in explanatory power of the "Modes with OLS" model compared to the "Modes Only" model. Therefore, in this case, simply dividing the bulldozer activity into modes enables a large degree of explanatory power. The multiple OLS approach has a slightly lower R^2 value than the "Modes Only" approach. From a practical perspective, the multiple OLS approach offers no predictive advantage, and it is not strictly appropriate because of the autocorrelation in the data. Therefore, of the three models shown in Figure 5-9, the "Modes Only" model offers the advantages of being the simplest, of dividing the time series into segments that reduces the influence of autocorrelation in the model, and of offering substantial explanatory power. Similar results were obtained for the models for CO_2 emissions for the bulldozer, as illustrated in Figure 5-10.

For the compactor, the explanatory power of the "Modes Only" model for NO_x emissions was not as high as for the bulldozer. There was a slight improvement in explanatory power when

OLS regressions were done for each mode using engine RPM as an explanatory variable. The multiple OLS regression approach had the highest R^2 value but is theoretically less appealing because of the time series nature of the data. For CO_2 emissions from the compactor, the "Modes Only" model offers a high degree of explanatory power. The "Modes with OLS" model does not offer much improvement in explanatory power.

For NO_x emissions from the scraper, the "Modes Only" and the "Modes with OLS" approaches offer similar explanatory power, with the latter being slightly better. Qualitatively, the comparison is similar for CO_2 emissions from the scraper. However, the explanatory power for CO_2 emissions from the scraper is less than that for NO_x, which is the inverse of the result compared to the compactor.

Overall, the simple modal approach employed to demonstrate a conceptual method performed reasonably well compared to more complicated alternatives. The modal approach is intuitive, and it is easy to combine data from multiple sources into a given bin. The modal approach can be complemented with regression analysis of the data within each mode in an effort to improve explanatory power. There was not a significant increase in explanatory power when OLS was used in combination with the modal approach. However, one likely reason for the lack of significant improvement in the model is the relatively homogenous nature of the data that were used to calibrate the model. The data came from one piece of equipment operated during one day under ambient conditions that do not represent seasonal variation, for example. It is likely that the equipment was operated by a single operator during that time. Thus, the activity pattern and the ambient conditions were relatively similar over the duration of the data collection. If data were collected for multiple operators, multiple days (with more variability in ambient conditions) or for multiple applications of the equipment to different tasks, then there would be more variability in the data set and key explanatory variables might emerge more clearly in addition to exhaust flow and engine RPM.

6.0 VALIDATION OF THE CONCEPTUAL MODELS

In this chapter, validation case studies for the LDGV, HDDV, and nonroad conceptual models, presented in Chapters 3, 4, and 5 respectively, are presented. The validation exercise involved making predictions of emissions based upon activity data provided by EPA for selected vehicles. The actual observed emissions for the selected vehicles were withheld by EPA until after NCSU reported the predictions in a presentation to EPA on January 22, 2002.

As noted in Chapter 2, possible causes of error in model predictions could include the following:

- The model may be incomplete in that it does not have a sufficient set of explanatory variables;
- the model may not have the most appropriate functional form;
- the model may have been calibrated with data that contained measurement errors;
- the validation data may contain measurement errors for either the explanatory variables and/or the observed emissions; and/or
- the validation data set may have been obtained under conditions substantially different than those for the data used to calibrate the model.
- data entry errors.

The most likely cause of disagreement between model predictions and observed values for the validation exercise is that the models may be incomplete. This is because the models are based upon a limited set of explanatory variables. The choice of explanatory variables, as explained in Chapters 3, 4, and 5, was based upon the anticipated availability of activity data for use in the validation component of this project.

Section 6.1 presents the validation case study for LDGVs. Section 6.2 presents the validation case study for HDDVs. The nonroad validation case study is given in Section 6.3. A summary of the key findings from the validation case studies is given in Section 6.4

6.1 Light Duty Gasoline Vehicles

The objective of this section is to report predictions made with the conceptual LDGV emissions models for CO, NO, HC, and CO_2 applied to a prediction data set provided by EPA. The prediction data set contained only a selected set of explanatory variables, as explained in Chapter 3. Predictions for the validation data set were done using the methodology explained in Chapter 3. Figure 6-1, presents the steps for the prediction process.

A first step in the prediction process, as illustrated in Figure 6-1, was to determine whether a cold start was likely to be present in the validation data sets and, if so, the likely duration of each cold start. Information was available in the prediction data set from which to estimate the soak time prior to startup of the vehicle. Using a statistical relationship between cold start duration and estimated soak time presented in Chapter 3, an estimate of the expected cold start duration was made for each trip in the prediction data set. Table 6-1 summarizes the analysis for cold-start determination. The soak time reported in Table 6-1 was provided by EPA. Using the relationship between soak time and cold-start duration, which is given in Figure 3-18,

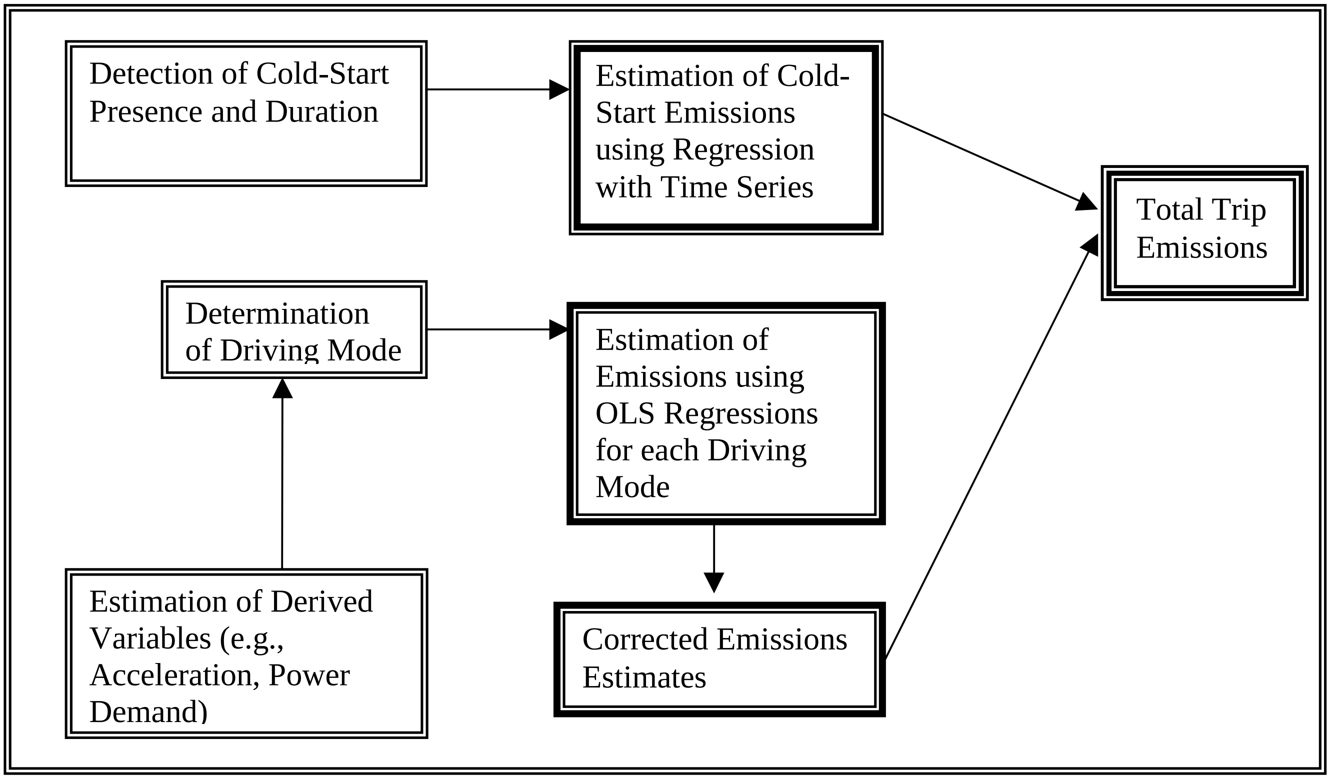


Figure 6-1. Simplified Schematic of Emissions Estimation Steps

Table 6-1. Determination of Cold-Start for Prediction Dataset

Vehicle	Trip	Soak Time (minutes)	Duration of Possible Cold-Start (seconds)	Decision
1	1	8.9	39	Hot-Stabilized
3	2	76.6	152	Cold-Start
3	3	27.9	99	Cold-Start
8	4	897.4	280	Cold-Start
8	5	3770.0	355	Cold-Start
8	6	25.7	95	Cold-Start

the duration of the possible cold-start was estimated. For example, for Vehicle 8 Trip 4, the cold-start was estimated to last for 280 seconds. Based upon these estimates, it is decided whether each trip had a cold-start or not. For Vehicle 1, Trip 1, the soak time was sufficiently short that a decision was made to model the emissions based upon hot stabilized driving modes only. For the other five trips for which predictions were made, the soak time was sufficiently long that a cold start was assumed.

After determining whether a cold start exists, the next step shown in Figure 6-1 was to estimate the emissions during cold start by assuming a specific cold start activity pattern. The regression model with time series terms developed for the cold start mode, as described in Chapter 3, requires an assumption regarding the coolant temperature time series profile during the cold start. Because coolant temperature was not provided for the prediction data set, a method was developed to estimate a typical coolant temperature time series by comparing the estimated cold start duration for each prediction trip to the cold start durations in the calibration data base. From the calibration data base, an actual coolant temperature profile corresponding most closely to the estimated cold start duration for each prediction case was selected. The selected coolant temperature profile was used as the basis for estimating second-by-second cold start emissions. Cold start emissions were estimated using the regression model with time series errors presented in Chapter 3, applied to the respective prediction case.

A key step in emissions estimation was calculation of the values of derived variables, such as acceleration and power demand, based upon the second-by-second speed data provided in the "prediction" dataset. The derived variables were estimated using the methodology explained in Chapter 3.

The approach for estimating hot stabilized emissions required binning each second of activity data in the validation activity data set into one of the hot stabilized driving modes. These modes include idle, low acceleration, high acceleration, low cruise, high cruise, low deceleration, and high deceleration, as defined in Chapter 3. The binning of data into these modes was based upon criteria of speed, effective acceleration, and power demand. Within each of the driving modes, OLS regressions unique to each mode were used to estimate second-by-second emissions in units of g/sec, which were summed to estimate the total mass emission rate for each mode. A Visual Basic program was written to estimate emissions automatically for each second in a trip. The OLS regression equations were log-transformed, as described in Chapter 3. Therefore, when back-transforming emission estimates, corrections for the log transformation were made as described in Section 3.3.5.

The model developed in this study predicts grams/second emissions for each trip. Therefore, in order to get the total emissions for that trip, grams/second emission rates were multiplied by the total time spent in each trip. The trend lines shown in the parity plots comparing observed values to predicted values in Section 3.3.7 were used to correct for biases in the model predictions. The corrected emissions estimate was obtained by entering the predicted emission rate into the respective equation for the appropriate pollutant trend line shown in Section 3.3.7.

For each prediction, a prediction interval is given. The prediction interval is based upon the inter-trip variability in emissions that is not explained by the model, as illustrated in the parity plots of Chapter 3. Because the conceptual model is being used in this case to make predictions for individual vehicles for individual trips, the appropriate measure of imprecision of the model is the unexplained inter-trip variability. On average, if the model predictions are accurate, it is expected that the prediction interval will enclose the true (observed) values with a 95 percent frequency. Of course, with a prediction data set of only six trips, it is possible that the frequency with which the prediction intervals enclose the true values may be less than 95 percent for any specific set of six predictions.

In some situations, the prediction interval as estimated using the SAS software may imply a lower bound of less than zero. Because emissions cannot be less than zero, it is not possible to have a prediction interval include negative emissions values. Therefore, in situations where the approximate prediction interval implies a negative value, it was assumed that the actual emissions must be not less than zero. As noted in Chapter 3, statistical methods that result in non-negative prediction intervals should be pursued in future work, such as the use of log-log plots when developing trend lines, as opposed to the linear plots used as examples in this work.

The average emission rates associated with the predicted emissions for each trip were compared to the range of average emissions rates among all of the trips in the calibration data set. In general, the average emission rates for the validation cases were within the range of the observed variability in average trip emissions rates for the calibration data set.

The predictions obtained from the conceptual models for LDGV are given in Tables 6-2 through 6-5 for HC, CO, NO, and CO_2 emissions, respectively. The observed values, obtained from EPA after these predictions were reported to EPA, are also presented in these tables. Table 6-6 presents the prediction interval estimated for each prediction. Figures 6-2 through 6-5 present the comparison of predicted values with the observed values for HC, CO, NO, and CO_2 emissions, respectively. The prediction intervals for each estimate are also shown in these figures.

The comparison of model predictions and observed values for HC are given in Table 6-2 and shown in Figure 6-2. The figure includes the prediction intervals that are summarized in Table 6-6. For three of the individual trip predictions, the observed value is enclosed by the prediction interval, indicating agreement between the model and the observed data. In three cases, the observed values are outside the range of the prediction interval. In two of these cases, the model under-predicts emissions, and in one case the model over-predicts emissions. On average, it appears that the model under-predicts the average of the six trip emissions by approximately 28 percent. However, this comparison is substantially influenced by the third trip prediction, where the model predicts HC emissions of 1.99 grams versus an observed value of 6.24 grams. If the third trip is set aside, the average predicted value for the other five trips is 1.84 grams compared to an average of the observed values of 1.89 grams, which is a difference of only two percent.

The ambient conditions for Trips 3, 5, and 6 were different than those of the calibration data set. For example, the average relative humidity in the calibration data set was 53 percent, whereas it was approximately 80 percent for these three trips in the validation data set. Therefore, it appears that the model was extrapolated in making predictions for the validation data set for these trips. Furthermore, Trips 2 and 3 in the calibration data set were made with the same vehicle. The predicted HC emissions were substantially lower than the observed emissions for this particular vehicle. In fact, as described later, the predicted emissions for CO and NO for the two trips made with this vehicle were also noticeably lower than the observed emissions, although for both CO and NO the observed emissions were enclosed by the 95 percent prediction interval. It is possible that there is some characteristic of this vehicle that differs from the vehicles contained in the calibration data set. Thus, the reasons for poor model performance for some of the trips may be attributable to vehicle-specific factors and different ambient conditions than those observed in the calibration data set.

Table 6-2. Summary of Predicted Values for the "Prediction Dataset" for Light Duty Gasoline Vehicles for HC (grams)

Trip	Predicted Value	Observed Value	Vehicle	Predicted Value	Observed Value	Fleet Predicted	Fleet Observed
1	2.62	2.93	1	2.62	2.93	1.87	2.61
2	1.55	3.02	3	1.77	4.63		
3	1.99	6.24					
4	2.65	1.56	8	1.68	1.16		
5	1.34	1.30					
6	1.06	0.63					

Table 6-3. Summary of Predicted Values for the "Prediction Dataset" for Light Duty Gasoline Vehicles for CO (grams)

Trip	Predicted Value	Observed Value	Vehicle	Predicted Value	Observed Value	Fleet Predicted	Fleet Observed
1	32.5	36.8	1	32.5	36.8	28.7	30.6
2	20.2	35.1	3	21	40.1		
3	21.7	45.1					
4	58.4	36.2	8	32.6	22.2		
5	24.2	19.8					
6	15.2	10.4					

Table 6-4. Summary of Predicted Values for the "Prediction Dataset" for Light Duty Gasoline Vehicles for NO (grams)

Trip	Predicted Value	Observed Value	Vehicle	Predicted Value	Observed Value	Fleet Predicted	Fleet Observed
1	6.1	5.1	1	6.1	5.1	4.5	6.7
2	3.4	7.4	3	3.2	7.8		
3	3.0	8.3					
4	6.7	10.8	8	4.8	6.6		
5	4.6	4.4					
6	3.0	4.5					

Table 6-5. Summary of Predicted Values for the "Prediction Dataset" for Light Duty Gasoline Vehicles for CO_2 (kg)

Trip	Predicted Value	Observed Value	Vehicle	Predicted Value	Observed Value	Fleet Predicted	Fleet Observed
1	12.9	10.5	1	12.9	10.5	6.3	5.6
2	5.5	5.2	3	6.8	6.6		
3	8.2	8.1					
4	3.4	2.9	8	3.8	3.3		
5	4.0	3.5					
6	3.9	3.4					

Table 6-6. Summary of Confidence Range for Prediction Values for the "Prediction Dataset" for Light Duty Gasoline Vehicles

Trip	95% CI for HC (g)	95% CI for CO (g)	95% CI for NO (g)	95% CI for CO_2 (kg)
1	< 9.4	< 201	< 23	11 — 15
2	< 4.6	< 97	< 11	4.6 — 6.3
3	< 6.7	< 139	< 14	6.9 — 9.6
4	< 4.5	11 —106	2 — 11	2.8 — 3.9
5	< 3.6	< 80	< 10	3.4 — 4.7
6	< 4.2	< 93	< 11	3 — 4.8

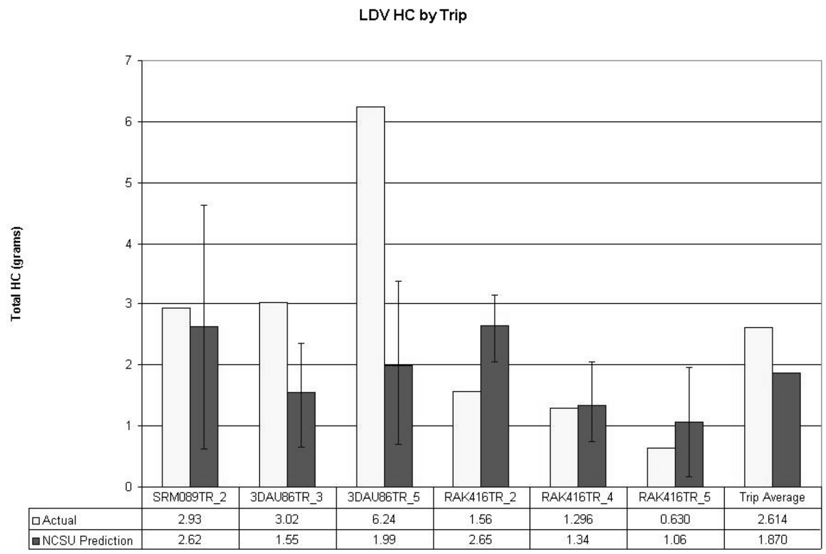


Figure 6-2. Comparison of Model Predictions and Observed Values for LDGV for HC (grams)

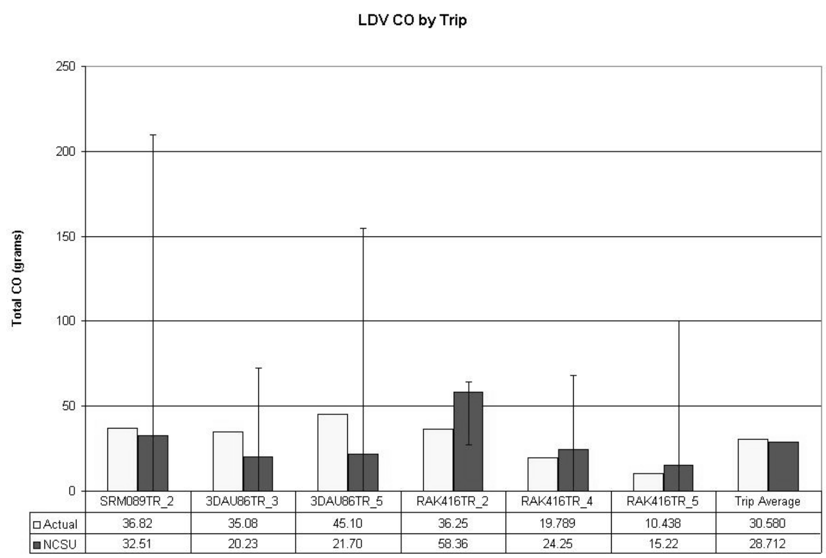


Figure 6-3. Comparison of Model Predictions and Observed Values for LDGV for CO (grams)

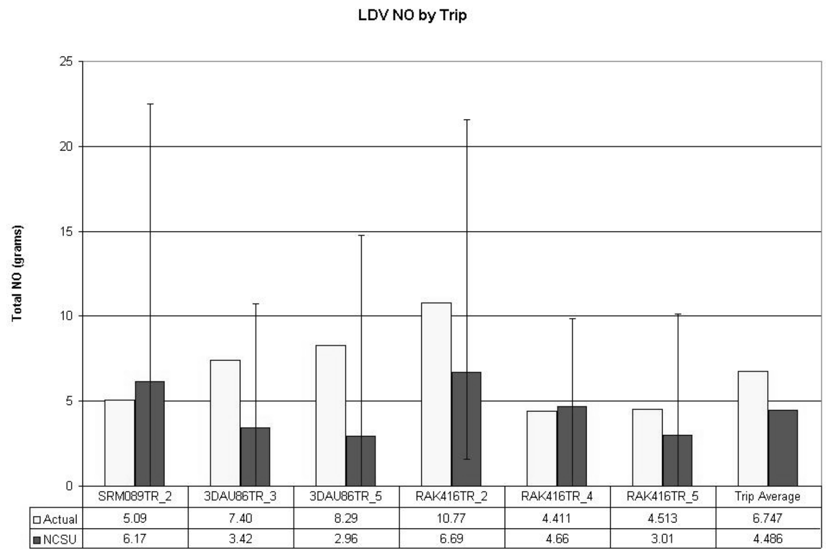


Figure 6-4. Comparison of Model Predictions and Observed Values for LDGV for NO (grams)

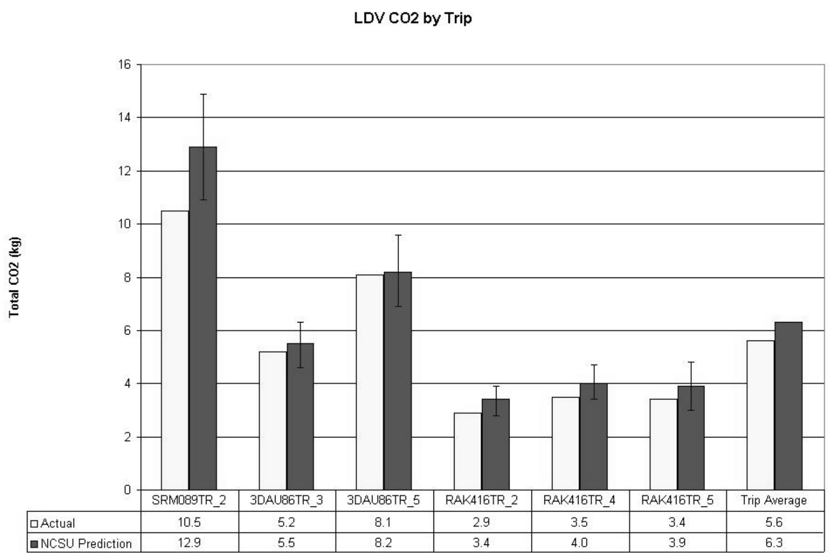


Figure 6-5. Comparison of Model Predictions and Observed Values for LDGV for CO_2 (kg)

Table 6-3 and Figure 6-3 show a comparison of observed and predicted values for CO emissions. As seen in Figure 6-3, the 95 percent prediction interval for the predicted values encloses the observed values for all six individual trip predictions, which indicates that the predicted values are not statistically significantly different from the observed values. The predictions averaged over all six trips agree to within six percent of the observed emissions averaged over all six trips. Therefore, on average, the model appears to accurately predict trip emissions even though in specific cases it may under- or over-predict emissions. As noted earlier, the predictions of CO emissions for Trips 2 and 3, which were made with the same vehicle, are noticeably lower than the observed values, differing by a factor of approximately two. However, the observations are enclosed by the 95 percent prediction interval for both trips, and therefore the model performance is deemed to be reasonable for these trips.

Table 6-4 and Figure 6-4 present comparisons of predicted versus observed emissions for NO. There is no statistically significant difference between the observed and the predicted values for each individual trip, since observed values are enclosed by the 95 percent prediction interval for all of the trips. In some cases, such as for the first and fifth trips, the model predictions are very close to the observed values. In the other four cases, the model tends to under-estimate the observed NO emissions. On average, the model tends to under-predict the observed emissions by 33 percent. However, since the individual observations are well within the prediction interval, the difference in the "fleet average" emissions is deemed to be within the precision of the model.

As noted in the discussion of HC emissions, the ambient conditions in the validation data set for Trips 3, 5, and 6 were different than those of the calibration data set, which may contribute to some of the apparent bias in the model predictions. Furthermore, the second vehicle in the validation data set, which was used for Trips 2 and 3, in general appears to have higher emissions than predicted by the model for HC, CO, and NO. The observed emissions for CO and NO were within the 95 percent prediction intervals. A detailed investigation of the second-by-second predictions for Trip 2 versus the second-by-second observed values revealed that there were several peaks in the observed emissions that were not captured by the model. Thus, there may be vehicle or driver-specific factors associated with the second validation vehicle that were not accounted for in the model.

For CO_2 emissions, the point estimates for the predictions of individual trip emissions are within 15 percent of the observed values in four of the six cases, based upon the data in Table 6-5 and also shown in Figure 6-5. The highest percentage difference between the predicted and the observed value was 23 percent, for the first trip. For the first trip, the observed value is less than the lower bound of the prediction interval. However, for all of the five other trip predictions, the observed value is enclosed by the prediction interval. On average, the predictions agree to within 13 percent.

The results of the comparison of model predictions and observed values for all four pollutants suggest that, overall, the conceptual model performs well in making average predictions over multiple trips, especially for CO and CO_2. For HC, there was one trip out of six for which the model prediction was low by a factor of almost three; however, the average predictions for the remaining five trips agreed to within two percent of the observed value. For NO, there is substantial variability between the model predictions and the observed values; however, the prediction intervals are also relatively wide. Therefore, although there was apparently an average tendency to under-predict emissions by 33 percent, there does not appear to be a statistically significant difference between the model predictions and the observed values. Many of the largest discrepancies in the comparison of the model predictions with the observed data appear to be attributable to the second vehicle and, in particular, Trip 3. This may be because of extrapolation of the model to driving conditions, ambient conditions, or vehicle characteristics that were not included in the calibration data.

Based upon the results for all four pollutants, the conceptual models perform reasonably well. It is possible to refine the conceptual models by investigating the second-by-second predictions in comparison to the second-by-second observations to search for situations that the model may have failed to adequately capture that significantly influence emissions. Such an investigation is recommended for future work. The models should be recalibrated based upon additional data that includes greater variability in explanatory factors than was present in the calibration data set.

6.2 Heavy Duty Diesel Vehicles

For the HDDV data set, predictions were made using a similar approach as followed for LDGV, with the exception that there was not a cold start process for HDDV. Figure 6-6 presents the steps used for the prediction process for HDDVs. A key difference in the method for making predictions when comparing HDDV and LDGV is that only average modal HC emissions were used for HDDV. OLS regressions were not used to supplement the modal average predictions in the case of HC. As explained in Chapter 4, OLS regression did not provide any significant increase in explanatory power for the HC emissions model. Modal OLS regressions were used for the other pollutants.

The model developed in this study predicts an average grams/second emission rate for each trip. Therefore, in order to get the total emissions for a trip, the grams/second emission rates were multiplied by the total time spent in each trip. For each prediction, a prediction interval is given, as explained in the case for LDGV dataset in the previous section. The prediction interval is based upon the inter-trip variability in emissions that is not explained by the model, as illustrated in the parity plots of Chapter 4.

The average emission rates associated with the predicted emissions for each trip were compared to the range of average emissions rates among all of the trips in the calibration data set. In general, the average emission rates for the predictions are within the range of the observed variability in average emissions rates for the calibration data set.

The predictions made with the conceptual model are compared to the observed values reported by EPA in Tables 6-7 through 6-10 for HC, CO, NO, and CO_2, respectively. The prediction intervals for all four pollutants are summarized in Table 6-11. The comparison of predictions and observations for individual trips and for the average of all trips is shown graphically in Figures 6-7 through 6-10 for HC, CO, NO, and CO_2, respectively. Predictions were made for two trips for each of three diesel transit buses of the same technology as the transit buses that were included in the calibration data set.

The model predictions agreed very well with the observed values in the case of HC emissions, as shown in Table 6-7 and Figure 6-7. The predictions for individual trips agreed with the observed values to within 12 percent for five of the six trips. The average of the trip predictions was identical to the average of the observed emissions to within two significant figures. The model predictions ranged from approximately two grams to three grams of emissions per trip, which is similar to the range of variability in the observations. All of the observed emissions for individual trips were enclosed by the prediction interval corresponding to each trip. Therefore, by several measures, the predictions for HC emissions are very good.

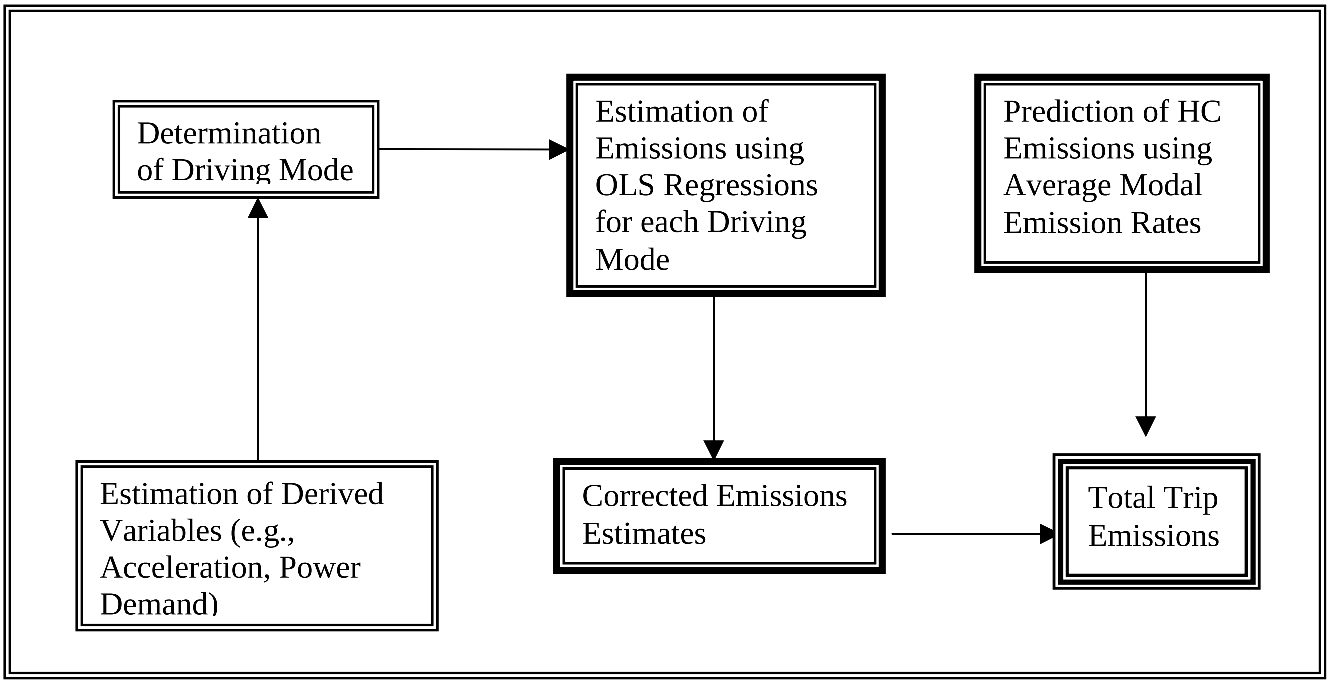


Figure 6-6. Simplified Schematic of Emissions Estimation Steps for HDDV Data

The CO predictions were generally higher than the observed emissions by 38 to 58 percent among each of the individual trip predictions, based upon the data given in Table 6-8 and Figure 6-8. On average, the model over-predicted trip CO emissions by 52 percent. All of the observed emissions for each individual trip were enclosed by the prediction interval corresponding to each trip. Thus, the discrepancy between the model predictions and the observed values appears to be within the precision of the model. However, the fact that all six of the trips are over-predicted suggests a possible bias in the model predictions. For example, a preliminary analysis revealed that the second-by-second emission rates of the validation data set were generally much lower during the acceleration mode than for the calibration data set. Specifically, CO emission rates during acceleration for the validation data set rarely exceeded 0.5 g/sec whereas emission rates of 1.0 g/sec during acceleration occurred frequently in the calibration data set. However, the specific reasons for this difference could not be determined at this time. It is possible that there is some type of extrapolation of the model that may account for the discrepancy in the comparison of the predictions and observed values. It is recommended that the reason for the bias be identified based upon a more thorough review of both the observed second-by-second data and the model predictions on a second-by-second basis.

The model predicted NO emissions with good precision as shown in the data reported in Table 6-9 and Figure 6-9. All of the observed emissions for each individual trip were enclosed by the prediction interval corresponding to each trip. The predictions for individual trips agree to within 15 percent in all six cases. The average of the predictions for the six trips agrees with the average of the observed emissions to within six percent. The model predicted trip emissions

Table 6-7. Summary of Predicted Values for the "Prediction Dataset" for High Duty Diesel Vehicles for HC (grams)

Trip	Predicted Value	Observed Value	Bus	Predicted Value	Observed Value	Predicted Fleet Avg	Observed Fleet Avg
1	2.9	3.2	3	2.6	2.9	2.5	2.5
2	2.3	2.5					
3	2.5	2.5	12	2.6	2.6		
4	2.6	2.7					
5	2.8	2.1	13	2.3	2.1		
6	1.9	2.0					

Table 6-8. Summary of Predicted Values for the "Prediction Dataset" for High Duty Diesel Vehicles for CO (grams)

Trip	Predicted Value	Observed Value	Bus	Predicted Value	Observed Value	Predicted Fleet Avg	Observed Fleet Avg
1	87	52	3	74	46	76	50
2	62	41					
3	80	59	12	82	55		
4	84	53					
5	83	54	13	71	48		
6	59	42					

Table 6-9. Summary of Predicted Values for the "Prediction Dataset" for High Duty Diesel Vehicles for NO (grams)

Trip	Predicted Value	Observed Value	Bus	Predicted Value	Observed Value	Predicted Fleet Avg	Observed Fleet Avg
1	257	252	3	211	198	253	238
2	164	143					
3	282	253	12	305	272		
4	328	290					
5	275	286	13	243	245		
6	210	203					

Table 6-10. Summary of Predicted Values for the "Prediction Dataset" for High Duty Diesel Vehicles for CO_2 (kg)

Trip	Predicted Value	Observed Value	Bus	Predicted Value	Observed Value	Predicted Fleet Avg	Observed Fleet Avg
1	17.1	17.1	3	14.2	13.6	14.5	15.5
2	11.4	10.1					
3	15.8	16.7	12	16.3	17.8		
4	16.8	18.9					
5	15.1	17.6	13	13.1	15.1		
6	11	12.6					

Table 6-11. Summary of Confidence Range for Prediction Values for the "Prediction Dataset" for Heavy Duty Diesel Vehicles

Trip	95% CI for HC (g)	95% CI for CO (g)	95% CI for NO (g)	95% CI for CO_2 (kg)
1	< 6.5	47 — 128	153 — 360	14 — 21
2	< 5.3	29 — 95	80 — 247	9 — 14
3	< 5.6	46 —114	193 — 372	13 — 18
4	< 5.9	48 — 121	232 — 424	14 — 20
5	< 6.3	44 — 122	174 — 377	12 — 18
6	< 4.3	32 — 86	140 — 280	8.8 — 13

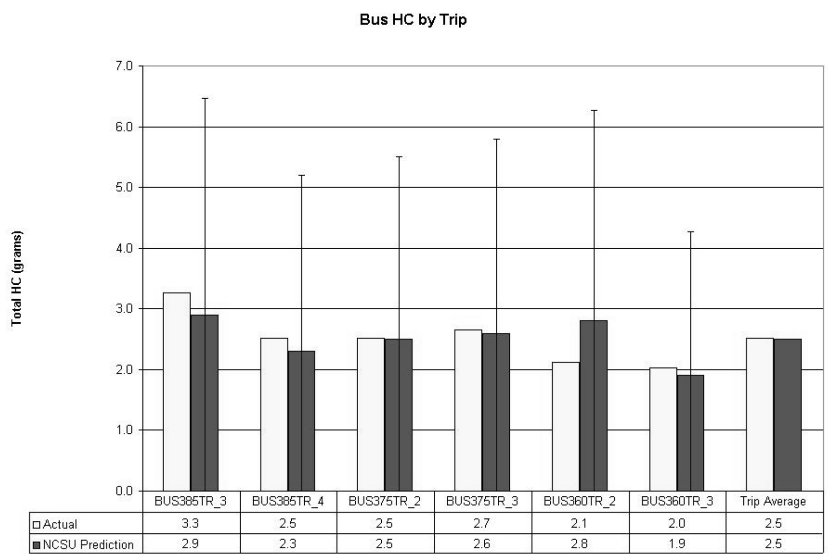


Figure 6-7. Comparison of Model Predictions and Observed Values for HDDV HC Emissions (grams)

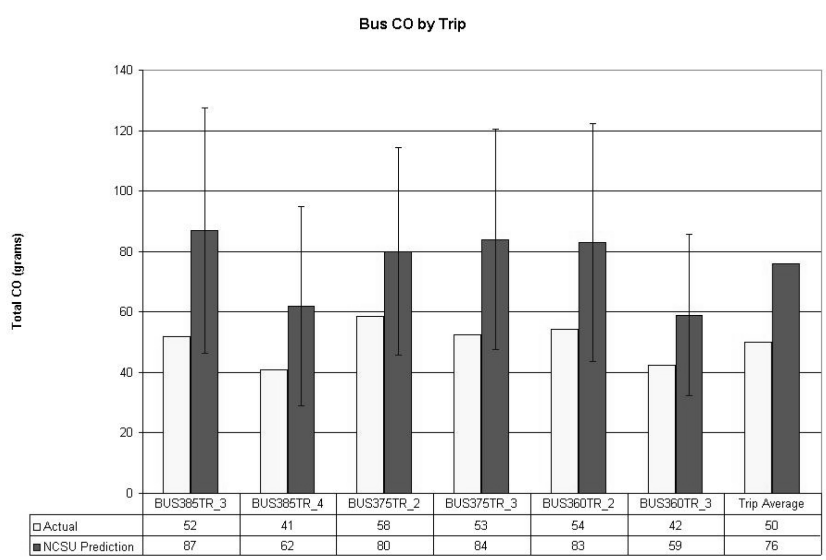


Figure 6-8. Comparison of Model Predictions and Observed Values for HDDV CO Emissions (grams)

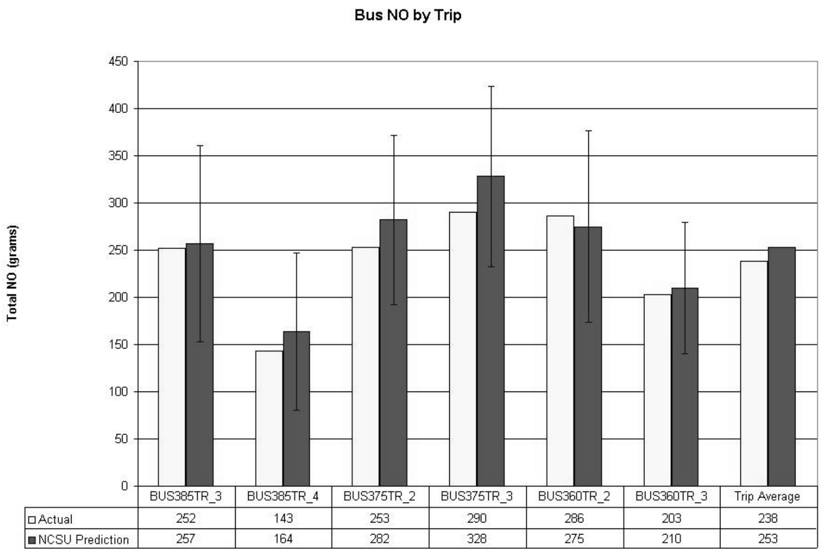


Figure 6-9. Comparison of Model Predictions and Observed Values for HDDV NO Emissions (grams)

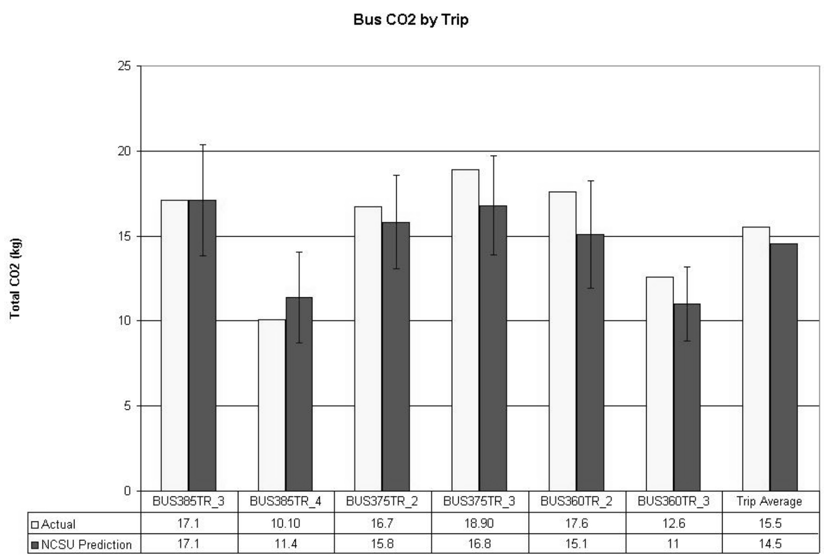


Figure 6-10. Comparison of Model Predictions and Observed Values for HDDV CO_2 Emissions (kg)

ranging from approximately 150 grams to approximately 300 grams, which is a factor of two and is similar to the variability in the observed emissions. Therefore, the model appears to capture the variability in the observations reasonably well. Thus, in all respects, the predictions for NO agree very well with the observations.

The model predictions for CO_2 are compared with the observed values in Table 6-10 and Figure 6-10. The average of the predictions for the six trips agrees with the average of the observed emissions to within six percent. All of the observed emissions for each individual trip were enclosed by the prediction interval corresponding to each trip. The individual trip predictions agree with the observed values to within 13 percent, with three of the cases agreeing to within five percent. On average, the model predicted trip emissions to within six percent of the average observed value. The variability in model predictions ranges from approximately 11 kg to 17 kg, which is similar to the observed range of variability from 10 kg to 19 kg. Thus, by a variety of measures, the performance of the conceptual model with respect to CO_2 emission estimates is very good.

Overall, the conceptual model for HDDV emissions performed very well for HC, NO, and CO_2 emissions, based upon comparison of prediction intervals with the observed data, the percent difference in individual trip and average predictions compared to observations, and the range of variability in model predictions versus the variability in the observations. The predictions for CO were the only exception to the generally excellent performance of the model. Although the observed values were enclosed by the prediction interval, we hypothesize the possibility of a model extrapolation. There was not sufficient time in this study to investigate the hypothesized extrapolation more thoroughly. Therefore, such an investigation is recommended for future work.

6.3 Nonroad Vehicles

For the nonroad vehicles, predictions were made using five methods, and the predictions were compared with observed values. These five methods are summarized briefly here. More detail on these is given in Chapter 5.

Average of Three-Hour Calibration Data Set: The simplest model is emissions equal to a constant. Therefore, we consider a model of emissions equal to the average value of the data provided in the three hour calibration data set.

Modes Only: Prediction with a model based upon modal averages obtained from the calibration data set and the distribution of time spent in each mode for the validation data set. The modes are categories or bins with respect to the relative exhaust flow rate.

Modes & OLS: Similar to Modes Only, but for each mode there is an ordinary least squares linear regression of emissions with respect to Engine RPM, which was typically found to be a statistically significant explanatory variable for each modal data set.

Multiple OLS Regression: The multiple OLS regression approach is based upon a direct application of multiple least squares regression to the second-by-second data set. Although this approach is technically not appropriate given the autocorrelation in the data, we were curious how predictions from this technique compare to the other methods, which more appropriately take into account or deal with autocorrelation.

Time Series: These predictions are based upon a time series model fit to the calibration data set.

The predictions with the five models were made before EPA revealed the “true” observed emissions values for the prediction data sets. Therefore, this was a blind comparison of model predictions to observed values. For validation purposes, EPA provided one hour of operating data for each of the three nonroad equipment for which individual emission models were developed. As noted in Chapter 5, the calibration data were based upon approximately three hours of operation. Typically, the hour of operation in the validation data set represents a fourth hour of consecutive operation compared to the calibration data. External factors such as ambient temperature typically changed continuously over the total four hour data collection period. Therefore, the ambient conditions of temperature, humidity, and barometric pressure during the fourth hour of operation may be different than the values observed during the first three hours of operation. Such differences are explored in more detail in Section 6.3.2 for each of the different types of equipment.

6.3.1 Comparison of Model Predictions with Observed Values

For NO_x, the predictions of each of the five alternative types of models are compared to the observed values for the bulldozer, compactor, and scraper in Table 6-12. A similar comparison is given for CO_2 emission in Table 6-12. A graphical comparison is given for the prediction of the "Modes Only" approach for NO_x with respect to the observed values in Figure 6-11. A similar comparison is given for CO_2 in Figure 6-12. The "Modes Only" predictions were used for the graphical comparison in Figures 6-11 and 6-12. The "Modes Only" approach was found in Chapter 5 to provide nearly as much explanatory capability as the "Modes & OLS" and "Multiple OLS Regression" approaches. The "Modes Only" approach has an advantage of being conceptually simpler than the two regression approaches. The Time Series approach is not recommended for model development but was included for comparison purposes only.

The "Modes Only" approach performed very well in predicting both NO_x and CO_2 emissions when compared to the observed values. The predictions for NO_x agreed to within eight percent for each of the three vehicles, and the average of the predictions for the three vehicles agreed with the average of the three observations to within two percent. The predictions for CO_2 agreed to within seven percent for each of the three vehicles, and the average of the predictions for the three vehicles agreed with the average of the three observations to within six percent. Although there is an apparent tendency of the "Modes Only" model to under-estimate the observed CO_2 emissions, the magnitude of the apparent bias is small. Furthermore, with only three comparisons and with a relatively small bias, it is difficult to make a reliable estimate of bias in the model predictions.

Table 6-12. Summary of Predicted Values for the "Prediction Dataset" for Nonroad Vehicles for NO_x (grams)

Vehicle	Predictions Based Upon Alternative Models					Observed Value
	Average of 3-hour data set	Modes Only	Modes & OLS	Multiple OLS Regression	Time Series	
Bulldozer	1,890	1,640	1,640	1,730	1,810	1666
Compactor	340	362	366	423	512	334
Scraper	670	610	624	627	710	655

Table 6-13. Summary of Predicted Values for the "Prediction Dataset" for Nonroad Vehicles for CO_2 (kg)

Vehicle	Predictions Based Upon Alternative Models					Observed Value
	Average of 3-hour data set	Modes Only	Modes & OLS	Multiple OLS Regression	Time Series	
Bulldozer	98	84	86	94	116	90
Compactor	82	85	85	75	75	89
Scraper	66	68	66	64	63	73

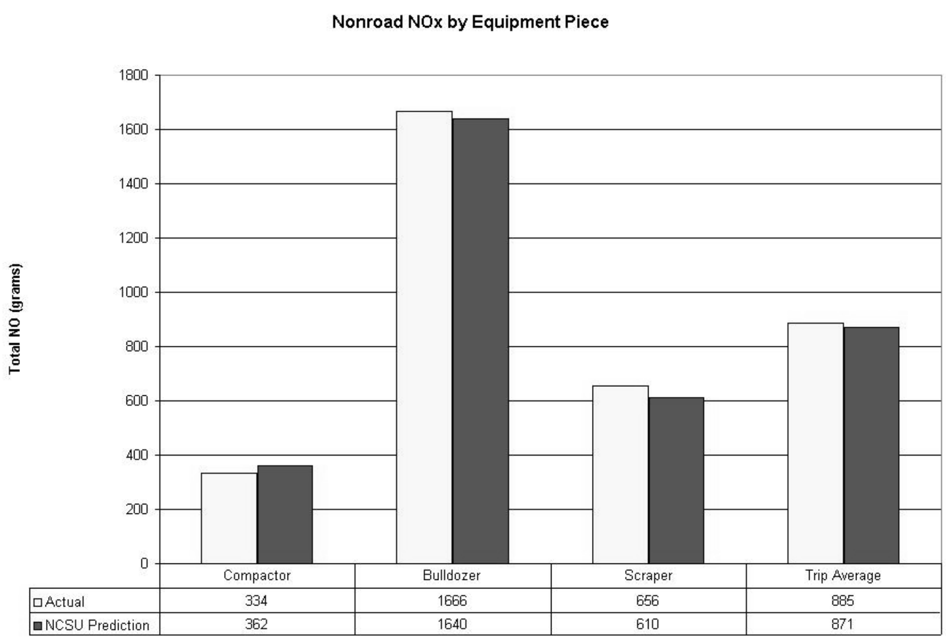


Figure 6-11. Comparison of Model Predictions and Observed Values for Nonroad Vehicles for NO_x Emissions (g)

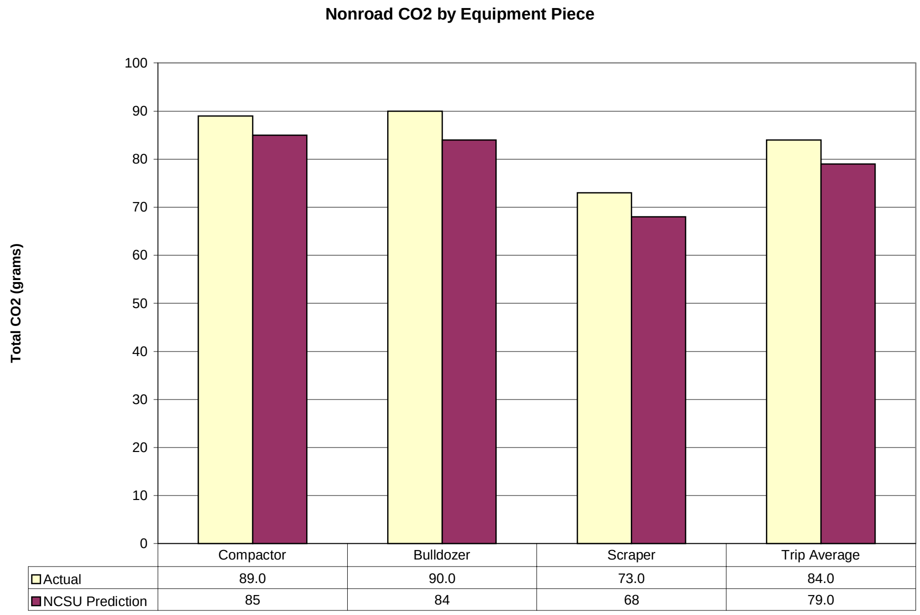


Figure 6-12. Comparison of Model Predictions and Observed Values for Nonroad Vehicles for CO_2 Emissions (kg)

The "Modes Only" approach generally performs better than the "Modes & OLS", "Multiple OLS Regression," and "Time Series" methods with respect to the validation cases. The best prediction is defined as the prediction with the minimum deviation from the observed value. For example, among these four modeling approaches, the "Modes Only" approach makes the best prediction for NO_x for the bulldozer and the scraper, and the best prediction for CO_2 for the compactor and the scraper. In the two cases where the "Modes Only" approach does not make the best prediction, for NO_x from the scraper and for CO_2 from the bulldozer, the prediction of the "Modes & OLS" approach is either the best or very close to the best. In most cases, the "Modes Only" and "Modes & OLS" approaches produce nearly the same prediction. These results implies that a modal approach performs well and that there is little incremental benefit in this case to a "Modes & OLS" approach.

6.3.2 Comparison of Calibration and Validation Data Sets

It is not expected that the model prediction for the bulldozer should agree with the observed “true” emissions for the prediction cases. This is because there are differences in the conditions of the prediction dataset versus those of the calibration data set. These differences are illustrated in Table 6-14, which compares the mean and average values of the five available possible explanatory variables for the calibration data set and the validation data set. The comparison shows that the validation data set has substantially lower relative humidity and higher ambient temperature than the calibration data set. There is less variability in relative humidity and ambient temperature in the validation data set than in the calibration data set. The mean engine RPM and exhaust flow are lower for the validation data set than for the calibration data set, although there are similar levels of variability in both cases

Table 6-14. Comparison of Calibration and Validation Datasets for Bulldozer

	Relative Humidity	Ambient Temperature	Barometric Pressure	Engine RPM	Exhaust Flow (SCFM)
Calibration Data Set					
Average	66.7	29.2	60.6	1466	599
Std. Deviation	14.3	3.7	0.1	432	246
Validation Data Set					
Average	34.3	38.5	60.5	1323	531
Std. Deviation	1.8	1.1	0.2	439	264

Table 6-15. Comparison of Calibration and Validation Datasets for Bulldozer

	Relative Humidity	Ambient Temperature	Barometric Pressure	Engine RPM	Exhaust Flow (SCFM)
Calibration Data Set					
Average	66.4	5.0	98.6	2357	319
Std. Deviation	9.1	3.0	3.7	800	108
Validation Data Set					
Average	49.1	9.7	99.5	2534	330
Std. Deviation	4.3	1.2	0.1	750	108

The effect of the difference in conditions between the validation data set and the calibration data set can only be estimated based upon judgment. From an inspection of the scatter plots for the calibration data set, it is apparent that average emissions of both NO_x and CO_2 tend to increase with an increase in exhaust flow, an increase in temperature (very weak effect) and an increase in barometric pressure. The relative humidity and ambient temperature are so highly correlated in the calibration data set that is it not possible to use both for prediction purposes. The higher ambient temperature in the validation data set suggests higher emissions, while the lower average exhaust flow rate suggests lower emissions, compared to the conditions of the calibration data set. Thus, overall, there may not be a strong effect of these differences with respect to bias in model predictions versus observed values.

For the Compactor, the validation and calibration data sets are compared in Table 6-15. The comparison illustrates that the validation data set has lower relative humidity, higher temperature, and higher barometric pressure than the calibration data set, on average. The average engine RPM of the validation dataset is slightly higher than for the calibration data set, although the variability is slightly less. The exhaust flow is similar in the two cases.

The conditions of the validation data set for the scraper are different than those of the calibration data set, as shown in Table 6-16. The average relative humidity is lower and relative humidity has less variability. The average ambient temperature is higher and also has less variability. The average engine RPM is higher by 280, but has less variability, indicating generally higher RPM than in the calibration case. The exhaust flow is similar on average but has less variability, and the peak values of exhaust flow in the validation case are less than the peak values in the

Table 6-16. Comparison of Calibration and Validation Datasets for Scraper

	Relative Humidity	Ambient Temperature	Barometric Pressure	Engine RPM	Exhaust Flow (SCFM)
Calibration Data Set					
Average	48.2	15.5	99.6	1558	427
Std. Deviation	5.3	2.4	0.0	659	193
Validation Data Set					
Average	40.7	20.2	99.6	1838	429
Std. Deviation	0.6	0.5	0.0	515	136

calibration case. The scatter plots from the calibration data set illustrate potentially strong sensitivity of emissions to engine RPM and exhaust flow, and only weak sensitivity to ambient conditions. Therefore, it is possible that the difference in engine RPM may be most responsible for any differences between model predictions and the observed values. The lower exhaust flow rates in the validation case will tend to result in lower emissions if all else were equal.

6.4 Summary of Validation Case Studies

This chapter documented blind comparisons of predictions made using conceptual models developed in Chapters 3, 4, and 5 with respect to observations revealed to NCSU by EPA only after NCSU completed the predictions.

For LDGVs, the model predictions are typically within 15 percent or better, on average, for CO and CO_2. For HC, the model prediction is within two percent, on average, for five of the six trips. The model substantially under-predicted emissions for one of the six trips. The observations for NO were enclosed by the 95 percent prediction interval for all six trips. There may be a bias in the NO predictions but the predictions are judged to be within the precision of the model. Of the 24 comparisons (6 trips for each of 4 pollutants), the observed values were enclosed by the 95 percent prediction interval 20 times, or with a frequency of 83 percent. Although the frequency of 83 percent is less than the desired value of 95 percent, with a sample of only 24 comparisons some random variation is expected regarding the actual observed frequency.

It appears that the second vehicle in the calibration data set was associated with the most significant discrepancies in the comparison of predicted and observed emissions. Ambient conditions, especially for relative humidity, were found to be substantially different for some of the validation trips compared to the calibration data set. Therefore, it is likely that a significant portion of differences in model predictions versus observed values is associated with either explicit or hidden extrapolation of the model. As a model such as this is calibrated with more data representing more combinations of the explanatory variables and of unobserved variables, the accuracy of the model would be expected to improve.

For HDDVs, the model predictions for the average of six trips were within six percent or better of the observed average values for HC, NO, and CO_2. There is an apparent bias in the CO predictions, which merits investigation in future work. It appears from the second-by-second CO emissions data that there is a substantial difference in the acceleration mode emission rates in the validation data set compared to those in the calibration data set. This finding implies a possible extrapolation of the model when making predictions for the validation data set, at least with respect to CO. However, for all 24 comparisons (6 trips for each of 4 pollutants), the observed values were enclosed by the 95 percent prediction intervals 24 times, or with a frequency of 100 percent. These results suggest that the HDDV conceptual emission models performed very well.

For the nonroad predictions, the "Modes Only" approach yielded predictions that were within eight percent of the observed values for individual trip predictions. Although in specific cases the "Modes & OLS" approach may yield a slightly more precise estimate, the "Modes Only" approach provided the most precise prediction in several cases. These results suggest that the "Modes Only" approach offers predictive capability comparable to other approaches but has the advantage of being a simpler approach.

Overall, the conceptual models performed well in making predictions for individual trips and for the average of only six trips. As noted in earlier chapters, the most demanding test of a vehicle emission model is how well it does in making predictions for individual trips. More commonly, vehicle emission modes are used to make predictions for fleet averages. Although it is generally the case that the conceptual models performed better at making predictions for the average of six trips than for individual trips, there were several examples of specific pollutants for which the model predictions were reasonably precise even for individual trips. Overall, the conceptual models and the validation exercise demonstrate that a modal-based approach for emissions estimation is a viable and practical method capable of performing well.

7.0 STRATEGIES FOR USING ALTERNATIVE EMISSIONS DATA

There is no one source of data that can serve as the sole basis for development of the NGM. Where available, on-board emissions data will often the best choice, because it reflects real world on-road conditions. However, there are limitations in the tailpipe emission measurements of the current generation of on-board instruments, particularly with regard to HC emissions, that motivate supplemental data collection in laboratories. On-board emissions measurement instruments do not currently address many pollutants that may be of concern in tailpipe emissions, such as air toxics. Some of the functional relationships between tailpipe emissions and activity data needed for the NGM can be developed with the aid of laboratory data. Furthermore, on-board techniques are not currently capable of measuring emissions from other than the tailpipe. Therefore, there is a continuing need for alternative sources of data regarding evaporative emissions. Creative opportunities should be sought to collect new data in conjunction with on-board studies. For examples, it may be possible to design a concurrent study of real world tire wear that could be implemented in conjunction with on on-board study.

EPA and others have collected a large amount of data based upon driving cycles and the use of dynamometer-based measurement methods. Therefore, a key question is whether such data can be included with on-board data in the development of the NGM. This question is addressed in this chapter.

The National Research Council (2000) provided a review of key considerations pertaining to the MOBILE emission factor models. These are listed in Table 7-1 to help guide the discussion in this chapter. Table 7-2 is based upon a table in NRC (2001) that lists specific areas of concern identified in an earlier report by the General Accounting Office (GAO), and whether they are to be addressed in Mobile6. Added to this table is a brief indication of how each area of concern can be addressed in the NGM.

The focus of the discussion in this chapter is on data required to develop an emissions model. There are also considerations regarding the availability of activity data to support use of the model by the user community. These concerns are important, but they are not addressed in detail here. A first step is to determine what input data are needed to make the best predictions of emissions. If the data requirements exceed the activity data available as part of current practice, then the choices are either for the user community to find ways to develop data needed for the new model, with the guidance and perhaps assistance of EPA, or to find ways to simplify the model to reduce the input data requirements. This will involve a trade-off between the explanatory power of the model and the data input requirements for the model. Such a trade-off can be difficult to evaluate *a priori*, but should be kept in mind during the process of model development.

The focus of this chapter is on the on-road emission source categories. However, a supplemental discussion of nonroad sources is provided near the end of the chapter.

Table 7-1. Key Considerations In Developing an Emission Factor Model

- High Emitters
  - Exhaust High Emitters
  - Evaporative High Emitters
- Cold Start Emissions
  - Accurate activity data
  - Accurate emissions model
  - Specification of locations of cold starts
- Driving Cycle Issues
  - Standard mix of cold start, hot stabilized, and hot start.
  - Standard assumptions regarding speed traces, which imply standard distributions of driving modes
- Sufficient range of speeds and accelerations
- Aggressive Driving
- Road Grade (new data requirements for model users)
- Accessory Loads – e.g., air conditioner (compressor on fraction, demand for A/C usage)
- Real-world behavior/effectiveness of electronic controls and emission control systems
- Simulating real-world driving
- Technology Groups
- In-Use Deterioration, especially above 50,000 miles
- Need for more representative driving cycles for development of correction factors (e.g., deterioration, A/C usage, cold start effects)
- I/M Program Effects on Emissions
- Evaporative Emissions
  - Diurnal emissions (SHED)
  - Resting Losses (multi-day diurnal tests)
  - Hot soak (SHED)
  - Running Losses (real-time)
- Fuel Effects – Reid Vapor Pressure (RVP), oxygenated fuel, Reformulated Gasoline (RFG), fuel sulfur content (effect on catalyst)
- Ambient Temperature

Table 7-2. Areas of Concern Regarding Tailpipe Emissions Estimates from Mobile Cited in GAO Report (Based Upon Summary in NRC (2000)) and How They Can Be Addressed in NGM

	Areas of Concern Regarding Mobile Cited in GAO Report	Addressed in MOBILE6?	How to Address in NGM
1.	High Speed Driving	Driving Cycles	Real-world data from on-board data collection
2.	Rapid Acceleration and Deceleration, including aggressive driving behaviors	Driving Cycles	Real-world data from on-board data collection
3.	Cold Start Emissions	Driving Cycles	Real-world data from on-board data collection
4.	Air conditioner use	Driving Cycles	Phased combination of correction factors from driving cycles, supplanted with real world on-road data
5.	Road grades (hills)	No	Real-world data from on-board data collection
6.	Representation of High-Emitting Vehicles	Yes	Real-world data from on-board data collection
7.	Various fuel formulations	Yes	Phased combination of correction factors from driving cycles, supplanted with real world on-road data
8.	Emissions system deterioration	Yes	Phased combination of correction factors from driving cycles, supplanted with real world on-road data
9.	Emissions Estimates and Assumptions for Vehicle I/M Programs	Yes	Phased approach – use current methods until sufficient data are available from on-board measurements
10.	Non-tailpipe evaporative emissions when vehicle is not operating	Yes	Same as Mobile6.
11.	Emissions estimates and assumptions for I/M of HDVs (8,501 lb or more)	No	Can address with long term (e.g., 5 year) on-board data collection in representative study areas
12.	Data characterizing vehicle fleet	Yes	Same as Mobile6, supplemented with new data
13.	Greater distinction in roadway classifications	Yes	Addressed through proper data collection and analysis in on-board studies
14.	Quantifying Uncertainty of the Model's Estimates	No	Appropriate sampling design and statistical techniques. Must be an integral part of model development, not a post-hoc add-on.

7.1 Strengths of On-Board Tailpipe Emissions Data

With respect to the key considerations listed in Table 7-1, it is clear that on-board tailpipe emissions measurements offer many benefits. Each of the main points listed in Table 7-1 is addressed here, with a discussion of the role for on-board measurement to address the consideration. From this discussion, gaps in the ability of on-board measurements to address specific concerns are identified. These are discussed in Section 7.2.

Through appropriate vehicle recruitment, it is possible to collect data on exhaust high emitters. In some cases, it may be worth including the price of purchasing older used cars in the budgets for the emission measurement centers, so that they can have an opportunity to work with such vehicles over a long time period during the five year data collection effort.

Cold start emissions can be measured and analyzed, as demonstrated by the LDGV example in Chapter 3. Second-by-second data will provide more quantitative knowledge regarding cold start duration and the relationship between emissions and vehicle activity during the cold start. The model developed in Chapter 3 includes consideration of the duration of the cold start. Data regarding factors influencing the duration of the cold start are needed and can be collected in on-board studies, including soak time and ambient temperature. Improved methods for modeling of cold start emissions are an expected output of an on-board emissions data approach to developing the NGM. This is likely to lead to additional input data requirements. However, from the on-board data, typical activity patterns for cold starts can be inferred and provided as defaults for those users who do not have site-specific data available.

On-board emissions data offers a key benefit of representing real world emissions because data are collected on-road during actual driving. However, the ability to represent real world conditions will be predicated on proper sampling of different vehicles, vehicle operation condition, routes, drivers, traffic conditions, ambient conditions, and fuels. A properly designed field study should be able to account for the key factors that influence real world emissions. Therefore, it is expected that the on-board data set upon which the NGM should be based will improve the representativeness of the model with respect to real world conditions. Standard assumptions are not needed *a priori* regarding driving cycles in this approach. Therefore, the limitations of a relatively small number of driving cycles that potentially constrain the representativeness of the MOBILE models will be addressed in the on-board data-based approach.

On-board data collection will encounter a wide range of speeds and accelerations, overcoming shortcomings of many driving cycles. Issues regarding the distribution of driving behavior and how it affects emissions need to be addressed. An on-board study itself can be used to determine the relationship between emissions and different styles of driving. Supplemental data will be needed regarding the distribution of driving styles in the real world.

Accessory loads have long been hypothesized to be an important factor influencing emissions. The effect of accessory loads can be assessed using on-board data by varying accessory loading during field studies and performing statistical analysis on the data to infer whether accessory loading is a useful explanatory factor. A key example is regarding air conditioning usage. It will be more useful to have second-by-second data regarding whether the compressor is operating than it will be to simply know whether the air conditioning button is in the off or on position.

There has been some concern about the ability of the MOBILE models to properly account for the real world behavior or effectiveness of electronic control and emission control systems. This concern is in part because such systems have been designed in the past to comply with tailpipe emissions limits when vehicles are operated on the standard certification cycle, but they may not operate in the same manner for "off-cycle" events in the real world. On-board data collection will allow identification of real world impacts associated with this particular set of issues.

There has been concern about simulation of real world driving in dynamometer tests used to produce data for the MOBILE models. With on-board measurements, the data will be collected in the field under actual driving conditions, including actual road grades. There are, however, some issues of data collection protocol that must be considered. For example, many state departments of transportation operate "floating cars" that are used to collect speed traces to understand traffic flow and congestion. Such agencies often have policies that govern driver behavior during data collection. For example, the driver is required to stay within a specified number of miles per hour of the speed limit, and may not exceed a particular speed based upon the speed limit plus the allowable tolerance above the speed limit. However, if the objective is to obtain representative real-world emissions values, then data should be collected at typical traffic flow speeds. In some cases, the typical traffic flow in the real world can be much faster than the posted speed limit. It will be important for EPA to develop a policy regarding how to handle situations such as this.

On-board emissions measurement systems can be deployed on a wide range of different vehicles. Although the simplest deployment is for vehicles with an OBD link, with the use of sensor arrays it will be possible to deploy this type of equipment on vehicles without electronic controls. This is especially important with respect to including older vehicles in the study design.

In-use deterioration is hypothesized to be a significant concern, especially for vehicles with more than 50,000 miles accumulated. The on-board technology can be deployed on a vehicle regardless of its mileage accumulation. However, a key question is whether a sufficient sample size can be obtained to infer a deterioration rate with statistical confidence.

On-board measurements can be made for vehicles in a variety of areas, with different I/M programs. However, a concern may be limited sample sizes of vehicles from which to make inferences regarding the average effect of different I/M programs. Also of key importance is knowledge of the I/M history of each specific vehicle (e.g., whether it is been repaired to correct an emissions problem), as opposed to knowledge only of the I/M program to which it is subject.

On-board measurement systems do not address evaporative emissions at this time.

The effects of different fuel formulations and of different fuels can be evaluated by collecting data for vehicles that use different fuel formulations or fuels.

Ambient temperature is not a controllable variable in an on-board study. Therefore, there will be variability in ambient temperature during data collection. Statistical techniques can be used to make inferences regarding the relationship between emissions and ambient temperature. Analyses in this project and in previous work have revealed statistically significant relationships between emissions and ambient over the range of variation observed in the data.

From the review of Table 7-1 and based upon additional considerations, some limitations of on-board measurements can be identified. These are discussed in the next section.

7.2 Limitations of On-Board Emissions Data Collection

Current on-board emissions measurement methods are aimed only at tailpipe emissions. In addition, the current generation of portable on-board emissions measurement systems are typically limited, at this time, to measurement of only selected gases (e.g., CO, NO, HC, CO_2, and O_2). Techniques for measuring PM emissions are commercially available as well. However, currently, portable on-board emissions measurement systems are not readily available for measuring other pollutants, such as air toxics. On-board systems do not measure evaporative emissions.

On-board emissions are collected under observational conditions. It is not possible to control on-board emissions measurement data other than indirectly through choices of drivers, vehicles, operating conditions, routes, and scheduling. At the same time, this is a strength in that one can identify real world effects that are missed in standardized driving cycles. Because it is not possible to control all key explanatory variables when collecting on-board data, there is still an important role for laboratory data. For example, ambient temperature may vary from one on-board emissions measurement run to another, and in reality will vary during the data collection run. If enough repeated runs are collected with the same vehicle/driver/route/traffic flow combination under a range of ambient temperatures, it may be possible to obtain a statistically significant relationship between emissions and ambient temperature. The same is true for relative humidity and barometric pressure. However, a parametric study under controlled conditions may help gain insight into the relationship between emissions and a single explanatory variable.

There are some questions about how effectively some relationships will be observed in on-board data sets until such time as a very large number of vehicles (thousands) have been tested. For example, inferences about deterioration rates have in the past been made on the basis of thousands of IM240 measurements for vehicles with variation in mileage accumulation. Even under the relatively controlled driving cycle of the IM240 (when compared to on-road conditions), there is tremendous variability in the data and the deterioration rates inferred from such data sets explain only a very small portion of overall variability in the data. Because on-road measurements are observational and not controlled, there will be greater variability in the data. Thus, there may continue to be a role for alternative sources of deterioration rate data.

Similar to the concern about deterioration rate, it is possible that it will be difficult to make reliable inferences regarding the effect of I/M programs and individual vehicle I/M repair history from on-road studies until a very large database is assembled. Therefore, there will be an interim role for the use of the other data, such as remote sensing measurements, to help assess the real world impacts of I/M programs on average emissions, at least for some pollutants, until sufficient on-board data are available for this purpose.

7.3 Bias in On-Board Hydrocarbon Emission Measurements

On-board emission measurement systems typically use NDIR to measure HC emissions. NDIR is also the technique used in many remote sensing instruments. An earlier study by Stephens *et al. (16)* compared hydrocarbon measurements made using gas chromatograph, flame ionization detector (FID), Fourier transform infrared spectrometer (FTIR), non-dispersive infrared analyzer (NDIR) and two remote sensors. Measurements were made on 10 individual hydrocarbon species, 12 vehicle exhaust samples, and three different volatilized fuel samples. The FID was taken as the benchmark instrument. The ratio of HC/CO_2 emissions obtained by each instrument divided by the corresponding HC/CO_2 measurement using FID was defined as the "response factor." NDIR systems are typically calibrated to measure propane. Stephens *et al. (16)* report that the NDIR response factor for straight chain alkanes varied from 0.94 to 1.11. The response factor decreased for measurements of chain-branched alkanes. The response factor for olefinic and aromatic compounds was low, varying from 0.05 to 0.5 depending on the compound. The overall response factors for measurements of total HC emissions from 12 tests of two vehicles ranged from 0.23 to 0.69. In contrast, RSDs typically perform well in measuring the CO/CO_2 ratio, with a response factor close to one. Thus, CO measurements are considered to be accurate, and are precise to within plus or minus 10 percent. The measurement of total hydrocarbon measurements is inaccurate. However, the magnitude of the systematic error may be difficult to quantify, since the speciation profile of vehicle emissions may change from one measurement to another, which in turn affects the overall HC response factor.

On-board equipment vendors have compared the total trip emissions measured with the on-board instrument to that measured in the laboratory. Typically, there is good concordance between the two measurements. When the measurements from the on-board instruments are plotted on a parity plot, with respect to the laboratory measurements, the R^2 values are very high. Thus, it may be feasible to develop a bias correction factor based upon the slope of the laboratory data plotted with respect to the on-board emissions data. We do not attempt to do this definitively at this time, because the available sample of comparison measurements from which to make an inference regarding the bias correction, and the unexplained variability in the bias correction, is very small. However, the development of a bias correction is a need for future work and should be addressed as part of the qualification procedure for accepting specific instruments for use in the field data collection studies.

7.4 Air Toxics and Other Pollutants Not Measured by On-Board Instruments

There is a need for alternative emissions data for pollutants that are not easily measured at this time with current on-board emissions measurement systems. Such data could be used to correlate emissions of other pollutants with those that can be measured with the on-board emissions measurement systems, or to develop predictive models for such pollutants using explanatory variables similar to those obtained from on-board emissions measurements.

Bammi (2001) evaluated air toxics data developed for the California Air Resources Board (CARB) to determine which method of estimating air toxic emissions had the least variability.

The alternatives considered, based upon the availability of data, were gram per mile emissions estimated directly for each air toxic (benzene, 1,2-butadiene, MTBE, formaldehyde, and acetaldehyde), and estimation of the air toxic emission rate as a fraction of total organic gases emitted. Analyses were conducted for both the FTP and the Unified cycles. When estimated directly from the data in g/mi units, the variability in the emissions data was found to be a factor of typically 100 to 300 for both cycles and for all five pollutants, when considering a 95 percent probability range. In contrast, the variability in emissions as a percentage of TOG was typically a factor of 2 to 30. Thus, there is at least an order of magnitude less variability when the toxics emissions data are normalized with respect to TOG emissions. The range of uncertainty in the average emissions when expressed as percent of TOG was found to be as low as approximately plus or minus 10 percent and as high as approximately minus 60 percent to plus 70 percent, with a typical result of approximately plus or minus 30 percent.

The results of the analysis reported by Bammi (2001) suggest that estimation of air toxic emissions as a fraction of TOG (or surrogates for TOG, such as total hydrocarbon emissions) may be a viable approach. A substantial amount of the variability in air toxic emissions, at least for organic molecules, can be explained by variation in emissions of TOG. Therefore, when air toxic emissions are normalized to TOG, there is a relatively modest amount of unexplained variability compared to the total observed variability in the data. The uncertainty in the average emission ratio is comparable to ranges as previously estimated by Kini and Frey (1997) and Pollack *et al*. (1999) for NO_x and HC emissions from LDGV. Therefore, in the NGM, a potentially viable approach is to estimate organic air toxic emissions as a function of hydrocarbon emission rates. Correction factors can be developed as appropriate if sufficient data became available to evaluate and include other explanatory variables, such as ambient conditions and others.

7.5 Representative Driving Cycle for Laboratory Testing

One or more new driving cycles should be developed based upon on-board data collection for use in laboratory dynamometer measurements to supplement the on-board data. For example, at this time, evaporative running loss and air toxics data are more amenable to measurement in the laboratory, and there is not a viable portable on-board method at this time to address these emission processes or pollutants. For some explanatory variables, such as temperature, fuel effects, a/c load, and perhaps others, laboratory data may be useful to help provide insight into the functional relationships between emissions and the explanatory variable. Those insights will be helpful when selecting the functional form of regression models to use in analyzing on-board emissions data. When collecting data using dynamometers, it is important to use a driving cycle representative of real world conditions.

An important benefit of on-board data collection is that a large amount of real-world vehicle activity data will be collected. This data includes speed traces on a second-by-second basis. The large database of speed traces that will be developed in a five year study, and even in just the first two years of the study, can be used to develop new dynamometer driving cycles that are truly representative of real-world driving. The driving cycles can include a combination of roadway facility types and traffic congestion. Thus, an important area for work is to develop a new standard driving cycle that will underlie the measurement of evaporative running losses and of other correction factors (e.g., fuel effects, accessory load) that could supplement the development of an on-board emissions data-based model.

7.6 Supplemental Laboratory Data for Tailpipe Emissions

Although it is possible to include a large number of explanatory variables in on-board data collection studies, such as ambient temperature, accessory load, and fuel effects, it is also important to be able to tease out the underlying functional relationship between emissions and individual effects such as these. Because on-board studies are observational in nature, it is not possible to control all factors except the one that is of interest in a particular study. Therefore, there will typically be a significant portion of variability that cannot be explained unless a sufficient set of explanatory variables are included in every analysis. For a given data set, there is the possibility of confounding variables. Therefore, it is valuable to have laboratory data to develop insight into specific relationships that are expected and to use this insight as an aid in analyzing the on-board data.

There are at least two approaches to the use of dynamometer data in combination with on-board data. One is to use the dynamometer data to develop correction factors that can be applied to base emission estimates developed from on-board data. This approach requires that the variable that is the basis for the correction factor, such as A/C usage, be "removed" from the on-board data, so that all of the on-board data can be converted to a standard basis to which the correction factor can be applied. Thus, an assumption must be made regarding the relationship between A/C usage and emissions, and the observed emissions must be adjusted to remove this relationship and convert data to the standard basis. For example, if the standard basis is no A/C usage, then all data for which A/C usage is reported would have to be adjusted to a non-A/C usage basis in this approach, using a standard correction factor. The base modal emission rates would then be estimated on a consistent "no A/C use" basis. The same correction factor would be used in the model to convert data from a "no A/C use" basis to an "A/C use" basis.

A second approach is to use the dynamometer data only for the purpose of developing insights into an appropriate functional form for the relationship between emissions and A/C usage, and then to use the insight regarding the appropriate form in developing statistical models of emissions as a function of many explanatory variables, including A/C usage. In this approach, the final parameter estimates for the relationship between emissions and A/C usage would be driven by information contained in the on-board database, and not by the dynamometer data. For example, based upon the dynamometer data, a functional form for the relationship between emissions and A/C usage would be specified, and the parameters of the model would be selected by fitting the model to the on-board data. However, the dynamometer data would play a critical role in helping to determine what the *form* of the relationship should be. As previously noted, the dynamometer tests should be based upon a representative driving cycle inferred from on-board data.

Aside from A/C usage, other effects that might be explored using laboratory approaches include the effect of ambient temperature and the effect of fuel characteristics.

7.7 Other Data Needs

As noted earlier, the on-board data will reveal more information about the real world nature of cold start emissions, and may in turn motivate additional input data requirements regarding where cold starts take place along with indicators for their duration and severity. For example, it is clear from the LDGV data set that cold starts are influenced by soak time prior to starting the vehicle, although at this time there are not enough data to evaluate soak time for every trip in the calibration data base. It is likely that soak time and ambient temperature should play a role in making average predictions of the duration of a cold start, perhaps as a function of vehicle characteristics such as engine size. This hypothesis should be explored in future work. The NGM may, therefore, require a distribution of soak times that can be used to make predictions of cold start emissions, and the distribution of soak times is likely to be a function of time of day. For example, the distribution of soak times will tend to have large values for early on a weekday, after a vehicle has sat overnight and just before startup for a morning commute. In contrast, the distribution of soak times will typically have lower average values for mid-day driving. An assessment of the maximum range of soak time that should be considered in developing relationships between soak time and cold start emissions should be determined based upon data analysis.

As noted elsewhere, and as discussed in Chapter 8 in more detail, driver behavior is hypothesized to be an important consideration for the on-road data collection. Thus, a method is needed for classifying drivers with respect to driving style. Specific suggestions are given in Chapter 8. It is possible that the NGM may require input data regarding the distribution of driving styles. In turn, this suggests the need for a study to recruit human subjects representative of the general population and to collect an example speed trace from them from which to make inferences regarding driving style. It may be possible to do this through use of a small GPS unit that can be installed in the subject's vehicle so that the location of the vehicle can be recorded on a second-by-second basis and used to make estimates of vehicle speed. Alternatively, other instrumentation might be used or developed to collect speed data from the OBD link or to measure it with a sensor array.

As noted earlier, inferences regarding deterioration rates are likely to be difficult to make with on-board data until a very large data set with thousands of vehicles becomes available. Therefore, there is likely to be a continuing need to make inferences regarding deterioration rates from other data sources, such as IM240-based studies. Deterioration rate correction factors can be applied to adjust on-board data to a nominal mileage accumulation, and the same factors can be used in the NGM to adjust base emission estimates to other mileage accumulations. However, the explanatory power of mileage accumulation should be explored in the on-board data sets. It may turn out that mileage accumulation is a statistically significant explanatory variable, in which case the use of alternative data may not be needed.

The effectiveness of I/M programs may be a consideration that will be difficult to assess with on-board measurements until a sufficiently large database is developed in the long run. Therefore, there is a role for alternative data sources from which to develop correction or adjustment factors for the effect of I/M programs. Data from remote sensing may be useful for this purpose.

It should be possible to collect on-board data for as many technology groups as desired, However, if for resource reasons it is not possible to do this, it may be appropriate or necessary to consider using comparisons of vehicle emissions measured on the same set of standard driving cycles as a basis for comparing emissions between technology groups.

7.8 Evaporative Emissions Data

There will be a long term need for the use of alternative data for evaporative emissions. As noted by NRC (2000), evaporative emissions are considered essential to the accurate estimation of total emissions of hydrocarbons for on-road vehicles. Evaporative high emitters are of concern and should be properly represented in the database. Previous studies have shown that data are skewed for hot-soak, running loss, and diurnal emissions. Even for fuel-injected models, high emitters are found. Running losses from liquid leaks may be especially important even for fuel injected vehicles.

The key evaporative emissions mechanisms are:

Diurnal emissions – fuel vapors, varies with ambient temperature during the day, fuel vapor pressure, and period of nonoperation.

Resting losses – permeation of fuel through tanks, lines, and fittings, and liquid leaks that are not the result of temperature variation.

Hot soak – first hour after shutdown, with most occurring during the first 10 minutes. Primarily from the fuel tank and, in carbureted vehicles, from the carburetor bowl. Hot soak emissions are lower for fuel injected vehicles, and are not as skewed as the other evaporative emissions.

Running losses – during vehicle operation. Measured on a chassis dynamometer. Depends on driving cycle, fuel vapor pressure, and ambient temperature. Liquid leaks can cause skewness in the data.

The Sealed-Housing for Evaporative Determination (SHED) testing procedure is an existing method for measuring hot soak and diurnal emissions. A test procedure introduced in 1996 for diurnal and running loss emissions is lengthy and, therefore, there is a practical limit on the number of vehicles that can be tested given time and other resource constraints.

7.9 Seeking Other Opportunities for New Data

Creative ways to piggyback collection of new types of data with on-board studies should be considered. For example, perhaps it would be useful to measure real world tire wear by periodically measuring tire tread depth on vehicles that will be part of long-term testing. It may be necessary to make notes regarding the type of pavement on the routes driven by the vehicles in order to develop explanatory models of real world tire wear as a function of driver behavior (or speed profile characteristics), pavement type, ambient conditions, and perhaps other factors.

7.10 Short-Term and Long Term Needs

The results from analysis of on-board emissions data will suggest in part what alternative data should be incorporated into the NGM. For example, if ANOVA analysis identify an important role for factors that cannot easily be controlled, then such factors should be candidates for development of laboratory-based correction factors or for the use of laboratory data to help develop insights regarding appropriate functional forms to use in fitting models to on-board data. Moreover, some effects may be difficult to measure or observe, such as compliance with I/M requirements. Alternative data for pollutants not easily measured with on-board emissions measurement systems, and for evaporative emissions, will need to be included and addressed as a long term need.

In addition to identifying useful alternative data, an area that will be valuable for future work is to figure out what alternative data is *not* useful. For example, there has been a proliferation of driving cycles. In previous work, some of these driving cycles have been found to be redundant (e.g., Kini and Frey, 1997). Specifically, in some cases, there is not a statistically significant difference in the mean emissions measured on one cycle versus those measured on another. To the extent that redundant or unnecessary driving cycles can be identified, then data from such cycles can be combined into larger databases and future work can focus on measurements with a smaller number of more useful cycles.

7.11 Strategies to Utilize Bag Data for Modal Analysis

EPA has been using driving cycle test data for developing emission factor models, and has accumulated a large database of such measurements. For example, thousands of such measurements are reported in the Mobile Source Observational Database (MSOD). Driving cycle tests are also referred to as "bag" data. This is because emissions for segments of a driving cycle, or for an entire driving cycle in some cases, were or are collected in tedlar bags, and the contents of the bags are analyzed to determine the total mass of pollutants emitted over the duration of the time required to collect the contents of the bag. Because the standardized speed trace during the period of collection of gases in the bag is known, it is therefore possible to estimate the emission rate with respect to the distance that a vehicle would have driven during the test if it had operated on the road, instead of on a dynamometer. Therefore, bag data are commonly used to make estimates of the average mass per distance driven emission rate.

Because of the availability of a large data base of driving cycle, or bag, data, it is desirable to develop methods to allow such data to be used in conjunction with on-board data when developing the NGM. The model development approach recommended in Chapters 3, 4, and 5 is based upon binning data into driving modes, and then stratifying the driving modes further and/or developing regression equations within each mode or strata. If second-by-second data are available for dynamometer tests, as is sometimes the case, then the same approach can be used to analysis driving cycle data. However, in many cases, only average emission rates associated with bags are available. Therefore, a key question is how can these data be analyzed in order to make estimates of modal emission rates?

The information available for bag data includes the following: (1) the average emission rate for the bag and the estimated distance traveled (or, equivalently, the total mass of emissions collected in the bag); and (2) the second-by-second distribution of speed during the standardized test. The modal modeling approach for on-road vehicles illustrated in Chapters 3 and 4 defines driving modes based upon criteria for speed and effective acceleration. From the second-by-second speed trace used for the bag measurements, and any other information regarding simulation of loads with the dynamometer (e.g., attempts to simulate road grade), it is possible to estimate second-by-second speed, observed acceleration, and effective acceleration. Therefore, it is possible to assign each second of the driving cycle test to one of the driving modes.

For example, in the case of the cold start portion of the FTP, either the entire cold start bag (505 seconds) or a portion of the cold start bag can be identified as an actual cold start. From data analyzed in this study, it is not typically the case that a cold start lasts as long as 505 seconds. Therefore, some portion of the cold start bag of the FTP likely includes hot stabilized emissions. A methodology similar to that illustrated in Chapter 6 for estimating the duration of the cold start can be used to estimate the likely actual duration of the cold start during Bag 1 of the FTP. Thus, it will be possible, in general, to categorize each second of the speed trace as being cold start or hot stabilized. For the hot stabilized portion of the test, the speed trace can be used to derive the acceleration. The effective acceleration can be estimated based upon information regarding the simulation of road grade, if any. Therefore, for the hot stabilized portion of a driving cycle test, each second of the speed trace can be categorized as a driving mode (e.g., idle, acceleration, cruise, deceleration). The result of the categorization of the speed trace into driving modes is knowledge regarding the fraction of total trip time spent in each mode. The total trip emissions on a mass basis can be divided by the total number of seconds of the test to estimate an average g/sec emission rate.

A system of equations can be developed to estimate the modal emission rates based upon the following relationship applicable to each test result:

$$ER_{cs} \times ft_{cs} + ER_{idle} \times ft_{idle} + ER_{accel} \times ft_{accel} + ER_{decel} \times ft_{decel} + ER_{cruise} \times ft_{cruise} = ER_{ave} \qquad (7\text{-}1)$$

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 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 the example shown in Equation (7-1), five modes are shown. Therefore, at least five simultaneous equations must be solved in order to estimate these five emission rates.

In this section, examples are given where modal rates were determined using the percent time spent in each mode and total emissions. For this purpose, data provided by the EPA for HDDV NO were utilized. As explained in Chapter 4, four driving modes were identified for HDDV for NO emissions. These driving modes are: idle, acceleration; deceleration; and cruise. In estimating emission rates for each of these modes, at least four equations are required since there are four unknowns. Systems where the number of equations is used is the same as the number of unknowns are identified as “square” systems, and have unique solutions (Kress, 1998). For “square” systems, an exact system 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 solution of these 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 latter 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).

A key consideration is that the modal emission rates are not constant from one test to another. This is because the modal emission rate is influenced by factors other than speed and acceleration, such as vehicle characteristics. Although driving cycle tests are based upon a prescribed speed profile, the test driver is allowed to deviate from the standard profile within an allowable tolerance. Therefore, the actual speed trace for a given test will not be identical to the standard speed trace. These considerations illustrate that there will be some variability in modal emission rates even if the same vehicle undergoes multiple tests on the same cycle under the same nominal conditions. Thus, an objective of analysis of bag data should be to develop reasonable estimates of average modal emission rates, recognizing that there is variability in the modal emission rate from one test to another. As a corollary, it should be recognized the solutions for any case based upon a small number of bag tests may deviate from the average of the modal rates that would be obtained with a larger data set.

Examples of solutions for modal rates using both “square” and “over-determined” systems are given. First, two examples are given for square systems, as summarized in Table 7-3 based upon NO_x emissions for four trips of a HDDV. Each of the four trips is based upon second-by-second on-board data. However, the data are summarized in a manner comparable to what would be known if the trips were measured as a single bag. The advantage of using on-board data to illustrate the method is that the actual modal emission rates are known and can be compared to the values estimated from the solution of a square system. In the example, only four driving modes are estimated. Therefore, four equations are required to solve the square system. For example, for Case 1, the system of four equations is:

$$
\begin{aligned}
ER_{idle} \times 0.19 + ER_{accel} \times 0.29 + ER_{decel} \times 0.25 + ER_{cruise} \times 0.28 &= 0.1661 \\
ER_{idle} \times 0.13 + ER_{accel} \times 0.34 + ER_{decel} \times 0.27 + ER_{cruise} \times 0.26 &= 0.1867 \\
ER_{idle} \times 0.25 + ER_{accel} \times 0.20 + ER_{decel} \times 0.17 + ER_{cruise} \times 0.38 &= 0.1366 \\
ER_{idle} \times 0.12 + ER_{accel} \times 0.25 + ER_{decel} \times 0.22 + ER_{cruise} \times 0.42 &= 0.1673
\end{aligned}
$$

Table 7-3. HDDV NO_x Emissions Data Used for Case Studies for Square Systems of Simultaneous Equations Data to Solve for Modal Emission Rates.

	Percent Time Spent				
	Idle	**Acceleration**	**Deceleration**	**Cruise**	**NO Emissions g/sec**
Case 1	0.19	0.29	0.25	0.28	0.1661
	0.13	0.34	0.27	0.26	0.1867
	0.25	0.20	0.17	0.38	0.1366
	0.12	0.25	0.22	0.42	0.1673
Case2	0.27	0.20	0.32	0.20	0.0761
	0.25	0.15	0.14	0.47	0.1187
	0.12	0.26	0.24	0.39	0.1789
	0.26	0.32	0.24	0.18	0.1082

Table 7-4. Comparison of Predicted Modal Emission Rates Based Upon Solution of a Square System of Equations Versus Observed Modal Emission Rates for Selected HDDV NO_x Emissions Data.

		NO Emission Rates for Driving Modes			
		Idle (g/sec)	**Acceleration (g/sec)**	**Deceleration (g/sec)**	**Cruise (g/sec)**
Case 1	*Predicted*	-0.02	0.34	0.14	0.13
	Observed	0.04	0.31	0.06	0.17
Case 2	*Predicted*	-0.26	0.34	0.08	0.26
	Observed	0.04	0.24	0.04	0.13

Where each equation has a form similar to Equation (7-1). The right hand side is the average gram/second emission rate for the trip given in Table 7-3, and the coefficients shown for each modal emission rate are the fraction of time spent in the mode as given in the table. A similar system of equations was developed for Case 2 shown in Table 7-3. For the two cases, the modal emissions rates were determined by solving the four equations simultaneously. The solution method employed was Gaussian Elimination and the solution was obtained using the SAS software. The solutions for both cases are shown in Table 7-4, along with the average of the observed modal emission rates for each of the four trips in each cases.

The results of the case studies are interpreted both qualitatively and quantitatively here. For both cases, the estimated value of the acceleration modal emission rate was larger than the estimated values for the other modes, which is consistent with the observed values. In Case 1, the estimated values of the deceleration and cruise emission rates were similar, while in Case 2 the estimated cruise emission rate was larger than the deceleration rate. The latter result is consistent with the observation that the cruise emission rate is larger than the deceleration emission rate. The idle emission rate had the lowest estimated values compared to the other modes. This is qualitatively consistent with the ordering of the observed modal emission rates. However, the idle emission rate was estimated to be negative in both cases, with Case 2 reported a negative value that was large in magnitude when compared to other modal emission rates.

Quantitatively, the modal solutions agreed with the observed values reasonably well in only one or two specifics. For example, the estimated acceleration modal emission rate of 0.34 g/sec compared well with the observed acceleration modal emission rate of 0.31 g/sec for Case 1.

However, in most cases, there were large relative differences in the estimated and observed emission rates.

Clearly, negative emission rates are not an acceptable result, and these results imply that solution of square systems is not likely to be a realistic or sole basis for estimating modal emission rates from bag data. The reasons why the solutions in these cases were relatively poor is explored in terms of the mathematical properties of the square systems associated with Case 1 and Case 2.

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). There are two indicators to check whether a linear system is well-conditioned or ill-conditioned. One of these indicators is that the determinant of the coefficient matrix. If the determinant is close to zero, then the system is ill-conditioned. Another indicator is the condition number, which is defined by Burden and Faires (1985) to be:

$$K(A) = \|A\|\|A^{-1}\| \tag{7-2}$$

where,

$K(A)$ = condition number

$\|A\|$: = norm of coefficient matrix (A)

$\|A^{-1}\|$: = norm of inverse of coefficient matrix (A)

In the examples given in Table 7-3 and 7-4, the determinants of coefficient matrix and condition numbers were estimated using Matlab. The determinant of Case 1 is -0.00025 and of Case 2 is -0.0042. The condition number for Case 1 is 84, and for Case 2 it is 10. In both of the cases determinants are very close to zero, which implies an ill-conditioned system. The condition numbers are substantially different from one, which also implies an ill-conditioned system. Therefore, based upon both of these tests, the square linear systems of Cases 1 and 2 are both "ill-conditioned". Therefore, it is not surprising that the solutions included negative values for the idle emission rate and that there was relatively poor quantitative agreement between the predicted and the observed modal emission rates.

As described by Kress (1998), solution of "ill-conditioned" systems is not straightforward. However, there are advanced mathematical techniques that can help in solving these types of problems. Some methods that can be used in the case of solving "ill-conditioned" linear systems are Singular Value Decomposition and Tikhonov Regularization, as suggested by Kress(1998). These methods should be explored in future work for their applicability to square systems of equations based upon bag data.

Another method to solve for modal rates is the use of "over-determined" systems, where the number of equations is more than number of unknowns. Such a system can be developed, for example, when many vehicles of the same technology group are tested on the same cycle. In solving over-determined systems, least-squares techniques can be used (Kress, 1998). Two examples are given here in which over-determined systems were developed for solving modal rates. The first of the over-determined examples, referred to as Case 3, is based upon trip data for

Table 7-5. Predicted and Observed Values of Driving Mode Emission Rates for Example Cases for HDDV NO_x Data using Least-Squares Solution Method for "Overdetermined" Systems.

		NO Emission Rates for Driving Modes			
		Idle (g/sec)	**Acceleration (g/sec)**	**Deceleration (g/sec)**	**Cruise (g/sec)**
Case 3	*Predicted*	0.02	0.39	-0.21	0.21
	Observed	0.04	0.24	0.04	0.13
Case 4	*Predicted*	0.05	0.29	-0.05	0.11
	Observed	0.03	0.23	0.04	0.12

54 trips for NO_x emissions from the HDDV data set used in Chapter 4. The second example, referred to as Case 4, is based upon 11 trips for NO_x emissions from the HDDV data set. The 11 trips were selected because they had similar modal emission rates. For both Case 3 and 4, a regression equation was fit to the data. The y-variable used in the regression was the trip average emission rate. The predictive variables were the fraction of time spent in each driving mode. The unknown coefficients were the modal emission rates. The unknown coefficients were obtained from a least squares fit with the data. The results are summarized in Table 7-5.

The results from the solution of the over-determined system are qualitatively slightly better than in the case of the square systems, but there are still problems with the solutions. For example, negative emission rates are estimated for deceleration in both case studies. However, the observed emission rates for idle and deceleration are nearly the same, and the problem of negative predictions is similar here compared to the cases of the square systems of equations. The acceleration mode is correctly found to have the highest emission rate, and in Case 2 the solution for the acceleration emission rate is comparable to that of the observed value. The cruise emission rate is correctly found to have the second highest emission rate, and in Case 2 the numerical value of the solution is close to the observed value. It seems likely that one difficulty that these methods have in finding a solution may be attributable to the similarity in the emission rate for both idle and deceleration.

The results of the illustrative case studies for both square and over-determined systems imply challenges to the use of bag data for estimating modal emission rates. However, it is possible that these challenges can be addressed given more time for study. Several areas for further investigation are recommended. One approach involves making some a priori assumptions regarding relationships between modal emission rates in cases where the modal rates are expected to be similar. For example, for HDDV NO_X emissions, the idle and the deceleration modal emission rates are almost identical. Very likely, the similarity of these two modal emission rates contributes to numerical instability of the solution to a system of simultaneous equations. Therefore, the number of unknowns can be reduced by adding a constraint that these two emission rates be equal. Because the emission rates for idle and deceleration are low, these two modes do not contribute substantially to total trip emissions. If combining these two similar modes into one variable improves the accuracy of the solution for acceleration and cruise, which have higher emission rates and contribute to a greater share of trip emissions, then the benefits of improved accuracy in the estimation of those two modes would be outweighed by possible errors in the constraint.

Table 7-6. Predicted and Observed Values of Driving Mode Emission Rates for Example Cases for HDDV NO_x Data using a Constrained Least-Squares Solution Method for "Overdetermined" Systems.

		NO Emission Rates for Driving Modes			
		Idle (g/sec)	**Acceleration (g/sec)**	**Deceleration (g/sec)**	**Cruise (g/sec)**
Case 5	*Predicted*	0.01	0.29	0.01	0.15
	Observed	0.04	0.24	0.04	0.13
Case 6	*Predicted*	0.04	0.26	0.04	0.13
	Observed	0.04	0.24	0.04	0.13

Another area for further investigation is to explore other methods that may be more appropriate for solving ill-conditioned systems, and/or methods that enable the analyst to impose non-negativity constraints on the solutions. Examples of the former include the Singular Value Decomposition and Tikhonov Regularization methods for square systems. Optimization methods should be explored for use with over-determined systems.

Based upon the findings for Cases 3 and 4, two additional cases were developed based upon the use of Constrained Linear Least Squares regression, performed using the Matlab software. Based upon analysis of HDDV data, it is expected that the modal emission rate for acceleration will be larger than for any other mode, and that the modal emission rate for cruise will be less than that for acceleration and greater than that for either deceleration or idle. Furthermore, the deceleration and idle emission rates were found in Chapter 4 to be approximately similar in the case of NO. Therefore, the following constraints were defined and were included in the solution method in defining Case 5:

$$ER_{accel} > ER_{cruise} > ER_{decel} >= ER_{idle} \qquad (7\text{-}3)$$

The solution obtained for Case 5, which was done for the same over-determined system based upon 54 trips as for Case 3, is given in Table 7-6. The predictions for the acceleration and cruise modal emission rates agree well with the observed values. The predictions for the idle and deceleration emission rates were the same, and both were lower than the observed value. Therefore, an additional case study, Case 6, was set up in which a lower bound on the modal emission rate was imposed:

$$ER_{accel} > ER_{cruise} > ER_{decel} >= ER_{idle} >= 0.04 \text{ g/sec} \qquad (7\text{-}4)$$

With the addition of a lower bound for the modal emission rates, the solutions for all four of the modes were found to agree very well with the observed values, as shown in Table 7-6. The results of Cases 5 and 6 illustrate that if some additional knowledge is entered into the solution process by imposing either the relative weak constraints of Equation (7-3), or the somewhat stronger constraints of Equation (7-4), the problem of obtaining negative emission rates can be eliminated and the accuracy of the solution can be substantially improved.

Since it will typically be the case that the rank ordering of the modal emission rates among the modes will be known based upon some sample of on-board emissions data or other second-by-second data (e.g., from dynamometer tests), it is not unreasonable that constraints similar to those shown in Equations (7-3) or (7-4) can be included in the solution method for inferring modal emission rates from bag data. The examples presented here illustrate the critical importance of seeking an appropriate solution method and for imposing some constraints on the solution. The constrained linear least squares solution method explored in Cases 5 and 6 appears to work well. The performance of this method should be more thoroughly investigated with other data sets. In addition, methods such as the Lagrange multiplier technique or iterative methods of optimization such as the conjugate gradient method or descent methods may also be useful. Luenberger (1969) describes these methods.

We recommend that constrained linear least squares regression be further explored and evaluated on a larger number of data sets and expect that it is likely to be a preferred technique for estimating modal emission rates from bag data.

7.12 Considerations for Heavy Duty Diesel Vehicles

The preceding discussion has focused on on-road LDGV. Engine dynamometer tests, as opposed to chassis dynamometer tests, are often used as the basis for HDDV emissions data. A key consideration and potential weakness in using engine dynamometer data is the use of a brake specific fuel consumption (BSFC) factor to convert emissions from a g/bhp-hr basis to a g/mi basis. On-board data will provide a significant advantage by providing chassis emissions data and by directly providing both gram per second and gram per mile emissions data.

The engine in a heavy duty diesel vehicle may be operated for a million miles or more, with one or two rebuilds taking place at approximately 500,000 miles and then 300,000 miles after that. Engines in medium heavy duty diesel vehicles have a life more typically on the order of 250,000 miles and may undergo one rebuild. Because of the long life of these engines, the deterioration rate is of concern. Data regarding deterioration rate has at times shown no statistically significant deterioration in emissions with mileage accumulation, and in some cases manufacturers have observed negative deterioration rates. EPA does not allow negative deterioration rates to be used in the MOBILE models. Engines tested for certification are properly maintained and meet manufacturer specifications. Therefore, they may not be representative of the fleet of real world engines.

A key need for HDDV emission data is regarding deterioration rate. The modeling of the change in emissions with regard to mileage accumulation on the engine should be based upon data and should not be limited by policy assumptions forced into the model. If there is a plausible reason as to why emissions might decrease with use, then the decrease should be included in the model. The ability of on-board data to serve as a basis for inferences regarding deterioration rate will be a function of sample size. For HDDV, it is important to record the engine characteristics and history when collecting on-board data.

Careful consideration should be given to the development of vehicle classifications for HDDV. For example, Duleep (1995) points out that there are significant differences in activity patterns for medium heavy duty and heavy duty trucks. Similarly, there are significant differences between school buses and transit buses. These differences include annual use, operating radius, useful life, and fuel economy. Duleep (1995) points out that most diesel vehicles are power limited, so that accelerations often take place at wide open throttle. Therefore, there may be less variability in acceleration emissions for diesel vehicles than for gasoline vehicles, which are usually not power limited.

There does not appear to be much concern regarding evaporative emissions from diesel vehicles, and therefore there is not a clear need for alternative data regarding evaporative emissions. This is presumably because of the low volatility of diesel fuel.

Diesel fuel formulation has a potentially significant impact on emissions (e.g., Clark *et al*., 2002). Comparison of fuel formulations for the same set of vehicles would be a good candidate for either engine dynamometer tests, chassis dynamometer tests, or a focused on-road study aimed at evaluating differences in emissions associated only with different fuels.

HDDV have in recent years had a problem with the use of "defeat devices" to override the appropriate electronic control settings to improve performance at the expense of higher NO_x emissions. The use of on-board emissions measurements may be beneficial in improving understanding of the real-world behavior of vehicles that still operate in this manner, assuming that such vehicles can be identified and recruited.

Emissions from diesel engines are likely to be sensitive to barometric pressure (altitude), ambient temperature, and relative humidity. These factors can be evaluated in an on-board study.

The data provided by EPA do not include particulate matter. However, on-board measurement techniques for PM are becoming commercially available and should be evaluated for use in the on-board study of HDDVs.

7.13 Considerations for Nonroad Vehicles

Frey and Bammi (2002a&b) have reviewed publicly available data for the Lawn and Garden and the CFI nonroad categories. Much of the available data are from steady-state modal tests, and relatively little information appears to be available regarding real world activity patterns of such vehicles. There are a few exceptions. For example, the Engine Manufacturers Association and EPA have jointly developed several transient emission cycles for an agricultural tractor, crawler dozer, and a backhoe loader (Beardsley and Lindhjim, 1998). A transient cycle, GGRASS, was recommended by Southwest Research Institute (SwRI) and is the basis for development of the Lawn Mower Cycle (Sun *et al*., 1995). The latter is a steady state modal cycle.

The availability of emissions data for the L&G and CFI categories is relatively limited. For example, for L&G engines, tests were found for a total of 27 4-stroke engines and 18 2-stroke engines, whereas for CFI test data were found for 55 engines. From the limited database, there are few statistically significant variables that were found that helped to categorize the data, such as with respect to engine size. For example, for CFI engines, significant differences were found for gasoline versus diesel engines, and for 2-stroke diesel versus 4-stroke diesel, when both NO_x and total hydrocarbon emissions were considered. Even though engine size varied from less than 100 hp to approximately 600 hp in the database, there was not a strong empirical relationship between emissions and engine size. The R^2 value for the linear trend of emissions versus horsepower was 0.07 for THC and 0.03 for NO_x, both for 4-stroke engines. Thus, there is not a compelling empirical basis for classifying engine emissions with respect to engine size based upon data obtained from steady-state modal testing.

Insufficient data were available to make estimates of deterioration rates, or the effects of temperature, fuel, relative humidity, barometric pressure, and other factors. Many if not all of these data gaps can be addressed by an on-board data collection study. However, some of these may be amenable to laboratory studies with engine dynamometers. The relationship between emissions measured in the field and on an engine dynamometer for nonroad source categories is an area of potentially useful investigation.

Evaporative emissions are likely to be a concern for gasoline-fueled nonroad equipment. An assessment should be made regarding the importance of evaporative emissions from Lawn and Garden use, including fuel spillage during filling of portable fuel tanks, fuel spillage during transfer of fuel from portable fuel tanks to Lawn and Garden equipment, breathing losses from portable fuel tanks, and other evaporative losses from the equipment itself, such as running losses, hot soak, resting losses, and diurnal effects.

8.0 TESTING STRATEGIES FOR ON-BOARD DATA

The objective of this chapter is to recommend a testing strategy for on-board data gathering over the next five years. The testing strategy addresses on-road and nonroad sources. A specific sampling plan is presented that focuses on populating the emissions component of the NGM. The main focus of this chapter is with regard to on-board emissions data, since alternative data sources are addressed in detail in Chapter 7.

8.1 Defining Study Objectives

The development of a five-year national testing strategy for on-board emissions data collection must begin with consideration of the key factors in study design unique to on-board measurements. The specific combination of factors for a study design is strongly dependent on a well-defined study objective. Examples of possible study objectives are given in Table 8-1, with a main focus on on-road vehicles. The implications for nonroad vehicles are discussed below. The study objective will influence the criteria for selection of vehicles, drivers, routes, instruments, scheduling of data collection, and selection of appropriate data screening, reduction, and analysis methods.

As examples, possible objectives for on-board emissions measurement studies include but are not limited to: (1) evaluation of emissions benefits of a transportation improvement, which requires before and after studies on a specific route or facility; (2) estimation of on-road emissions on specific facility types, which requires a vehicle fleet deployed on representative facility links (e.g., freeway, arterial, secondary roads); (3) estimation of emissions benefits of alternative routing, which requires measurement of alternative routes between a fixed origin and destination; (4) estimation of area-wide fleet average emissions, which requires a representative vehicle sample on a representative sample of trips in a given geographic area; and (5) evaluation of driver behavior, which requires measurements with multiple drivers using the same vehicles and routes. The study objective should be clearly defined. The study should be designed to appropriately isolate any key factors of interest, to control for as many other factors as possible, and to make observations if possible for any factors that are uncontrollable. The latter is necessary to attempt to account for variation in uncontrollable factors (e.g., ambient temperature) that might play in a role in comparison studies or that would have explanatory power in the development of a model.

The main focus here is on a study objective of supporting development of the NGM. However, it is useful to consider other study objectives to illustrate that study design is a function of the study objective, and that the data obtained to support one type of study objective may not fully support another study objective. For example, a study objective aimed at evaluating the relative change in emissions associated with a specific transportation control measure (TCM) or transportation improvement project (TIP) can be based on measurements with a relatively small set of vehicles. However, a study objective aimed at populating the NGM would require a larger representative sample of vehicles. Furthermore, for some study objectives, the data collection strategy can be substantially different than for others. For example, in evaluating the effect of a

Table 8-1. Examples of Alternative Study Objectives for On-Board Data Collection Studies

Support Development of the NGM – This study objective would be supported by a study design involving deployment of a representative sample of vehicles on a representative sample of roadway facility types over a representative schedule with respect to time of year and time of day at multiple regions of the country.

Evaluation of Specific Transportation Control Measures – This study objective would be supported by a "before" and "after" comparison of emissions for a small fleet of vehicles deployed in consistent vehicle/driver/instrument combinations on a specific route or corridor under similar ambient and traffic flow conditions for the purpose of evaluating changes attributable to the implementation of the TCM. Frey et al. (2001) present examples of a study such as this. This type of study requires repeated measurements to obtain statistically stable estimates of average emissions in both the before and after case.

Evaluation of Alternative Routing – Studies can be performed to compare emissions for travel to/from the same origin/destination pair using alternative routes for the same vehicle/driver/instrument combination under similar ambient conditions and for the same time of day. This type of study requires repeated measurements to obtain statistically stable estimates of average emissions for each route.

Identification of Emissions Hotspots – Locations of high average emissions can be identified based upon spatial analysis of emissions data collected for specific routes, corridors, segments, or facilities. This type of study requires repeated measurements to obtain statistically stable estimates of average emissions at each critical location along the travel route.

Emissions Implications of Driver Behavior – This type of study focuses on the real world differences in emissions attributable to different driving styles, and would require deployment of different drivers with the same vehicle/instrument/route/time of day combination with sufficient repetition to obtain statistically stable estimates of average emissions.

Evaluation of Transportation Improvement Projects – this is similar to "Evaluation of Specific Transportation Control Measures" but would involve "before" and "after" evaluation of a modification (e.g., lane additions)

Evaluation of Specific Types of Transportation Facilities (e.g., toll plazas, rest areas, roundabouts, etc.) – this would involve baseline characterization of emissions at such facilities in comparison to other facilities.

Validation of Emission Factor Models – the study design would be similar in nature to that for "Support Development of NGM" and would depend on the specific model to be validated (e.g., Mobile6)

Development of Public Education/Outreach Tools – This study objective could involve development of a simple driving simulator or other educational tool that would demonstrate to the public how driver behavior influences emissions.

TCM or TIP, it is necessary to obtain estimates of facility-specific mean emissions that are statistically reliable for both before the change is made and after the change is made. Therefore, the same set of drivers, vehicles, and instruments must be deployed in both a before and after study, and in both the before and after cases there must be a sufficient number of repetitions of data collection runs to obtain sufficiently narrow confidence intervals for the mean emissions to enable meaningful comparisons. In contrast, to support development of the NGM, which would be aimed at making predictions of fleet average emissions for various categories of vehicles, it is less important to have a large number of repeated runs with individual vehicles and it is more important to have runs with a larger number of vehicles.

The study objective for nonroad vehicles may differ for that for on-road vehicles depending upon the specific nonroad category that is addressed. Examples of nonroad categories include lawn and garden (L&G), construction, farm, and industrial (CFI), rail, general aviation, commercial aviation, marine, and others. A study objective related to supporting development of the NGM would require data collection for a representative sample of vehicles under representative real-world operating conditions. Similar to the on-road category, there may be issues of "driver behavior" that need to be addressed in a nonroad study. For example, there may be differences in style in the operation of a bulldozer or backhoe that could influence emissions. The notion of different operating environments may be analogous to the notion of different roadway facility types that pertain to on-road vehicles. For example, are there differences in activity patterns and emissions associated with CFI equipment operated at a specific location (e.g., clearing of a construction site) versus similar CFI equipment used for preparation of roadways over large distances and relatively level terrain? Are there differences in lawnmower emissions for the person who trims the lawn every week versus the person who tries to cut very high grass after several weeks of no lawn care? Do these need to be separate categories in a model, or are their emissions sufficiently similar that they can be aggregated? Many of these types of questions should be posed and answered with exploratory studies before committing to a particular specific model development strategy.

Thus, at least two phases of data collection should be pursued, especially for nonroad categories where relatively less information may be available to make good *a priori* judgments regarding criteria for grouping data. The first phase should be exploratory in nature, with a main focus on identifying the key factors that influence variability in real world emissions. With the insight from the first phase, a preliminary model design can be specified, and data collection can focus on filling data gaps associated with the most important (influential) explanatory variables.

8.2 Key Characteristics of a Study Design

The design of an on-board emissions data collection study is in many ways more complicated than that for a laboratory study. An on-board study is essentially an observational, as opposed to a controlled, study. Unlike the laboratory, where factors such as temperature and humidity can be controlled to within a specification, and where a vehicle can be operated on a standard speed or engine load trace, the on-road or in-field operation of a vehicle is subject to uncontrollable variability in ambient conditions and, in the case of on-road vehicles, in traffic conditions. Thus, the scheduling of data collection in an on-board study is more critical than it would be in the laboratory. The opportunities for collecting data under desired conditions of ambient temperature, relative humidity, traffic flow, and other ambient or external uncontrollable factors are limited. The study designer has some influence over what ambient and external conditions are encountered during data collection through prudent selection of calendar days for data collection, as well as day of week and time of day of data collection. However, it will never be possible to completely eliminate variability in ambient and external conditions. Because of this, it is critically important to make measurements of uncontrollable factors that may influence vehicle emissions, so that the effects of variability in such factors can be properly accounted for in model development.

Table 8-2 summarizes the key considerations in designing and analyzing the results of a on-board emission measurement study. In discussing the content of Table 8-2, we assume that the study objective is to support development of the NGM.

Selection of Study Areas. Because the NGM is intended to predict emissions for almost every state in the United States, it is important to select multiple study areas that increase the opportunity to obtain a nationally representative sample of vehicle fleets, roadway facility types, terrain, climate, population density and other factors that might be useful in explaining variability in on-road emissions. A study area would be a geographic region, perhaps of approximately the scale of a typical urban area (e.g., perhaps several hundred square miles or so) in which there would be significant deployment of on-board instruments and significant data collection activity. Of the various considerations that one might have in selecting studies areas, climate, terrain, and population density are perhaps the most compelling factors to consider. Climate is a surrogate for ambient conditions. Terrain is a surrogate for road grade and roadway geometry (e.g., tight curves on mountain roads versus expansive curves in coastal plains). Population density is a surrogate for general traffic flow and congestion.

As a simple illustrative example, consider the question of what is a typical representative study area for a given state, such as North Carolina. North Carolina has a coastal plain with relatively moderate temperatures, a piedmont region that contains most of its major urban areas (e.g., Charlotte, Raleigh, Durham, Greensboro, Winston-Salem), and a mountainous region to the west that contains some smaller cities (e.g., Asheboro, Boone) and very hilly terrain and that is typically subject to cooler temperatures. To develop an emissions model that is simply representative of North Carolina would require data collection in the piedmont and in the mountainous regions, which have differences in ambient conditions and in terrain. The coastal area may be important as well, since the traffic patterns in the summer time during the peak ozone season will be influenced by tourist activities. The coastal area would also provide opportunities to collect data for relatively flat terrain (e.g., EPA uses US 70 for data collection with an instrumented HDDV for this reason), which may be representative of many other areas of the country. Thus, North Carolina is an interesting state to consider as comprised of multiple study areas because of variability in terrain, population density, and ambient conditions.

Another consideration in selection of a study area is population density. Although the most significant air quality problems seem to be influenced more by urban areas, such as tropospheric ozone formation, if the NGM is intended to be used at the microscale or mesoscale to evaluate local emissions, then it will be important to have a good database to support emissions estimation for rural areas, including rural highways, primary arterials, and secondary roads. These roads may have different activity patterns than similar roads in urban areas (e.g., consider the pickup

Table 8-2. Key Considerations in Design of an On-Board Tailpipe Emissions Data Collection Strategy for On-Road Vehicles

Study Area – Terrain, Climate, Population Density (Urban, Rural), Availability of Roadway Functional Classes, Special Facilities (e.g., toll booths, rest areas, weigh stations, parking decks)

Vehicle Selection – Categories of primary vehicles and secondary vehicles, Model Year, Manufacturer, Model, Engine Size, Transmission (Automatic, Manual), Fuel Delivery, Emission Controls, Vehicle Weight, and others.

Vehicle Operation – use of accessories (e.g.,. A/C), load, trailer towing

Route Selection – Specific origin/destination pairs for data collection runs. Could include or focus on:

- Specific roadway functional classes
- Traffic congestion (peak vs. off-peak, level of service)
- Road grade
- Effect of Lane Closures (Construction/Work Zones)
- Effect of Incidents (see text)
- Specific facility design features (e.g., intersections, ramps, roundabouts, toll plazas)
- Roadway Geometry, Traffic Signalization, Segment Lengths

Define categories of primary routes and secondary routes

Driver Selection and Driver Behavior – Development of driver behavior classes based upon speed profiles (e.g., gentle, moderate, and aggressive drivers). Specify primary drivers and secondary drivers

Scheduling – Time of year (e.g., season, different ambient conditions), day of week (e.g., weekend, weekday, holiday), time of day (e.g., different traffic conditions, different ambient conditions). Specify primary schedules and secondary schedules.

Fuel Selection – gasoline formulations, gasoline/ethanol blends, reformulated fuels, etc.

Sample Sizes – number of repeated runs for same driver/vehicle/instrument/route/time of day combination

Resources - Personnel (director, on-road drivers, data analysts, equipment/instrumentation technicians); vehicles (volunteer, rented, purchased); equipment (on-board measurement instrumentation, supplemental instrumentation, computers, hardware, calibration gas); software (data screening, data reduction, data storage and retrieval).

truck driving just a half mile at slow speed between two cross streets, and the effect it has on traffic stuck behind it, or the effect of a farm tractor going 20 mph in a 55 mph zone). In some cases, rural highways and other roads may serve as a good location for baseline data on what emission rates would be on such facilities in urban areas in the absence of traffic congestion. This type of data would be useful in benchmarking the potential of traffic flow improvement projects to change emissions.

If we expand the discussion of study areas to not just North Carolina, but to the entire United States, then challenges and opportunities for the selection of study areas become apparent. For example, perhaps there is a need for data collection at high altitudes, such as in Denver, Colorado. There is likely a need to collect data in urban core areas, such as mid-town traffic in New York City or Chicago, as well as in suburban areas, such as Wake County, NC, Fairfax County, VA, and in sprawling urban areas such as Houston and southern California cities. Semi-tropical locations, such as South Florida, may also be appropriate places to collect data because the climate there may be conducive to more months of measurement of what would be considered "summer time" conditions in other parts of the U.S.

Other considerations in selecting study areas include the availability of specific roadway functional classes or facilities that may be of special interest. For example, in order to characterize emissions at different types of freeway interchanges, it would be useful to collect data for clover leaf, diamond, and newer designs such as single-point interchanges. For example, there are new single-point interchanges on I-40 and I-540 in the Research Triangle Area that have simultaneous protected dual left turn movements for both travel directions. They also have sharper curves as you enter the freeway ramp via a left turn, and in most cases there is a merge prior to traffic entering the freeway. The emissions characteristics of an interchange such as this may be different than for the clover leaf or diamond designs. Other roadway facilities that may be of interest include toll plazas, rest areas, and (for HDDV) weigh stations. For example, what is the difference in emissions for a car traveling on the Pennsylvania Turnpike, in which one has to stop only twice – once when entering the turnpike to get a ticket, and once when exiting pay, versus Florida’s Turnpike, where one has to stop every 10 to 20 miles to pay a 75 cent toll. In the latter case, all vehicles traveling on the turnpike accelerate to freeway speed while simultaneously weaving and merging within a short distance of the toll plaza, and likely are causing a severe emissions hotspot at that location. In contrast, on a turnpike such as in Pennsylvania, only those vehicles entering or leaving a particular exit would be accelerating as they leave the ticket booth and the collection booth.

Looking into the future, some urban areas are considering the adoption of new roadway facility designs. For example, in Raleigh, NC, there are plans to replace conventional intersections with roundabouts on Hillsborough Street, which is one of the main east-west arterials in the urban core. The conventional wisdom appears to be that the roundabouts will improve traffic flow and reduce emissions, but to our knowledge there are no real-world U.S. data to confirm this.

Incident management capabilities may be another important criteria for selecting study areas. To the extent that traffic flow can be restored to pre-incident levels more quickly, there may be an impact on emissions.

With respect to nonroad emission sources, many of the same considerations of climate and terrain may apply, although surrogates for on-road traffic flow may be less important. Construction, farm, and industrial equipment are common throughout North Carolina, for example, as is lawn and garden equipment, recreational boats, railroads, and other nonroad sources. EPA needs to clearly define the scope of the nonroad component of the NGM.

An advantage of on-board measurements is that, because the equipment is not as expensive as for dynamometer measurements, it is feasible to consider setting up a network of local emission measurement centers, such as at specific universities or research institutes. Each measurement center would be coordinated by a central group with the responsibility for developing and specifying the study objective and study design. Each measurement center would be required to use standard protocols and techniques for data collection, data screening, and data reduction, and would be required to report data to a depository for use by the performing organization(s) involved in model development, which may include some of the measurement center organizations as well as others.

Before committing to data collection in a substantial number of study areas, it is prudent to conduct pilot studies aimed at determining whether the conditions in a particular area lead to differences in emissions that are substantial enough to justify a larger model calibration-scale data collection effort. Furthermore, some of the considerations in selecting a study area, such as climate, can also be addressed to some extent by selection of the time of year of data collection, especially in areas that have well defined seasons. For example, it is possible to collect data in cold and hot conditions in many parts of the country.

Vehicle Selection. Vehicle selection is an important consideration for all emission source categories. Here we comment on LDGV, HDDV, and nonroad categories as illustrative examples.

For LDGV, ideally one would select a representative fleet of vehicles with respect to model year, make, and model in proportion to the distribution of actual VMT or vehicle registrations. Issues associated with recruiting vehicles for on-board emissions measurement will be important, such as how to get on-road fleet vehicles submitted by volunteers. In our NCDOT study we relied on vehicles obtained from the state motor pool, vehicles volunteered by study participants, and vehicles volunteered by others. Clearly, a substantial effort is required to recruit vehicles, and some type of compensation will likely be required if vehicles are recruited from the public. The issues for vehicle recruitment for on-board studies are different than for a laboratory study, since the volunteer would have to be comfortable with having their vehicle driven by others or with the responsibility of driving with a measurement instrument on-board. Furthermore, careful attention must be paid to fueling of the vehicle, whether it be to properly characterize what fuel is in the vehicle or to refuel the vehicle prior to data collection. Data regarding vehicle characteristics, including VIN, year, make, model, body style, engine size, odometer reading, fuel delivery system, emission control system, and other factors must be recorded.

If data collection takes place in multiple study areas with multiple regional emission measurement centers, then the vehicle selection should include consideration of benchmarking and "inter-laboratory" comparison among the study areas and/or measurement centers. Specifically, there should be three categories of vehicles that are included in the field study: round-robin vehicles, primary vehicles, and secondary vehicles.

Round-robin vehicles would be a very small fleet of perhaps two to five vehicles that are available throughout the study time period and maintained by US EPA or a contractor. These vehicles would be delivered to each of the measurement centers and/or study areas for data collection on a similar set of facility types under ambient and traffic conditions as similar as possible when comparing all study areas. The data obtained from the round-robin vehicles would help verify consistency in protocols and data collected in different study areas and/or may help to identify differences in conditions that reasonably account for differences in measurements among the study areas. Ideally, the round-robin activity should include the same driver at each study area. The round-robin activity would also provide an extensive database that will enable comparison of different driving conditions for the same vehicles taking into account inter-study area variations.

Similar to the notion of round-robin vehicles, opportunities should be explored by EPA/OTAQ to coordinate with other parts of EPA, such as in the RTP area, that have instrumented vehicles. For example, the instrumented vehicle operated by Richard Shores could be deployed in multiple study areas for benchmark comparisons and for supplemental data collection of some pollutants not measured by conventional commercially-available on-board systems.

Primary vehicles would be a set of approximately 20 year, make, and model specifications that each measurement center would be required to deploy in its study area. For example, each study area could be required to conduct testing with a 1999 Ford Taurus sedan with 4 cylinder engine. Each study area would obtain its own 1999 Ford Taurus sedan with 4 cylinder engine. Although there can be variability in emissions among 1999 Ford Taurus sedans with 4-cylinder engines (see Frey *et al*., 2001 for a comparison of six such vehicles), there is less variability in emissions for a single year, make, and model of vehicle that is properly maintained than there would be when comparing emissions for different makes and models. The primary vehicles would be deployed on a schedule to capture all major aspects of the study, including (for example) facility types, time of year, day of week, and time of day.

Secondary vehicles would be a larger set of vehicles that each study center would recruit based upon guidelines established in the study design. The study centers could select the year, make, and model of such vehicles. There may be as many as 50, 100 or more secondary LDGVs in a given study area. Each vehicle would be tested over a relatively short time period (e.g., days or weeks), with the assumption that these vehicles are recruited and cannot be kept for large time periods.

The discussion above focuses primarily on typical gasoline vehicles available in all areas of the U.S. However, consideration should be given to alternative fuel vehicles as well.

For HDDV vehicles, it will be most productive to obtain agreement from fleet operators to deploy the instrument on multiple vehicles within a fleet. For example, the NCSU Department of Transportation has in the past expressed interest in cooperating regarding the deployment of a portable instrument to collect data from large diesel transit buses operated for the university. Agreements should be sought from transit authorities in the selected study areas in order to collect measurements on transit and school buses. Opportunities should be sought to tie such data collection efforts to other incentives that such authorities may have to participate, such as clean cities initiatives or perhaps evaluation of transportation improvements.

Other on-road HDDV categories may pose interesting logistical challenges. In some cases, such as for local delivery vehicles, it may be possible to instrument a vehicle for an entire day of operation, and to repeat this for different vehicles on different days. For long-haul over-the-road tractor-trailers, however, the logistics of deployment may be difficult. For example, who would have responsibility for operating and maintaining the measurement equipment? There may be opportunities to instrument HDDV vehicles of this type that do not operate over large distances. At the same time, there may be opportunities to instrument long-haul vehicles that travel from one study area to another, with support from two or more emission measurement centers.

Similar to the LDGV category, there should be consideration of round-robin, primary, and secondary vehicles in the HDDV category. Round-robin vehicles might be recruited or obtained based upon existing instrumented vehicles, such as at EPA in RTP or perhaps other agencies, universities, or research institutes. These vehicles should be deployed in multiple study areas based upon specific test plans developed in coordination with the measurement center for a given study area.

For HDDV vehicles, it is well-known that the engines are typically rebuilt or replaced during the life of the vehicle and that a chassis may not contain the original engine from when the vehicle was new. Thus, care must be taken to properly record the history of the vehicle, including the age and condition of the engine as distinct from the age and condition of the chassis. Thorough maintenance records for the entire history of the vehicle are more likely to be available from large fleet operators than from individual operators, although there may be exceptions and opportunities with a variety of vehicle operators.

For nonroad vehicles, it is critically important that EPA first define the scope regarding what nonroad source categories are to be included in the study. Examples of major categories include:

Lawn and Garden (L&G)
Construction, Farm, and Industrial (CFI)
Rail
Marine (Recreational, Commercial - Passenger, Freight, Size)
Aviation (ground support, general aviation, commercial aviation)

The testing strategy for nonroad vehicles should be based upon determining the key parameters for these types of vehicles. Some of the important parameters that are currently used to group nonroad vehicles are: fuel type; engine age; vehicle technology; engine type; and engine size (Frey and Bammi, 2001). These parameters as well as engine RPM and load are usually hypothesized to be the most important variables that affect emissions for nonroad vehicles. However, it is less clear that these hypotheses have been evaluated in a rigorous statistical manner.

An experimental design is needed that involves identification of significant parameters that affect emissions. Similar to the on-road case, for the nonroad category a two-phase data collection effort is recommended over the five year time frame suggested in the RFQ. We suggest that there be a Phase 1 data collection effort in the first two years which has a key objective of helping to verify hypotheses regarding what potential explanatory factors are really important with respect to emissions. Given the wide range of nonroad source categories, it will be important for EPA to clearly define which nonroad categories are highest priorities and what resources are available for the data collection effort in order to set a specific scope at this time. One can begin with a priority list of nonroad emission sources based upon current estimates of their relative contribution to the national emission inventory of selected pollutants.

It may be easy from a logistical perspective to instrument vehicles on a daily basis at specific sites, such as a construction, farm, or industrial site. It should be possible to recruit individuals to volunteer lawn and garden equipment for use in the study (perhaps with an incentive to mow their lawns as part of the study) as well as recreational boats. Deployment of equipment on railroad equipment, for example, will require negotiation with the appropriate authority or company. Deployment of equipment at an airport will be subject to security scrutiny.

The process of recruiting vehicles can be time consuming, and sufficient time and budget should be allowed for this purpose as part of the on-board data collection effort.

The on-board emissions measurement technologies may vary somewhat in how they can be deployed and this may be a function of the vehicle. For example, the OEM-2100 manufactured by Clean Air Technologies International, Inc., does not involve any modification to the vehicle as long as the vehicle has an OBD interface compatible with the data link capabilities of the instrument. The installation can be completed in approximately 15 minutes. For vehicles that do not contain an appropriate OBD link, such as older vehicles or nonroad vehicles without electronic controls, a sensor array is needed in order to measure or estimate the variables required to predict mass air flow. For example, CATI has developed a sensor array to obtain data such as engine RPM, manifold absolute pressure, and intake air temperature. From these data, the mass flow rate of air and exhaust can be estimated for use in converting the volume fraction or ppm gaseous pollutant measurements from the gas analyzer to a mass per time basis.

On-board emission measurement has been demonstrated for a wide range of vehicles. For example, in this study, data were provided by EPA for LDGV, HDDV, and diesel non-road vehicles. The OEM-2100 developed by Clean Air Technologies International, Inc. has been deployed on the following types of equipment: on-road LDGV, on-road HDDV, a compactor, a bulldozer, a front end loader, a lawnmower, an ATV, a yard tractor, a recreational boat, a GE 44-ton switchyard locomotive with a 27.4 liter engine, and a single engine airplane (ground-use only at this time).

Vehicle Operation. For on-road light duty vehicles, there are several choices regarding how the vehicle is operated that may influence emissions. These choices include, for example, air conditioning usage, passenger load, and towing loads. For on-road heavy duty vehicles, freight load or passenger load (in the case of buses) may be important factors to consider in explaining emissions. For non-road sources, such as backhoes and other construction equipment, other measures of load may be needed, such as the typical volume of material moved or the typical weight per load. Activity data should be recorded regarding these types of factors.

Route Selection. On-board data collection is very flexible in terms of site selection compared to other field measurement methods such as remote sensing or tunnel studies. Selection of sites for on-board data collection depends on objectives of the study.

For on-road sources, the key considerations in route selection include:

Roadway functional classification – there should be a representative distribution of freeway, primary arterial, minor arterial, secondary, and feeder/collector roadways.

Facility Design and Control Features – for a given roadway functional class, there should be an adequate representation of design features such as different types of freeway interchanges, signalized intersections, stop signs, traffic "calming" devices (e.g., speed bumps), toll plazas, rest areas, weigh stations, roundabouts, lane drops, lane additions, protected turning movements, permitted turning movements, long versus short acceleration lanes, sharp curves, etc.

Road Grade – there should be a representative sample of road grades, with emphasis on road grades that lead to substantial differences in emissions.

Traffic Flow – there should be a representative sampling of different levels of traffic congestion and traffic flow patterns, which is influenced also by the scheduling of the data collection activity.

Direction of Travel – traffic flow patterns can be very different for travel in one direction versus the other direction on a specific road at a particular time of day. Therefore, the direction of travel (such as on commuter routes during peak commuting periods) is an important consideration in study design.

Miscellaneous Considerations – a representative sampling of work zones and other typical obstructions to free flow traffic movement should be included. Over the course of on-road measurements, it is likely that there will be situations in which traffic flow is influenced by an "incident", such as rubbernecking at the site of an accident. Data should be recorded so that data from this type of situation can be compared to data in the absence of this type of situation, perhaps for the purpose of developing an "incident" correction factor or for developing activity estimates for traffic and emissions in the presence of incidents.

In order to enable measurement on a wide range of facility types under various conditions, while at the same time obtaining data for a representative fleet, it is recommended that the study design include at least two categories of routes or sites: Primary routes/site; and secondary routes/sites.

A **primary route or site** would be intended for data collection with all primary vehicles and with most if not all secondary vehicles. The routes can be selected so that they contain multiple roadway facility types and variation in conditions over the course of the day. A **secondary route or site** would be intended for stratified data collection with a subset of vehicles, including some primary vehicles and some secondary vehicles.

For non-road sources, the considerations are likely to be different depending on the specific source category. For lawn and garden equipment such as a lawnmower, for example, emissions are likely to be a function of factors such as height of grass and the speed with which the operator attempts to cut the grass. For a compactor, emissions are a function of engine load and engine RPM. To the extent that some nonroad sources have characteristic activity patterns that do not vary from one situation to another, it may be possible to develop average emission factors from a representative sample of on-board measurements without the need for detailed explanatory models. However, to the extent that nonroad emissions are influenced by variation in activity from one situation to another, more detailed explanatory models and information on activity may be warranted. In the absence of pilot data regarding these issues, it is difficult to make specific recommendations regarding the key study design factors to be considered in site/route selection for non-road sources.

Driver Selection. It is widely assumed and yet not extensively quantified that driver behavior plays an important role regarding real world emissions.

For on-road sources, NCSU has collected data with different drivers for the same vehicle and has found in some cases that two drivers can produce very similar on-road emissions, but that in other cases two drivers can produce very different on-road emissions. For example, a driver with "aggressive" behavior will typically accelerate more rapidly and produce higher emissions than a driver with more moderate behavior. Some studies have quantified the difference that driver behavior has in the laboratory. For example, Webster and Shih (1996) have found that the variability in repeated emissions measurements of the same vehicle on driving cycle tests, such as the IM240 test, can be as large as an order-of-magnitude. Some of these differences may be attributable to differences in typical driving behavior, while others may have been artifacts of the study (e.g., throttle snaps).

The selection of drivers, therefore, can play an important role regarding on-road emissions measurements. In a particular study area, it is suggested that all on-road drivers be asked to conduct multiple runs in which they drive on the same route, and the average speed traces obtained can be compared. Speed traces can be averaged if speed is plotted versus distance driven, and if averages are taken in bins with respect to a specific distance segment of the route. Averaging over multiple runs is needed in order to smooth out some of the inherent variability in the on-road measurement technique. Speed cannot be averaged on an elapsed time basis because trip durations will differ from one run to another. Drivers could be classified into categories such as "gentle", "moderate," and "aggressive" based upon measures such as maximum acceleration rate, maximum speed, average speed, and acceleration noise, with respect to the average speed trace obtained from the multiple runs. Acceleration noise is a measure of the variability in acceleration during a trip. Drivers should be scored in specific behavior categories and the emissions for these categories should be compared. If there are statistically significant differences in these categories, then the categories are useful explanatory variables. If emissions do not differ among two or more of the categories, then it will be possible to combine or eliminate some categories without loss of explanatory power. Specific numerical criteria for the categories are not proposed here because there are not sufficient data in the calibration data set to develop such categories.

It is recommended that the study design include primary drivers and secondary drivers. Each **primary driver** would be assigned to a specific subset of the primary vehicles, and all data with that subset of primary vehicles would be collected with the same primary driver. Each primary driver would also operate a subset of the secondary vehicles. Methods for benchmarking and comparing the primary drivers with each other on the same vehicle and route are needed. As noted in the NCSU study (Frey at al., 2001), it is possible that several drivers may have similar behavior and, therefore, produce similar emissions on the road.

Secondary drivers would be used to supplement the primary drivers in collecting data with both primary and secondary vehicles. In some cases, secondary vehicles that are recruited might be driven by their owners, who would be considered to be secondary drivers. Secondary drivers, with driving behavior different from the primary drivers, could be used to repeat some of the data collection runs made with the primary driver for purposes of comparing driving behavior.

Similar considerations may apply to most if not all nonroad source categories. For many nonroad equipment categories, such as CFI equipment, vehicle speed is not the most useful measure of activity. Other measures of activity, such as engine RPM and engine load on a microscale, will be more useful and offer a great deal of explanatory power for NO_x and CO_2 emissions from diesel engine powered equipment, as indicated in Chapter 5. Driver behavior can be evaluated with respect to how rapidly engine RPM and load change in these types of equipment. If differences are found that significantly influence emissions, then a driver behavior scoring system similar to the one suggested for on-road vehicles can be developed. A key consideration is to create driver behavior categories only if they offer explanatory power with regard to emissions, and not to create categories without verification that this is the case.

Scheduling. The scheduling of data collection plays an important role in determined the uncontrollable conditions that will be faced regarding ambient conditions, traffic conditions (in the case of on-road vehicles), and other conditions that may influence emissions for various source categories.

Key considerations in scheduling include:

Time of Year – In locations where there is seasonality, the selection of a time of year for data collection will influence the range of ambient temperatures and weather conditions that can be expected during the study period.

Day of Week – for on-road studies, the day of the week will influence the range of variation and the typical conditions that can be expected for traffic flow. For example, there are differences in traffic patterns for weekdays, weekends, and holidays. Some weekdays, such as Fridays, have different traffic flow patterns that other weekdays, because of the influence of flextime and other commuting/shopping patterns, especially in the afternoon. Traffic patterns may be influenced by large employers or industries, as well as by special events.

Time of Day – Time of day clearly influences the traffic congestion and traffic flow expected, such as for peak travel time periods during “rush” hours, versus lunchtime periods, versus other times of day. Time of day also influences the average ambient temperature that can be expected. The variation in ambient temperature between a morning data collection period and an afternoon data collection period can be especially important in spring or fall.

Scheduling can be categorized broadly into a primary schedule and a secondary schedule. The **primary schedule** would represent the highest priority combination of time of day, day of week, and time of year for which data collection is desired for the largest portion of drivers, vehicles, and routes. The **secondary schedule** would represent other combinations for which supplemental data are needed.

For nonroad equipment, there may be few issues analogous to those that impact traffic flow for the on-road equipment, but factors that influence ambient conditions, such as time of year and time of day, are likely to be important. L&G equipment and CFI equipment, for example, do not have to contend with traffic flow problems, but they may have to contend with environmental conditions (e.g., dry versus wet ground) that may influence activity.

Fuel Selection. A key benefit of on-board emissions measurement is the opportunity to measure emissions during real-world operating conditions. This includes the fuel used for the vehicle. It would be logistically difficult to require that all vehicles in a real-world on-board study use a standard fuel, such as Indolene, although this could be done if sufficient resources were devoted to fueling vehicles this way. However, the use of a non-real world fuel would defeat the main purpose of a real-world field study. A more practical approach would be to collect data based upon the typical fuel available in the study area, and to obtain data to the extent possible regarding the fuel formulation. However, care regarding the fueling of the vehicle is needed, especially for vehicles recruited from motor pools or fleet operators. For example, the North Carolina motor pool fuels its vehicles with a gasoline/ethanol blend that is different from the retail gasoline available in the state.

Sample Size. As previously noted, on-board data collection is essentially an observational experimental technique. Therefore, there will be variability in uncontrollable factors that will lead to variability in emissions. Depending on the objective of the study, it may be important to minimize the influence of this type of variability by collecting data for repeated runs with the same vehicle, route, travel direction, driver, time of day, and instrument and to take the average of the repeated runs. The confidence interval for the average can be calculated using appropriate statistical methods and used to evaluate the stability of the mean. A narrower confidence interval would imply a more stable or reliable estimate of the mean than would a wider confidence interval. If the objective is make comparisons of emissions between two situations, such as before and after a TCM or TIP is implemented, between alternative routes, or between alternative drivers, then it will be important to have sufficiently narrow confidence intervals for the mean that the statistical significance of the comparison can be meaningfully evaluated. Of course, confidence intervals can be narrowed by increasing the sample size, and so it is possible to obtain statistically significant differences with very large sample sizes even though the difference may not be of practical significance. However, a more common problem with emissions data is that the sample sizes are too small, and therefore the confidence intervals are too wide, to reliably infer differences with statistical significance when they really exist and are of practical importance. In the study by NCSU regarding the effect of traffic signal timing and coordination on emissions, runs were repeated approximately 20 times for each driver/vehicle/route/time of day/travel direction combination in both the before and after cases (Frey *et al*., 2001).

Although comparison studies may motivate a large number of repeated runs, studies aimed at characterizing fleet average emissions do not require a large number of runs per vehicle, but they do require that a sufficient number of vehicles be deployed so as to produce reliable results. In, the case of estimating fleet average emissions, the key sample size consideration is the number of vehicles deployed on a given facility type under similar conditions. An overall sample size of 50 to 100 vehicles, or more if possible, would be preferred in each study area on primary routes. A smaller sample of approximately 20 vehicles should be deployed on secondary routes.

8.3 Illustrative Examples of Specific Study Designs for LDGV, HDDV, and Nonroad Vehicles

In this section, we discuss and illustrate some of the key considerations in developing specific study designs for LDGV, HDDV, and nonroad vehicles.

8.3.1 LDGV

For a typical emission measurement center and/or study area, a preliminary estimate of the number of data collection runs for LDGV can be made based upon the following example assumptions:

Number of Round-Robin Vehicles:	5
Number of Primary Vehicles:	20
Number of Secondary Vehicles:	80
Number of Primary Routes:	5
Number of Secondary Routes:	10
Number of Time of Day Periods:	5 (e.g., AM peak, PM peak, lunchtime, daytime off-peak, night-time off-peak)
Day of Week Categories	4 (e.g., Mon-Thur, Friday, Sat, Sun)
Seasonal Categories:	4 (Winter, Spring, Summer, Fall)

Round-robin vehicles should be deployed, if possible, on all primary routes during all time of day periods during a week, and data should be collected in the same season or similar ambient conditions in each study area to the extent possible. This results in (5 vehicles) x (5 primary routes) x (5 time of day periods) x (4 day of week categories) = 500 data collection runs at each study area. If a typical data collection run takes 20 minutes, then a total of 167 hours of data collection is involved, or 33 hours of data per vehicle.

All primary vehicles should be deployed on all routes during all time periods, all days of week categories, and all seasons. For each vehicle, therefore, the minimum number of runs would be: (15 routes) x (5 time of day periods) x (4 day of week categories) x (4 seasons) = 1,200 data collection runs/primary vehicle. At 20 minutes per run of on-road driving, this would be a total of 400 hours of data collected with each primary vehicle.

Secondary vehicles should be deployed on the primary routes for purposes of developing fleet emissions characterizations under similar conditions. However, it may not be possible to have the secondary vehicle during the entire study period, and therefore it may not be possible to deploy secondary vehicles in all seasons. For each secondary vehicle, there would be a minimum of (5 routes) x (5 time of day periods) x (4 day of week categories) = 100 data collection runs/secondary vehicle. At 20 minutes per run of on-road driving, this would be a total of 33 hours of data per vehicle.

Based upon these example estimates, an *illustrative* (but not definitive) number of data collection runs for a single study area would be as follows (assuming 20 minutes per data collection run):

Vehicle	No. of Vehicles	No. of routes	Time of Day Categories	Day of Week Categories	Seasonal Categories	Number of Runs	Total Hours of Data
Round-robin	5	5	5	4	N/a	500	167
Primary	20	15	5	4	4	24,000	8,000
Secondary	80	5	5	4	N/a	8,000	2667
Total						32,500	10,834

The resources to conduct such a study in a given study area would include time, personnel, equipment, vehicles, computer data storage, software, and money.

By comparison, the NCSU on-board emissions study aimed at evaluating the effects of traffic congestion and signal timing and coordination involved a total of approximately 1,200 one-way trips and produced 160 hours of data.

The actual study design may not require the number of runs as indicated here. For example, the estimate above assumes that it is necessary to collect data for 5 time of day categories on Saturday and Sunday. However, fewer time of day categories may be needed on these days of the week. On the other hand, it would be desirable to repeat some of these runs during each year of a five year study, which can increase the total number of runs. In addition, the study design above does not include different drivers for each vehicle, which could cause a doubling or tripling of the number of runs if two or three drivers with different behaviors are used for each combination of vehicle, route, time of day, day of week, and season indicated above. A "run" is defined as a one-way trip. If a round-trip is made on each route, then the number of "runs" and the number of hours of data collection would be twice that shown above. However, the actual scheduling of round-trips versus one-way runs may not be affected, because it is typically just as easy to make a round-trip of data collection in a given time of day period as it is to make a one-way run of data collection.

For each hour of data collection, it is prudent to assume that there is a comparable amount of time involved in data screening, data reduction, and data analysis. At a conceptual level, the cost of a study such as this would include a study area director, a senior analyst or engineer, several assistants with respect to data analysis, and several assistants who serve as the primary drivers. Of course, vehicle owners or others can be included as secondary drivers, and it is not essential that all vehicles be driven by all primary drivers. Each study area would need typically five or more on-board measurement systems, with sufficient hardware and technical support to keep them operational. Each study area would need to recruit vehicles, with costs in some cases for payments for rental fees, incentives to private owners, or purchase of some vehicles (e.g., older, used vehicles that might be high emitters and that would otherwise be under-represented in the study). Each center would require sufficient computer capability to store and handle the large amount of data generated by the field data collection effort.

The example given here illustrates that it is not possible or prudent to conduct a study based upon a combinatorial specification of all possible study conditions. Instead, the study should be based upon a base case comprised of primary drivers, primary vehicles, primary routes, and primary schedules, with incorporation of secondary drivers, secondary vehicles, secondary routes, and secondary schedules, to supplement the base case data collection efforts in order to observe a wider range of variation in activity and emissions. For example, the secondary vehicles could be deployed only in weekday time periods that represent the largest contribution to total vehicle-miles traveled, and do not need to be deployed in all of the time periods for which the primary vehicles are deployed. While there can be a component of the study that involves instrumentation of vehicles operated by their owners as part of their regular business, the study design should include stratification as well to make sure that variability in factors influencing emissions are captured with sufficient sample sizes to support model development.

8.3.2 HDDV

The scope of data collection for HDDV should take into account activity patterns unique to these types of vehicles. While there are many specific variations in the application and duty cycle of diesel equipment, the main categories include medium heavy duty trucks, which typically are applied to local service, heavy duty trucks applied to long-haul service, transit buses, and school buses. A representative set of vehicles should be included in the test plan from each of these four major categories. These categories need not receive equal weight in the study design. The number of vehicles selected in each category should be proportion to the expected contribution of each category to overall emissions. In the absence of good prior estimates of such contributions, surrogates such as registration fractions or VMT fractions could be used to make an initial priority list of HDDV vehicle types for recruitment and testing. EPA should solicit advise from experts involved in HDDV work, either directly or through contractors, to be sure that the unique activity patterns of HDDV vehicles are properly accounted for in specific study designs.

In the case of HDDV, opportunities should be sought to identify round-robin vehicles. For example, a research group at EPA in the RTP area has conducted studies with instrumented HDDVs, and perhaps this equipment can be deployed in the various study areas on the primary data collection routes during primary data collection times. However, the selection of routes and scheduling for HDDVs may differ from that of LDGVs. In some cases, some roads are not open to truck traffic and, therefore, trucks would not be permitted to operate on all segments of any routes that contain such restrictions. Bridge clearances may also limit the deployment of the largest of the HDDVs on specific routes. Furthermore, some routes may not represent realistic choices for some types of vehicles. For example, a long haul truck is not likely to travel to a residential feeder/collector street, with the exception of a moving van. On the other hand, garbage trucks, recycling trucks, and other local service vehicles routinely travel on a daily basis, with frequent stops, to residences.

As an illustrative example of factors to consider in a study design for HDDV, the following are considered:

- HDDVs should be sub-categorized with respect to major categories of duty cycles. These duty cycles may typically include the following illustrative but perhaps not exhaustive set of examples:
  - Local delivery service (e.g., express delivery trucks)
  - Local solid waste management services (e.g., garbage trucks, recycling trucks)
  - Local commercial services (e.g., furniture/appliance delivery, plumbing/electrical services, and many others)
  - Local construction support vehicles (e.g., dump trucks)
  - Short-haul freight (e.g., 14 to 20 foot vans)
  - Long-haul freight (e.g., larger vans, tractor-trailer combinations), including yard, city, suburban, and interstate service
  - Mass transit (transit buses)
  - School buses
- Vehicle recruitment should be based upon a representative selection of vehicle applications (or "vocations" in the terminology of Clark *et al*., 2002).
- Fuels should be carefully selected or characterized
- Exhaust after treatment systems should be characterized in the database
- Vehicle age and engine age should both be recorded.
- Engine technology should be recorded carefully
- Information regarding the transmission should be recorded
- Timing of in-cylinder fuel injection should be assessed if possible, either directly or via surrogates, related to the issue of "defeat" devices but also related to an understanding of factors influencing real world emissions.
- Routes driven by HDDVs may be different than those for LDGVs, and peak duty cycles may occur at times of day different than peak driving for LDGVs.
- Some duty cycles may essentially be continuous repetition of the same pattern throughout a work day, such as for a delivery truck or garbage truck.

Based upon considerations such as these, it is clear that a study design for HDDVs must have the following elements:

- Appropriate representation of different duty cycles and vehicle types within the four major subcategories of medium heavy duty, heavy duty, transit bus, and school bus. A small subset of primary vehicles should be identified.
- The routes selected should be appropriate for the given type of vehicle. In many cases, routes will be defined by the operator of the vehicle, and not by the emissions study team. For example, if a school transit authority agrees to allow measurement of

school buses, they will do so for existing routes and are not likely to do so for arbitrarily defined routes. The same is likely to be true for most other fleet operators.

It may not be possible to test a vehicle on more than one route, such as a specific transit bus dedicated to a particular driver or route. However, opportunities could be explored to see if a transit authority might be willing to agree to switch buses for a given driver/route during the study design period to help in assessment of inter-vehicle variability.

The scheduling of data collection should be appropriate to the service cycle of the vehicle. If possible, for a vehicle involved in service during a workday or shift, data should be collected for the entire workday or shift.

A key measure of the "size" of a study of HDDV is the number of vehicles to be tested. In essence, the study design, including vehicle operation, route selection, driver selection, and scheduling, will be individually tailored to each vehicle depending on the typical service that the vehicle facilitates. For practical reasons, the specifics of the study design will be constrained by the cooperation of various fleet operators and individual vehicle owners/operators. Concerns about safety and the impact of data collection on regular business will likely be critical areas that must be addressed in approaching those organizations and/or individuals who may be willing to volunteer vehicles for the study. Creative methods for providing incentives may be needed in some cases, or monetary compensation may be required.

8.3.3 Nonroad

For the nonroad source category, it is important to first define the key types of sources that must be addressed in the on-board study. For the purposes of discussion, it is assumed that the highest priority sources are Lawn and Garden (L&G) equipment and Construction, Farm, and Industrial (CFI) equipment.

The EPA defines the L&G category to be typically based upon "small land based spark ignition" (SI) engines (EPA, 2000). These engines usually run on gasoline include, lawnmowers, string trimmers, leaf blowers, chain saws, commercial turf equipment, and lawn and garden tractors. Utility equipment is generally defined by California Air Resources Board (CARB) as equipment used in a variety of L&G applications and in numerous "general utility" applications (CARB, 1990). Equipment in the L&G Category includes walk behind mowers, riding mowers, lawn tractors, fixed blade edgers, roto tillers, shredders/grinders, blowers/vacuums, string trimmers, snow blowers, chainsaws, and hedge trimmers.

A vast majority of L&G equipment is powered by gasoline-fueled internal combustion engines of less than 25 HP (19 kW). Electric motors, powered by either battery or household line current, are also available and used in selected Lawn and Garden equipment; particularly in lower power hand-held equipment such as blowers, vacuums, string trimmers, and hedge trimmers. Residential-use edgers and chainsaws are also available in electric powered versions as are walk behind mowers.

Based upon a review by Bammi (2001), nonroad engine emissions have been grouped in a variety of ways, including:

By type of application as for the NEVES study by EPA (EPA, 1991)

By power rating as for NONROAD model by EPA (Beardsley *et al*., 1998a)
Type of cycle, two-stroke or four-stroke (EPA, 1991 and CARB, 1990)
Type of design, overhead valve or side valve as used by CARB (CARB, 1990)
Handheld or non-handheld as used by CARB (CARB, 1990)

Data collected and analyzed by Frey and Bammi (2002) indicate that the most useful groupings that lead to statistically significant differences in mean emissions include: 2-stroke vs. 4-stroke gasoline engines; and size ranges for the 4-stroke engines separated into less than 8 hp and greater than or equal to 8 hp. Thus, engine design and, for the 4-stroke design, engine size are useful in binning the database to categories that have different average emission rates. It should be noted, however, the engines were tested on the same or very similar steady-state modal test cycles. Therefore, differences in emissions that might be attributable to differences in engine operation are not captured by the comparison.

Examples of CFI engines include agricultural equipment such as tractors, construction equipment like backhoes, material handling equipment like heavy fork lifts and utility equipment like generators and pumps. Similar to the L&G engines, these engines are tested most typically on steady-state modal test cycles. Engine RPM and engine load are key factors in defining modes for most such test cycles. The CFI category includes both gasoline and diesel engines. Because much of the equipment in this category is large, diesel engines are very common. An analysis by Frey and Bammi (2002b) indicated that CFI engines should be divided into separate categories for gasoline versus diesel engines, and that diesel engines should be further categorized as either 2-stroke or 4-stroke. These categories resulted in mean emissions that were significantly different from each other. However, as for the L&G category, it is possible that the test cycles do not adequately represent real world operation. In particular, the variability in real world operation for different types of equipment, and when comparing equipment with different services/applications, may not be properly captured by the data.

For both the L&G and CFI categories, a key need is to better understand real world activity data and the implications for differences in emissions. This information is needed before committing to a full scale study design. Therefore, a two-phase approach is recommended in which data are collected over a two year period for a hypothesized representative sample of equipment and applications. The data should be analyzed and interpreted within the two year period in order to make findings regarding the key factors that influence vehicle activity and emissions, the key factors that can be used to explain emissions in developing the NGM, and the key factorial considerations in developing the study design for Phase Two. Phase Two would focus on filling data gaps identified based upon the results of Phase One.

The study design for the nonroad study will be analogous in some ways to the study design for the HDDV category, because there will be similar recruitment and operational issues that will be faced. In order to obtain data under real world conditions, it will be desirable to instrument equipment during typical use, which means piggybacking data collection with the regular business activity of the owners of CFI equipment. The study area will be determined by construction sites, farm sites, and industrial sites where such equipment is already in use. Vehicle selection will be governed by the ability to recruit vehicles and gain cooperation from companies and other organization that operate such equipment, such as state DOTs. Consideration must be given to proper recording of vehicle characteristics, engine characteristics (including rebuild and replacement history), and fuel characteristics. Observations must be made regarding load-related factors that might influence emissions and might help in developing a national activity database for each specific type of equipment. Driver selection will likely be a function of the owner/operator, since special skills and/or training are needed for many of these types of equipment, and insurance and liability issues are likely to be a factor constraining selection of drivers and access to the vehicle while in operation for purposes of checking the measurement equipment. Scheduling should be done in a manner appropriate to the activity pattern of specific subcategories of equipment.

For the L&G equipment, it may be possible to pursue more flexible and creative methods for recruiting equipment and conducting studies. For example, a homeowner might gladly allow their lawn equipment to be instrumented if the study team will collect the data while performing lawn care activities for the homeowner. A cooperative homeowner might also be willing to lend equipment for comparison studies.

Because L&G equipment can be relatively less expensive than the other types of emissions sources to be addressed in a national scale study, the opportunity to use round-robin equipment should be pursued. For example, EPA and/or its contractors at specific study sites can procure examples of individual pieces of L&G equipment for use in long-term evaluation studies and for use in benchmark comparisons with other study areas for purposes of comparing and validating protocols, analysis, and reporting methods.

8.4 Measurement Equipment Issues

Equipment issues for an on-board study are briefly summarized in Table 8-3.

Sufficient equipment must be available for each study area to support the schedule of data collection. It is typically a good practice to use the same equipment with the same driver, so as to avoid additional variability in the data set for a given driver associated with differences in equipment response to the same exhaust gas composition.

The general technique for the on-board emissions instrument should be validated in comparison to laboratory dynamometer testing. For example, both Clean Air Technologies International, Inc., and Sensors, Inc. have compared their on-board emissions measurement systems using dynamometer tests. Typically, the instruments perform very well for CO, NO, and CO_2 emissions measurements when comparing total trip emissions estimated from the on-board equipment to total trip emissions measured by the laboratory instrumentation. Because many of the on-board emissions instruments use NDIR to measure hydrocarbons, there is a known bias in the HC measurements. Comparisons with laboratory data based upon FID measurements, for example, can help in developing correction factors for adjusting the on-board NDIR HC measurements to at an approximate total HC basis. More insight is needed as to whether the bias might vary under different conditions. If so, it would be desirable to develop a predictive capability for estimating the bias and correcting for it under varying conditions.

Because there are potentially many commercial vendors of on-board emissions measurement and related equipment, and because vendors continually seek to improve their product, EPA should develop a qualification procedure for accepting specific instruments from alternative vendors for use in the national on-board emission measurement studies that allows for innovation, while at the same time ensuring minimum criteria for data precision and accuracy.

It is critically important to properly calibrate and maintain the emissions measurement equipment. Thus, a regular schedule of calibration and maintenance is recommended. The on-board instruments are typically very stable and hold a calibration well. However, it should be noted that calibration gases are typically representative of very high emissions and may not provide good calibration of the instrument for more typical emissions values encountered during data collection. EPA and the equipment vendors are strongly encouraged to seek ways to calibrate equipment for calibration gas compositions that are more realistically representative of the typical span in second-by-second data expected during typical measurements. Cooperation from industrial gas vendors may be required in order to obtain reasonably priced and sized calibration gas samples. For example, a small tank is often sufficient for a year or more of calibration for a single instrument.

A key area where improvement is needed in the instrumentation is regarding automatic diagnostic tests and message indicators of specific maintenance needs. For example, potential problems that could occur in an instrument but that might not be immediately detected by an operator include partial pluggage of the gas sampling line, which in turn can lead to errors in the synchronization of emissions and engine data streams. Vendors, with encouragement from EPA, should develop procedures for detecting problems such as this.

Standard protocols should be followed for installing, operating, and removing equipment. These protocols may vary in specific details from one instrument to another, but in general installation includes connection to a power source, obtaining an exhaust sample, and obtaining data regarding vehicle activity, such as via the OBD link or a sensor array. Operation should address the proper period for warm up and zeroing of the instrument prior to data collection, as well as safe procedures for working with the instrument during actual driving. For example, it is helpful for the operator to know when there is a loss of data collection by the instrument, so that a run can be terminated to allow for correction of the problem, but to learn of the problem via an audible signal as opposed to having to visually monitor an instrument panel.

A key issue is whether the instrumentation can be operated by the driver of the vehicle, or whether there must be an instrument operator in addition to the driver. This issue may be a function of the data collection objective. For purposes of developing emission factor data, the instrument may be able to automatically collect all necessary data. However, if the intent is to include information on specific time stamps representing important or unusual events, then the driver may be able to simply touch a key or perhaps make a statement verbally that is recorded by the instrument. Alternatively, a second person may be needed to make notes regarding field conditions that should be entered in the vehicle trip database.

Equipment removal procedures should be clearly specified. In the process of recruiting vehicles, vehicle owners will appreciate reassurance that the installation, operation, and removal of the instrument is not likely to cause damage to the vehicle.

Table 8-3. Equipment Issues in On-Board Studies

Equipment Deployment – pairing of specific pieces of equipment with specific vehicle/driver combinations throughout test period **Validation –** standardized qualification process for comparison of on-board equipment to dynamometer measurements **Calibration–** standard protocols for calibration, warm-up, and zeroing of equipment **Diagnostics and Maintenance –** requirements for identifying and correcting equipment and data problems **Installation –** standard protocols for installing, operating, and removing equipment from vehicles **Other Equipment –** ambient conditions, additional instrumentation for non-electronically controlled vehicles, recording time stamps and special situations/conditions.

Depending upon the study objective, other equipment may be needed to provide supplemental data streams. The on-board instrumentation itself may have accessories, such as sensor arrays or monitors for ambient conditions such as temperature and humidity, that must be properly deployed. In addition, creative opportunities for on-road data collection should be sought. For example, perhaps it is possible to obtain a data base of real-world tire wear by taking measurements of tread depth before and after each data collection run. Opportunities to validate estimates of fuel economy obtained with on-board instrumentation should also be pursued where possible. Because CO_2 emissions are almost exactly a linear function of fuel use in many cases, methods for validation of fuel use measurements by on-board instruments can also serve to help validate CO_2 emission measurements.

8.5 Data Screening, Reduction, and Analysis

Many of the key considerations for data analysis for on-board studies are addressed in the examples in Chapters 3, 4, and 5 for LDGV, HDDV, and nonroad sources, respectively. The major steps in the process of obtaining data from an on-board instrument and using such data for model development are summarized in Table 8-4. These steps include identifying variables for which data should be collected, collecting the data, screening the data for errors, reducing the data to standard formats and databases, and analyzing the data to gain insights and for model development purposes.

The set of variables for which data are to be collected is essentially a part of the study design, and becomes explicit when instrumenting the vehicle and when working with the data. The data from an on-board study can be categorized in a variety of ways. One example of categories is shown in Table 8-4, including vehicle data, route data, and ambient data. In general, there can be static data that represents unchanging characteristics of the vehicle, route, or study area, run-specific data that represent conditions that are constant for a run but that may differ from one run to another, and dynamic data that represents conditions that change during a single data collection run. Some of these data can be collected automatically using instrumentation, while others typically have to be collected manually (e.g., static vehicle characteristics).

Table 8-4. Data Analysis Issues for On-Board Studies

Data Requirements –

Vehicle Data

Static Data (data that do not change from one data collection run to another)- e.g., year, make, model, VIN, engine size, number of cylinders, curb weight, body style, fuel delivery system, emission control system, I/M program. For HDDV, information regarding engine manufacturer, make, model, engine history, and engine miles accumulated is needed.

Run Data (data that change from one run to another but that do not have to be recorded on a second-by-second basis) - e.g., odometer reading at the start and finish of the run, fuel characteristics, passenger or freight load, soak time prior to a cold start.

Dynamic Data (data that change on a second-by-second basis) - speed, engine RPM, mass air flow, manifold absolute pressure, coolant temperature, percent throttle, time stamps, etc.

Route Data

Static Data - e.g., route, roadway classification of specific segments, roadway geometry (e.g., number of lanes, type of movement in each lane), traffic control measures, road grades

Run Data - e.g., work zone locations

Dynamic Data - incidents, unusual or notably traffic conditions

Ambient Data

Run Data - e.g., ambient temperature, humidity

Dynamic Data - e.g., ambient temperature, humidity

Data Screening – processing data to remove or correct data containing errors

Data Reduction – standard methods for reducing data, creating databases, and storing and archiving data

Table 8-5. Examples of Typical Measurement Errors

Zeroing – zeroing of instrument in an area with high ambient concentrations of pollutants being measured.

Loss of Power – loss of power, such as from batteries, causing interruption of data collection

Engine Scanner Errors – loss of data stream from on-board diagnostic link

Gas Analyzer Errors – failure to update emissions values (“freezing” at a specific value)

Negative Emission Values – can result from improper zeroing or may indicate instrument drift

Synchronization Errors – improper synchronization of gas analyzer, engine scanner, and other data streams (e.g., can result from pluggage in gas line).

Lack of Field Data Entry – loss of data associated with failure to enter time stamps or other supplemental “field” data.

Data screening should be done to identify and, if possible, correct for errors or suspected errors in the data. Specific examples of data screening techniques are illustrated in Chapter 3 and in Frey *et al*. (2001). Examples of typical types of problems encountered in on-board emissions data are given in Table 8-5. They include problems with zeroing, loss of power to the instrument, engine scanner errors, gas analyzer errors, negative emission values, synchronization errors, and lack of sufficient data entry. This list is not exhaustive, but is illustrative of typical problems that might be encountered. Data collection protocols should be developed with the aim of minimizing these types of errors. For example, sometimes loss of data is caused by a loose connection of the engine scanner to the OBD link on the vehicle. A simple solution, such as the use of removable duct tape to secure the connection, can avoid at least some problems with loss of data. Zeroing problems can be avoided by zeroing the instrument in an open area with good air movement, and with the zero air intake hose pointed upwind and the vehicle exhaust pointed downwind. Loss of power can be avoided in part by having secure connections and in part by having properly charged backup battery power available. Lack of field data entry can be avoided in part by following a standard checklist of tasks.

Some errors identified during data screening cannot be corrected, such as missing data or data based upon improper zeroing or calibration of the instrument. In such cases, erroneous or missing data should not be admitted to the screened database that is stored for archival purposes or for model development purposes. Other errors can be corrected. For example, if there is an error in synchronization of the gas analyzer and engine scanner streams, and if an appropriate time delay can be determined, then the raw gas analyzer and engine scanner data (if available) can be re-analyzed to estimate mass emissions based upon proper synchronization. The recent study by Frey *et al*. (2001) reported that over 80 percent of the attempted data collection runs resulting in a valid complete dataset. The percentage is expected to be higher in future work as a result of improvements in equipment and protocols.

A possible concern with on-board emissions measurements is the synchronization of the vehicle activity data stream from either the on-board diagnostic link or sensor array, and the gas analyzer data stream. Based upon a detailed review of vehicle activity and emissions data, Frey *et al*. (2001) concluded that macroscale emission results were not sensitive to errors in synchronization of as much as approximately five seconds. However, mesoscale results, such as for estimates of average emissions for individual driving modes, could have much larger errors. Thus, the implications of errors in synchronization will have varying importance depending on the objective of the data collection study.

Since on-board emissions measurements will be collected by different investigators using different instruments, it is important that there be a consistent method required for data screening, data reduction, and data reporting.

A dataset that passes the screening process would be considered to be an adequately quality assured and quality controlled data set that can be used for analysis or model development. Databases from individual vehicle runs should be screened and converted into a standard format for later retrieval. The standard format should be one that is readily accessible to the public, such as an ASCII or spreadsheet format, so that the data can be subject to external review and so that others may make use of the data.

Data reduction involves calculation of inferred values based upon the values reported by the on-board emissions measurement system. For example, although acceleration is not directly measured in most cases, it can be inferred from the speed trace. Similarly, power demand, or driving mode categories, can be inferred from the data reported by the instrument. Inferred quantities are not part of the original measurement process. For model development purposes, the screened databases should be processed using standard data reduction steps, such as estimation of inferred quantities of acceleration, power demand, equivalence ratio (when possible), road grade, fuel flow (if not reported), driving mode flags (e.g,. cold start, and hot-stabilized idle, acceleration, deceleration, and cruise), and others that may later be determined to be important. The data reduction process will result in a new database that should be properly stored so that it is readily accessible to the public and to those involved in model development.

Data analysis is a less standardized category than the data screening and reduction steps, depending upon the objectives of the analysis. However, for development of the NGM, there should be a minimum set of procedures for exploring the data to uncover any errors in the data that might have escaped the screening process and to uncover unusual or interesting situations that merit consideration in the model development process. For example, standard visualization methods of multiple scatter plots should be used to review data for an individual vehicle based upon one or more runs with that vehicle, as illustrated in Chapter 3. Visualization methods help provide insights regarding possible key relationships in the data.

It is rarely the case that any one method of analysis can fully reveal patterns in the data. In this study, a variety of approaches have been used, including various graphical, statistical, and engineering-based methods for exploring relationships in the data. These methods are summarized in Table 8-6. Future studies should employ more than one technique to determine the robustness of results. Moreover, it is important to account for variability in the data when making comparisons, such as has been done in Chapter 3 in comparing modal emission rates or in making before and after comparisons of the effect of traffic signal timing and coordination in the Frey *et al*. (2001) study. Because vehicle emissions exhibit substantial variability, mistakenly overconfident inferences can be made if variability is not properly accounted for.

It should be noted that multi-factor experiment development techniques should be utilized in order to be able to isolate the effects of parameters. Otherwise, the effects of different parameters might mask the other ones and it would be difficult to find the relations between those parameters and vehicle emissions. Different experiment designs might be needed to determine the effect of different parameters. For example, for the effect of roadway functional class on vehicle emissions one would try to isolate roadway functional class parameters from other parameters. In order to do that a representative number of data should be collected on the same vehicles by same drivers and on different roadway functional classes. However, environmental conditions can not be controlled and might cause a difference in the dataset. In that case, data should be adjusted for environmental changes by using the relations developed for these environmental parameters and emissions. Another way of handling multiple uncontrolled variables is to use statistical techniques such as ANOVA that allow analysis of multi-factor problems.

Table 8-6. Examples of Useful Methods for Data Analysis

Scatter Plots – pairwise comparisons among second-by-second emissions data and potential explanatory variables, evaluation of correlation between emission data streams

Time Traces – plot data streams versus time to identify unusual or important events

Empirical Cumulative Distribution Functions – plot the data as ECDFs to identify modality in the data and to characterize the central tendency and range of variation of the data, as well as the shape of the distribution of the data.

Multicomparisons – systematic approach for comparing the means of subsets of a data set to determine statistical significance of differences in the means

ANOVA – a technique for evaluating potential dependencies in a database

Parametric Regression – Parametric regressions involve fitting model functions defined a priori to a data set. Ordinary least squares (OLS) is an example of parametric regression.

Nonparametric Regression – do not require specification of a functional form, useful for identify trends in the data

Classification and Regression Trees (CART) – a technique for dividing a database into subsets that are statistically different from each other, similar to Hierarchical Tree-Based Regression (HTBR)

Time Series Modeling – a technique for fitting a model to second-by-second data that takes autocorrelation into account.

Goodness of Fit Tests – compare distributions of data to determine if they are statistically significantly different

GIS methods – visualize data spatially and help identify hot-spots. Effect of roadway classification, intersections, and other facility types or operating areas or activity patterns (e.g., for nonroad sources) can be evaluated.

A consistent finding in the Frey *et al*. (2001) study and the analysis of LDGV emissions in this study is that the definitions of hot stabilized driving modes used by Frey *et al*. (2001) typically result in statistically significant different average values when comparing one mode with any of the other modes. Thus, this provides strong empirical support to the modal modeling approach recommended in this study. The fact that there are statistically significant differences in modal emission rates indicates that mesoscale analysis of driving modes can explain some of the variability in on-road vehicle emissions. Vehicle emissions are generally the highest while vehicles are accelerating and generally the lowest while vehicles are idling.

The conceptual model in this study did not require exploration of vehicle categories because all of the LDGV vehicles were sufficiently similar that they could be analyzed as one group. However, in developing the NGM, it will be necessary to seek opportunities to classify vehicles into different groups. If at all possible, the classification scheme should be derived from exploration of the data, and should not be constrained by past classification schemes used in the MOBILE models. The grouping of vehicles for emissions modeling purposes need not be based solely on *a priori* notions of technology groups, such as has been done in the past (e.g., for Tech5). The grouping of vehicles can be determined by first looking at vehicles that have similar emission characteristics and then by identifying what such groups of vehicles have in common with each other that is also different from some common characteristic for a different group of vehicles. Frey *et al*. (2001) illustrate that the small fleet of vehicles that were tested in their study could be grouped based upon similar emission trends with respect to key explanatory variables, and that the trends for one group were dissimilar than the trends for other groups for at least one of the three pollutants addressed in that study. For example, one set of groups exhibited an increase in average NO_x emissions with an increase in average corridor speed, while a second group exhibited no sensitivity of average emissions to average speed, and while a third group displayed an increase in average NO_x emissions associated with an increase in average speed. These findings suggest that the vehicles could be grouped into three categories and that factors that might explain these different emission sensitivities should be identified as a criteria for the classification scheme.

Average corridor speed, average control delay per stop-mile and the average number of stops per mile were found in the Frey *et al*. (2001) study to have some explanatory power with respect to average emissions for a corridor. These types of traffic flow measures are often simulated in traffic flow models. Therefore, if an objective is to make the NGM compatible with existing or future traffic flow models, it will be useful to include these and perhaps other traffic flow measures in the on-board emissions database and to develop relationships between emissions and these explanatory variables. All three of these can be determined based upon the speed trace, using techniques described in Frey *et al*. (2001).

It is important to have a good model for the modal emission rates. Frey *et al*. (2001) found that for a specific study objective, the emission estimates were relatively insensitive to the fraction of time spent in each driving mode, and they were highly sensitive to the trip duration and to the average modal emission rate employed. Thus, it will be important in future work to have well-refined models for emissions within each of the driving modes.

The driving mode approach recommended in this work is similar in some respects to the “bag” approach of the FTP. However, unlike the bags of the FTP, the modes defined in this work are not required to be based upon a consecutive time series of data. In fact, an advantage of the modal definition is to break a time series of data into shorter or intermittent time segments, which is a technique for reducing the influence of autocorrelation in the analysis. If autocorrelation had to be modeled, it would be necessary to use a time series type of approach, or to have explanatory variables based upon several previous seconds of emissions estimates, in the model. The incorporation of time steps would substantially complicate the model and make it perhaps less practical for widescale use. The modal definitions do account, to some extent, for a short-term temporal history in the data, and therefore capture to some extent the time series nature of the data. As noted in Chapter 5, we have compared time series and modal approaches for the nonroad emissions category, and found that both produce similar results. Thus, as a practical matter, the two approaches may not produce fundamentally different emission estimates. The modal approach is a simpler approach that is more intuitive and easier to explain.

Table 8-7 summarized the variables identified in this work and in previous work (Frey *et al*., 2001) that have been found to be useful in explaining some of the variability in on-board emissions measurements. The examples in the table are specific to on-road emissions. However, there are analogies with nonroad emissions. For example, for nonroad emissions,

Table 8-7. Examples of Explanatory Variables Identified as Useful Based Upon Analysis of On-Board Data

Driving Mode (Cold Start, Idle, Acceleration, Cruise, Deceleration): Cold start is a period of high average emissions. For hot stabilized operation, the acceleration mode has the highest average g/sec emission rate and is statistically significantly different from the other modes. Road Grade – emissions are not highly sensitive to moderate road grades

Power Demand – can help refine definition of driving modes into subcategories

Ambient Temperature

Relative Humidity

Air Conditioning Usage

Average Speed (for a corridor)

Average Number of Stops per Mile

Average Control Delay per Mile

Equivalence Ratio – this can be a helpful explanatory variable for some pollutants (e.g., CO for LDGV, HC for HDDV).

Fuel Flow – this can be a helpful explanatory variable for some pollutants (e.g., NOx).

Traffic Flow – e.g., on-road emissions differ for congested versus uncongested traffic flow (Frey *et al*., 2001)

Vehicle Characteristics – there was not sufficient data in this study to investigate this quantitatively; however, Frey *et al*. (2001) found statistically significant differences in emissions for different vehicles, including different vehicles of the same year, make, and model.

modes can be defined based upon engine RPM and engine load, with additional consideration of ambient conditions such as temperature, humidity, and barometric pressure to refine the model.

8.6 Variability and Uncertainty

The National Research Council (2000) strongly recommended that EPA and others quantitatively account for uncertainty in predictions from mobile source emission models. The use of on-board emissions data will address a major area of uncertainty in the MOBILE models, which is the question regarding whether the dynamometer data that underlie the models are representative of real-world emissions. Thus, an approach to development of the NGM based upon real world data should result in an improvement in the emission predictions compared to earlier models, and should promote more confidence in the use of the model.

However, there is also a large amount of variability in mobile source emissions data, not all of which can be explained by a model for reasons previously discussed. Therefore, it is critically important to quantify the unexplained variability in the model predictions, and to quantify the uncertainty in the fleet average emission estimates based upon the model. Without information about unexplained variability and about uncertainty in averages predicted by the model, model users will tend to be overconfident in their use of the model. Although there are often expressed concerns that uncertainty analysis complicates the regulatory applications of a model, these concerns can be addressed with policy directives from the appropriate policy makers at EPA or elsewhere. At times, it is important for the scientific community to clearly define what is acceptable scientific practice, and what is not, and to encourage agencies such as EPA to do things in the best manner possible. Uncertainty analysis is in this category. EPA is a diverse agency, and there are parts of EPA, such as those that deal with human exposure assessment, that routinely deal with uncertainty analysis and incorporate it into exposure assessments. Similar, the parts of EPA that deal with greenhouse gas emission inventories have also incorporated concepts of uncertainty. There are many other examples aside from these. Because the mobile source emission factor models are among the most important and influential models that EPA produces, it is critically important that EPA/OTAQ be at the forefront of the best scientific practice regarding quantification of variability and uncertainty.

The NRC (2000) study reviews previous work to develop uncertainty estimates for mobile source emission factors and for model predictions. Two of the most relevant studies mentioned in the NRC (2000) report are those by Kini and Frey (1997) and Pollack *et al*. (1999), which pertain to uncertainty assessments for Mobile5a and EMFAC7G, respectively. Work by Frey *et al*. (1999) refined the earlier Kini and Frey (1997) study. With regard to nonroad emissions, Frey and Bammi (2002a&b) have recently reported an analysis of variability and uncertainty in Lawn & Garden and in CFI categories, respectively. Frey *et al*. (2001) quantified confidence intervals in mean emission estimates obtained from on-board data collection. Frey and Eichenberger (1997) quantified inter-vehicle variability and fleet average uncertainty in emissions based upon remote sensing of school and transit buses. Rouphail *et al*. (1999) quantified uncertainty in mean estimates for LDGV based upon remote sensing data. This is an illustrative set of examples to show that methods for quantifying variability and uncertainty have already been applied for a wide variety of mobile source emission categories.

The approach of Frey *et al*. (1999) is a bootstrap approach based upon actual data, free of functional form assumptions associated with curve fits in a model such as Mobile5a. In developing the NGM, it is important that estimates of uncertainty be developed for the average values of modal emission estimates, and that these be properly combined using appropriate statistical techniques. Simple examples of uncertainty assessment are illustrated in Chapter 3. Knowledge of uncertainty in the model predictions helps the model user appreciate the precision of the predictions.

Because the NGM is likely to produce different estimates of emissions than its predecessor models, it is critically important to understand which predictions are significantly different than those obtained from earlier models, and which differences are within the range of uncertainty of the NGM and/or the previous model. For example, suppose that the NGM predicted an emission rate equivalent to 1 g/mi for a particular pollutant and situation, and that Mobile6 predicted a value of 0.7 g/mi. Are these two predictions significantly different? If each model has a precision of plus or minus 1 percent, then we would judge that these two predictions are very different from each other. If each model has a precision of minus 50 percent to plus 200 percent, then the two predictions would be judged to be essentially the same. Cases where the model predictions are found to be significantly different can be studied further to determine if the difference can be attributable to improved representativeness of the activity and emissions data in the NGM.

NRC (2000) points out that uncertainty analysis is important to identify areas of the model that produce the largest contribution to uncertainty for the purpose of targeting efforts to collect more data and/or in other ways improve the model. Air quality modelers, such as Hanna *et al*. (2001) are increasingly including uncertainty analysis as a component of air quality predictions. Therefore, there will be increasing demand for estimates of uncertainty in emission inventories. More importantly, in the process of developing air quality management strategies, it is important to find management strategies that are robust to uncertainties in emission estimates, so that strategies can be devised that will yield benefits even in the face of lack of complete knowledge. Because air quality management decisions have widespread economic implications, it is important to base such decisions on the best possible process.

The NRC (2000) also points out that it is important to have criteria for model precision and accuracy. In the absence of such criteria, it is difficult to determine how much data to collect or what components of the model to focus on for data collection or refinement. For example, a clearly stated data quality objective, such as a precision of plus or minus 20 percent for average fleet emission predictions of tailpipe CO, NO, and HC emissions for LDGV operating on uncongested freeways during summer ambient conditions, will help model developers determine how much data are needed and to have a benchmark for determining when the model complies with the objective.

The model precision will typically vary depending upon the case study. It should be recognized that the model will not be equally precise in making predictions as input assumptions vary. For example, in cases where model predictions are primarily a function of sample size, the model is likely to have higher precision for the types of vehicles and conditions that were the main focus of the data collection study, and less precision for conditions that were represented with lower frequency in the data collection study.

8.7 Key Findings and Recommendations

The key findings and recommendations based upon the conceptual model development activities are summarized in Table 8-8. The key findings and recommendations regarding a five year on-board emissions measurement strategy and regarding development of the NGM are summarized in Table 8-9. The detailed justifications of these findings are given in earlier sections of this chapter.

Although not related directly to the objective of this project, a key opportunity should not be missed in the development of the NGM and in the use of new data collected for that purpose. There is a key opportunity to educate the public regarding the relationship between their choices and emissions from vehicles that they drive. Real-world on-road data help make a convincing case to the public regarding what really influences emissions and what an individual person can do about it.

The recommendations given throughout this report are with regard to key considerations in development of a detailed and specific strategy for on-board measurement of on-road and non-road equipment and with regard to alternative data needs for both types of emission sources. An illustrative example of a detailed study design for the example of LDGV was provided,

Table 8-8. Key Insights and Recommendations From Conceptual Model Development Approaches Explored for LDGV, HDDV, and Nonroad Data Sets

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The Domain of Applicability of a Model is Limited by Study Objectives and Study Design for the Data Collected to Calibrate the Model

Need Complete Information Regarding Instrumentation and Data Collection Protocols

All Data Fields Must be Thoroughly Defined

Data Should be Reported in a Consistent Format

Data Screening Must Be Performed Prior to Data Reduction

Data Reduction Should Result in Standardized Files and Databases

Exploratory Data Analysis Provides Key Insights Regarding Trends and Possible Relationships

Models should be developed with an emphasis on explaining variability in emissions, and not motivated solely by categories defined previously without verification of their ability to explain differences in emissions.

Second-by-second on-board data are time series with statistically significant autocorrelation. Modeling approaches must recognize and appropriately deal with this.

There are trade-offs with respect to choice of time series modeling methods and other methods. Time series methods explicitly account for autocorrelation but are more difficult to calibrate to data from multiple vehicles/trips with many explanatory variables than a modal approach and require multiple seconds of initial values when making predictions. The trade-off of the modal approach is some loss of explanatory power with the benefit of increased convenience.

Methods for Binning Data Should Account for Autocorrelation in Categorizing Data

A Modal Approach (Cold Start, Idle, Acceleration, Cruise, Deceleration) to Binning Data for On-Road Sources Is Intuitive, Mesoscale, and Has Explanatory Power

A Modal Approach Can Support Macroscale Predictions (modal predictions can be aggregated to make trip predictions).

A Modal Approach Can Be Refined With Regression or Other Modeling Approaches to Predict Emissions on a Second-by-Second Basis (Microscale)

Modal Approaches Can Be Developed for Any Source Category (e.g., based upon engine RPM and engine load for nonroad sources)

On-board data collection will provide insight into typical or representative activity patterns that can be used as default inputs to the NGM

Model predictions can be based on weighted combinations of different activity patterns (e.g., different driving cycles for on-road or different activity cycles for nonroad).

(Continued on next page)

Table 8-8. (continued).

Modeling should be done on the basis of a minimum desired averaging time, and model predictions should be developed for one or more averaging times depending on user needs.
Model performance should be evaluated by comparing observations with model predictions, as illustrated for LDGV, HDDV, and nonroad examples in Chapters 3, 4, and 5.
Mesoscale and Macroscale analysis of second-by-second data should be done on the basis of a standardized averaging time or definition of a trip, which can be different for different mobile-source categories consistent with typical operating practice and/or with anticipated model applications. For example, an averaging time of one-hour is consistent with many air quality modeling applications. An averaging time of 20 to 30 minutes may be consistent with typical LDGV driving.
Microscale analysis is based upon short averaging times (e.g., one second), and can be used to produce aggregate emission estimates for any arbitrary larger averaging time.
Unexplained inter-trip and/or inter-vehicle variability should quantified and conveyed to model users
Uncertainty in model predictions for fleet average emission should be quantified and conveyed to model users.
Opportunities to education the public about driving behavior and emissions should be explored.
A modal approach is intuitive to the public.

Table 8-9. Summary of Key Recommendations Regarding a Five Year On-Board Emissions Data Collection Strategy and Development of the NGM

Clearly define study objective(s)

For each study objective, develop an appropriate study design that includes the following elements:
- Selection of appropriate study area(s)
- Vehicle Selection
- Vehicle Operation
- Route/Site Selection
- Driver/Operator Selection and Driver/Operator Behavior
- Scheduling
- Fuel Selection
- Sample Size

Develop and Employ Appropriate Protocols for Instrumentation
- Equipment Deployment
- Validation and Acceptance Criteria for Equipment
- Calibration and Zeroing Procedures
- Diagnostic and Maintenance Procedures
- Installation Procedures
- Field Data Collection Protocols
- Interface and Synchronization of Other Equipment

Develop and Employ Appropriate Protocols and Procedures for Data Screening, Data Reduction, and Data Analysis
- Clearly Define Data Requirements Consistent with Study Objective(s)
- Data Screening to remove or correct errors
- Data Reduction to create standardized databases for archival and public distribution
- Data Exploration and Analysis Methods
- Model Development Methods

Data Collection Should be Decentralized
- Regional or Local "Emission Measurement Centers" for Specific Study Areas and/or Source Categories
- Use approved instrumentation
- Use standard protocols for instrumentation, field data collection, and data reduction

Responsibilities for Study Objectives and Study Design should be clearly defined and assigned at EPA, with an appropriate advisory board or mechanism for timely external input, review, and comment

Model development activities should be appropriately subdivided and contracted (e.g., for different source categories)

(Continued on next page)

Table 8-9. (Continued).

Employ Appropriate Modeling Approaches
- Modal Approach
  - Modal Definitions Based Upon Time Series Considerations
  - Reduce Influence of Autocorrelation By Binning Data
  - Employ Regressions Techniques to Develop Additional Explanatory Power Within Each Mode/Bin
  - Can Support Microscale, Mesoscale, and Macroscale Analyses
- Time Series Approach
  - Theoretically Appealing
  - May be impractical with many explanatory variables

Develop and Employ Representative Driving Cycles from On-Board Data For Use in Developing Supplemental Correction Factors or Insights Regarding Sensitivity Under Controlled Conditions (e.g., a/c load, ambient temperature, fuel effects)

Employ Supplemental Methods for Measurement of Evaporative Emissions (e.g., SHED)

Incorporate Data Regarding Other Pollutants (e.g., air toxics) using appropriate normalizations (e.g., organic air toxics as a fraction of total hydrocarbon or total organic gas emissions)

Develop Adjustment Factors for Hydrocarbon and PM Emissions from On-Board Measurements and/or Use Improved Instrumentation Methods

Study Design Could Include Supplemental Measurements Regarding Tire Wear (e.g., measure tread depth before and after each data collection run or other defined time period, simultaneous with recording of odometer readings)

Quantify Unexplained Inter-trip and/or Inter-Vehicle Variability in Model Predictions

Quantify Uncertainty in Predictions of Fleet Average Emissions

Employ a Phased Approach for a Five-Year Study
- *Phase One - Pilot Study*
  - Contains all of the elements of a full-scale study, but allows time to learn from a first-round of data collection, to identify key explanatory variables, to identify previously unknown data gaps, and to iterate and improve upon study objectives, study design, data collection protocols, equipment, data analysis methods, and modeling techniques
- *Phase Two - Production Study*
  - This phase would focus on data collection in multiple study areas to develop a national database from which the NGM would be derived, based upon lessons learned in the pilot study.

Devote Adequate Resources to all Key Elements of Study Design, Data Collection, Data Analysis, and Model Development, consistent with the long-term importance of the policy applications of the NGM through its useful life.

(Continued on next page)

Table 8-9. (Continued).

Devote Sufficient Resources to Data Analysis and Model Development - these can require as much or more effort than the field data collection itself.
Make Data Publicly Available Through the Web, in Data Formats that are Convenient for the Public
Develop procedures manuals for study design, field data collection, data screening, data reduction, and suggested methods for data analysis.
Develop handbook of methods for quantitative analysis of variability and uncertainty applied to mobile sources.
Properly and Thoroughly Document the Model: Technical Manuals Regarding Data and Algorithms Used in Manual Software Engineering Manuals Regarding Software Implementations User Manuals
The Model Must Be Public Domain - No Proprietary Restrictions with Regard to Algorithms
Obtain External Peer-Review of Each Major Document
Publish All Manuals/Documents on the Web
Submit Each Key Aspect of the Study Design, Data Collection Methodology, Data Analysis Methods, and the Model for Peer-Review in Journals
Keep in mind the advice of the National Research Council: "The model must be seen as an accurate reflection of mobile-source emissions, not as a tool that is used to support proposed regulations."

indicating the scope of the data collection effort a single measurement study area. Three or more study areas should be included in the testing strategy.

Key recommendations are that: (1) the study objective must be clearly defined; (2) an appropriate study design should be developed; (3) protocols should be established and employed for instrumentation, data collection, and data reduction; (4) data collection should be decentralized; (5) study design and model development should be centrally coordinated but specific tasks can be decentralized; (6) appropriate modeling approaches should be used; (7) variability and uncertainty in model predictions should be quantified; (8) a phased approach should be employed, with a pilot study in the first two years and a production study in the last three years of a five year plan; (9) data should be archived in a consistent format and made publicly available; (10) manuals should be developed to clearly communicate key procedures and suggested methods for data collection, analysis, and model development; (11) the model and constituent data should be subject to peer review, including publication in journals.   A key finding of this study is that a modal approach to modeling emissions is a viable approach and is recommended for the NGM.

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APPENDIX A

- **Negative Emissions for LDGV Dataset**
- **Summary Table for LDGV Vehicles**
- **Inter-Vehicle Variability for HC, NO, and CO_2 Emissions**
- **Inter-Trip Variability for CO, NO, and CO_2 Emissions**
- **Scatter Matrices for CO, NO, and CO_2 for Vehicle 2**
- **Spatial Analysis for NO and HC Emissions**
- **Cold-Start Identification Example**
- **Summary Table for Cold-Start Duration**
- **Improved Modal Rates for HC, NO, and CO_2**
- **Modal Distribution for Time and Emissions for Each Trip**
- **Regression Coefficients for NO, HC, and CO_2**
- **Comparison of Cold-Start Emissions for NO and HC**

A1. Negative Emissions for LDGV Dataset

Vehicle	Trip Number	Seconds of Negative HC Emission data	Trip Averaged HC Emission (g/sec)
2	3	44	0.00086
6	1	10	0.00061
6	2	650	0.00065
6	3	65	0.00121
7	1	41	0.00028
7	2	166	0.00062
7	3	201	0.00115
11	1	58	0.00146
11	4	101	0.00156
12	1	2036	-0.0014
12	2	59	0.00169
13	1	163	0.00303
13	2	79	0.00147
14	7	247	0.00227
15	3	46	0.00141
16	2	96	0.00189
16	8	8	0.00150
17	4	78	0.00037
17	5	11	0.00018
18	1	10	0.00075

A2. Summary Table for LDGV Vehicles

Vehicle No	5			6		
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip1*	*Trip2*	*Trip3*
Vehicle Characteristics						
Plate No	UWG36			UQW872		
Vehicle Make	SATURN			CHEVROLET		
Vehicle Model	SATURN			MALIBU LS		
Vehicle Model Year	1998			1999		
Engine Displacement	1.9			3.1		
Transmission Type	AUTO			AUTO		
GVWR	3327			4013		
Vehicle Operation						
Average Speed (mph)	13.2	42.1	26.7	7.9	28.9	29.8
Acceleration						
Average Engine Load (%)	33	34	29	23	28	30
Average RPM	1266	2005	1568	889	1293	1307
Average Torque (ftlbs)	0	0	0	0	0	0
Average Throttle (%)	4	9	6	3	7	7
Average Inlet Air Temperature (F)	35	27	26	56	31	22
Average Coolant Temperature (F)	84	81	85	91	93	87
Average MAF (g/sec)	N/A	N/A	N/A	9	13	13
Average Exhaust Temp (F)	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	55	57	48	0	0	0
Average Fuel (lb/sec)	0.0013	0.0020	0.0014	0.0013	0.0020	0.0020
Average Power Demand (s*a)	1.00	0.91	1.06	1.34	1.04	0.75
Average KE (s^2*a)	31.5	46.8	42.4	35.2	47.5	28.5
Average HC (g/sec)	0.0048	0.0018	0.0007	0.0006	0.0007	0.0012
Average CO (g/sec)	0.0239	0.0099	0.0046	0.0041	0.0033	0.0123
Average CO2 (g/sec)	1.7510	2.9274	2.0505	1.8062	2.8068	2.9180
AverageNO (g/sec)	0.0040	0.0031	0.0012	0.0012	0.0025	0.0028
Environmental Characteristics						
Average Ambient Temperature (C)	28.0	34.1	33.6	27.8	29.3	25.0
Average Ambient Pressure (kPA)	99.0	99.0	99.0	99.0	99.0	99.0
Average Humidity (%)	37	23	28	48	42	39
Roadway Characteristics						
Average Latitude (degree)	42.31	42.27	42.27	42.30	42.31	42.27
Average Longitude (degree)	-83.71	-83.68	-83.71	-83.71	-83.62	-83.62
Average Altitude (feet)	943	905	886	568	871	792
Average Grade (%)	0.186	-0.274	0.078	24.166	-0.197	0.088
Time of Day	12:31:35	13:41:48	N/A	17:56:16	18:23:45	8:05:11
Day of Week	9/20	9/20	9/20	9/19	9/19	9/20
Number of Seconds of Data	568	1067	2422	181	1850	2517

A2. Summary Table for LDGV Vehicles

Vehicle No	7			11			
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip1*	*Trip2*	*Trip3*	*Trip4*
Vehicle Characteristics							
Plate No	RHG594			XPE50			
Vehicle Make	SATURN			FORD			
Vehicle Model	SATURN			TAURUS SE			
Vehicle Model Year	1999			1998			
Engine Displacement	1.9			3			
Transmission Type	MANUAL			AUTO			
GVWR	3237			4721			
Vehicle Operation							
Average Speed (mph)	17.6	35.0	38.3	49.1	20.3	21.9	53.3
Acceleration							
Average Engine Load (%)	7	34	31	33	27	27	34
Average RPM	1299	1599	1719	2015	1283	1303	2123
Average Torque (ftlbs)	0	0	0	0	0	0	0
Average Throttle (%)	0	0	0	0	0	0	0
Average Inlet Air Temperature (F)	37	30	18	N/A	N/A	N/A	N/A
Average Coolant Temperature (F)	N/A	N/A	N/A	200	192	194	189
Average MAF (g/sec)	N/A	N/A	N/A	2038	1144	1127	2216
Average Exhaust Temp (F)	0	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	50	56	50	0	0	0	0
Average Fuel (lb/sec)	0.0004	0.0017	0.0016	0.0032	0.0018	0.0017	0.0034
Average Power Demand (s*a)	0.89	0.64	0.80	0.80	1.41	1.34	0.64
Average KE (s^2*a)	25.4	28.8	38.3	45.2	46.9	42.3	32.6
Average HC (g/sec)	0.0003	0.0006	0.0011	0.0015	0.0022	0.0017	0.0016
Average CO (g/sec)	0.0017	0.0042	0.0117	0.0448	0.0146	0.0141	0.0175
Average CO2 (g/sec)	0.5269	2.4120	2.3268	4.4810	2.5073	2.4742	4.8188
AverageNO (g/sec)	0.0003	0.0104	0.0091	0.0040	0.0037	0.0039	0.0034
Environmental Characteristics							
Average Ambient Temperature (C)	31.1	33.2	22.3	33.7	36.2	34.6	21.0
Average Ambient Pressure (kPA)	98.8	98.8	99.1	99.1	99.1	99.1	99.1
Average Humidity (%)	29	30	57	21	19	24	53
Roadway Characteristics							
Average Latitude (degree)	42.30	42.39	42.41	42.25	42.26	42.26	42.25
Average Longitude (degree)	-83.71	-83.75	-83.75	-83.47	-83.26	-83.25	-83.49
Average Altitude (feet)	0	933	926	754	661	636	736
Average Grade (%)	0.000	-0.045	-0.074	-0.141	0.130	-0.185	0.122
Time of Day	12:53:11	20:41:28	8:21:25	16:19:35	18:53:17	20:43:52	7:33:27
Day of Week	8/28	8/28	8/29	9/5	9/5	9/5	9/6
Number of Seconds of Data	1495	2235	2007	2352	628	587	2165

A2. Summary Table for LDGV Vehicles

Vehicle No	12			13	14		
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip1*	*Trip1*	*Trip2*	*Trip3*
Vehicle Characteristics							
Plate No	NUJ712			TXL734	5DFW90		
Vehicle Make	FORD			MERCURY	FORD		
Vehicle Model	ESCORT			SABLE GS	TAURUS SE		
Vehicle Model Year	1997			1998	1998		
Engine Displacement	2			3	3		
Transmission Type	AUTO			AUTO	AUTO		
GVWR	3485			4721	5166		
Vehicle Operation							
Average Speed (mph)	45.2	39.4	3.2	41.6	5.9	9.2	17.6
Acceleration							
Average Engine Load (%)	42	37	25	40	26	25	26
Average RPM	1979	1965	903	1911	1073	1172	1332
Average Torque (ftlbs)	0	0	0	0	0	0	0
Average Throttle (%)	0	0	0	0	0	0	0
Average Inlet Air Temperature (F)	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Average Coolant Temperature (F)	189	190	193	182	144	178	197
Average MAF (g/sec)	1771	1670	484	2449	901	1021	1236
Average Exhaust Temp (F)	0	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	0	0	0	0	0	0	0
Average Fuel (lb/sec)	0.0026	0.0025	0.0007	0.0037	0.0013	0.0015	0.0018
Average Power Demand (s*a)	0.46	1.03	0.62	1.12	0.92	1.26	1.15
Average KE (s^2*a)	32.9	62.4	6.7	59.0	24.5	36.2	41.5
Average HC (g/sec)	-0.0014	0.0017	0.0004	0.0030	0.0040	0.0025	0.0013
Average CO (g/sec)	0.0594	0.0712	0.0068	0.0955	0.0273	0.0243	0.0048
Average CO2 (g/sec)	3.6982	3.4560	0.9638	5.2410	1.7952	2.1677	2.6167
AverageNO (g/sec)	0.0071	0.0075	0.0006	0.0000	0.0023	0.0023	0.0015
Environmental Characteristics							
Average Ambient Temperature (C)	27.0	27.2	30.0	26.6	29.0	23.5	23.5
Average Ambient Pressure (kPA)	98.2	99.0	99.1	98.5	98.6	98.6	98.6
Average Humidity (%)	37	31	30	39	32	38	43
Roadway Characteristics							
Average Latitude (degree)	42.10	42.25	42.30	42.24	42.30	42.30	42.27
Average Longitude (degree)	-83.96	-83.92	-83.71	-83.70	-83.71	-83.70	-83.74
Average Altitude (feet)	951	969	921	893	932	962	925
Average Grade (%)	0.088	-0.061	0.544	0.014	0.014	-0.051	-0.047
Time of Day	21:01:53	8:58:12	9:36:21	20:10:39	15:46:21	17:34:09	18:18:09
Day of Week	9/9	9/10	9/10	9/8	9/13	9/13	9/13
Number of Seconds of Data	2160	3877	124	909	258	855	1486

A2. Summary Table for LDGV Vehicles

Vehicle No	14					
Trips	*Trip4*	*Trip5*	*Trip6*	*Trip7*	*Trip8*	*Trip9*
Vehicle Characteristics						
Plate No	5DFW90					
Vehicle Make	FORD					
Vehicle Model	TAURUS SE					
Vehicle Model Year	1998					
Engine Displacement	3					
Transmission Type	AUTO					
GVWR	5166					
Vehicle Operation						
Average Speed (mph)	34.8	8.2	10.5	25.6	3.8	3.8
Acceleration						
Average Engine Load (%)	31	29	29	29	24	25
Average RPM	1896	1235	1166	1614	961	990
Average Torque (ftlbs)	0	0	0	0	0	0
Average Throttle (%)	0	0	0	0	0	0
Average Inlet Air Temperature (F)	N/A	N/A	N/A	N/A	N/A	N/A
Average Coolant Temperature (F)	184	112	146	181	186	185
Average MAF (g/sec)	2035	1136	1040	1680	717	829
Average Exhaust Temp (F)	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	0	0	0	0	0	0
Average Fuel (lb/sec)	0.0031	0.0017	0.0015	0.0025	0.0010	0.0012
Average Power Demand (s*a)	0.84	0.63	0.89	1.08	0.67	0.84
Average KE (s^2*a)	49.2	15.4	20.6	50.1	9.8	22.1
Average HC (g/sec)	0.0027	0.0043	0.0036	0.0023	0.0008	0.0011
Average CO (g/sec)	0.0917	0.0298	0.0182	0.0792	0.0027	0.0161
Average CO2 (g/sec)	4.2599	2.3637	2.1922	3.5424	1.4780	1.6644
AverageNO (g/sec)	0.0045	0.0017	0.0048	0.0023	0.0025	0.0032
Environmental Characteristics						
Average Ambient Temperature (C)	24.0	15.2	25.0	25.0	28.0	30.0
Average Ambient Pressure (kPA)	98.6	98.6	98.6	98.6	98.6	98.6
Average Humidity (%)	38	44	34	30	28	26
Roadway Characteristics						
Average Latitude (degree)	42.24	42.25	42.25	42.27	42.30	42.30
Average Longitude (degree)	-83.72	-83.69	-83.69	-83.72	-83.72	-83.72
Average Altitude (feet)	884	854	857	885	928	949
Average Grade (%)	-0.166	0.079	0.087	0.013	0.079	0.086
Time of Day	19:16:53	9:18:17	10:10:39	10:53:21	11:22:18	11:31:48
Day of Week	9/13	9/14	9/14	9/14	9/14	9/14
Number of Seconds of Data	872	408	316	2102	190	155

A2. Summary Table for LDGV Vehicles

Vehicle No	15			16		
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip1*	*Trip2*	*Trip3*
Vehicle Characteristics						
Plate No	GFL311			278EAT		
Vehicle Make	CHEVROLET			CHEVROLET		
Vehicle Model	CAVLIER			CAVLIER		
Vehicle Model Year	1996			1998		
Engine Displacement	2.2			2.2		
Transmission Type	AUTO			AUTO		
GVWR	3670			N/A		
Vehicle Operation						
Average Speed (mph)	2.4	26.1	22.5	6.4	31.5	21.3
Acceleration						
Average Engine Load (%)	23	30	33	26	29	29
Average RPM	805	1353	1265	1030	1747	1377
Average Torque (ftlbs)	0	0	0	0	0	0
Average Throttle (%)	1	9	8	2	9	6
Average Inlet Air Temperature (F)	N/A	N/A	N/A	33	29	35
Average Coolant Temperature (F)	63	89	82	51	87	69
Average MAF (g/sec)	N/A	N/A	N/A	N/A	N/A	N/A
Average Exhaust Temp (F)	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	42	49	51	45	46	46
Average Fuel (lb/sec)	0.0006	0.0016	0.0015	0.0010	0.0018	0.0014
Average Power Demand (s*a)	0.16	0.74	0.47	2.85	2.13	1.20
Average KE (s^2*a)	1.9	29.5	17.3	46.5	49.9	40.6
Average HC (g/sec)	0.0046	0.0020	0.0014	0.0039	0.0016	0.0023
Average CO (g/sec)	0.0956	0.0302	0.0211	0.0773	0.0848	0.0852
Average CO2 (g/sec)	0.6624	2.1813	2.1330	1.2547	2.4920	1.8748
AverageNO (g/sec)	0.0010	0.0035	0.0012	0.0031	0.0049	0.0040
Environmental Characteristics						
Average Ambient Temperature (C)	30.4	29.5	18.3	28.7	32.6	26.8
Average Ambient Pressure (kPA)	99.1	99.1	99.1	99.1	99.1	99.1
Average Humidity (%)	27	31	39	26	22	27
Roadway Characteristics						
Average Latitude (degree)	42.30	42.23	42.24	42.30	42.34	42.29
Average Longitude (degree)	-83.71	-83.72	-83.73	-83.71	-83.45	-83.27
Average Altitude (feet)	784	884	857	981	762	651
Average Grade (%)	-0.737	0.048	-0.016	-0.494	-0.104	0.005
Time of Day	15:26:42	16:35:31	5:10:54	0:08:14	0:29:52	0:30:55
Day of Week	9/13	9/13	9/14	9/14	9/14	9/14
Number of Seconds of Data	216	2530	2523	246	3699	599

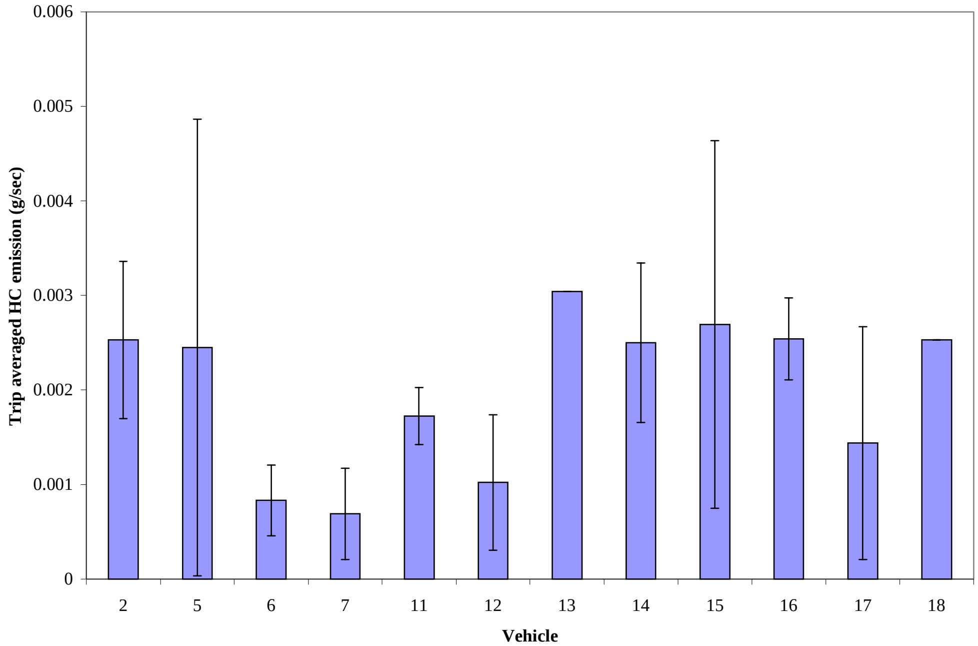
A2. Summary Table for LDGV Vehicles

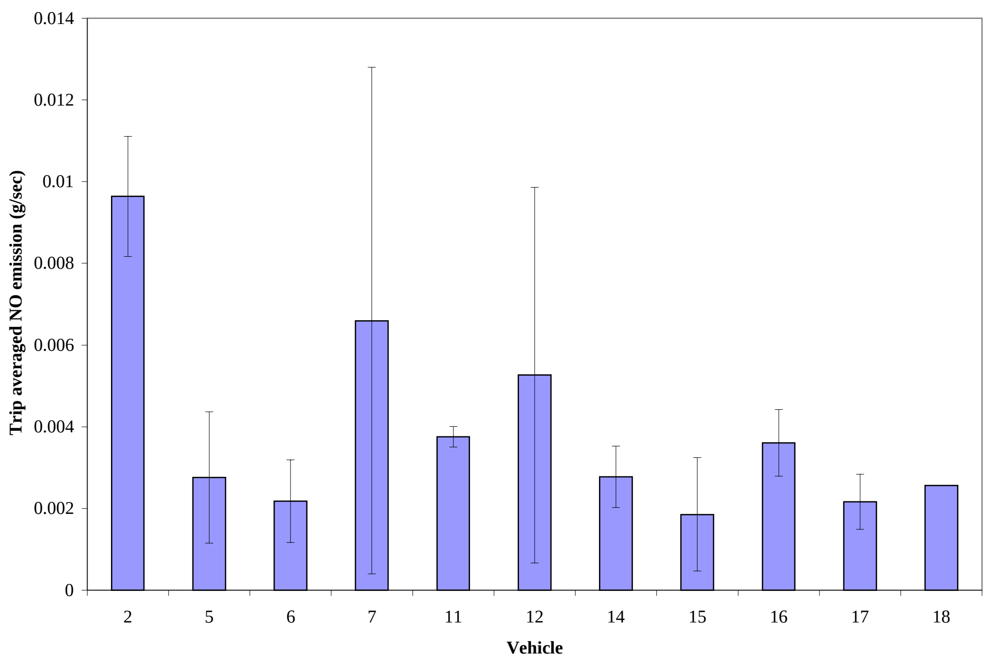
Vehicle No	16					
Trips	*Trip4*	*Trip5*	*Trip6*	*Trip7*	*Trip8*	*Trip9*
Vehicle Characteristics						
Plate No	278EAT					
Vehicle Make	CHEVROLET					
Vehicle Model	CAVLIER					
Vehicle Model Year	1998					
Engine Displacement	2.2					
Transmission Type	AUTO					
GVWR	N/A					
Vehicle Operation						
Average Speed (mph)	18.3	23.4	26.5	34.6	11.7	8.1
Acceleration						
Average Engine Load (%)	27	30	30	31	28	22
Average RPM	1283	1543	1514	1807	1044	918
Average Torque (ftlbs)	0	0	0	0	0	0
Average Throttle (%)	5	9	8	10	5	3
Average Inlet Air Temperature (F)	29	19	28	17	35	35
Average Coolant Temperature (F)	70	62	70	75	78	85
Average MAF (g/sec)	N/A	N/A	N/A	N/A	N/A	N/A
Average Exhaust Temp (F)	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	44	46	47	46	46	39
Average Fuel (lb/sec)	0.0013	0.0018	0.0016	0.0020	0.0011	0.0008
Average Power Demand (s*a)	1.14	1.46	2.10	1.13	1.34	0.61
Average KE (s^2*a)	33.2	63.3	48.1	53.2	44.4	16.7
Average HC (g/sec)	0.0024	0.0025	0.0028	0.0025	0.0029	0.0018
Average CO (g/sec)	0.0943	0.0932	0.1048	0.1162	0.0588	0.0300
Average CO2 (g/sec)	1.6531	2.4247	2.1181	2.6704	1.4192	1.0454
AverageNO (g/sec)	0.0028	0.0046	0.0021	0.0042	0.0043	0.0017
Environmental Characteristics						
Average Ambient Temperature (C)	26.0	21.8	29.8	21.6	23.0	23.3
Average Ambient Pressure (kPA)	99.1	99.1	99.1	99.1	99.1	99.1
Average Humidity (%)	25	37	29	41	36	39
Roadway Characteristics						
Average Latitude (degree)	42.30	42.30	42.31	42.31	42.30	42.30
Average Longitude (degree)	-83.27	-83.31	-83.32	-83.45	-83.71	-83.71
Average Altitude (feet)	655	645	661	721	929	944
Average Grade (%)	-0.133	0.014	-0.037	0.115	0.000	-0.206
Time of Day	0:12:04	0:25:43	0:47:01	0:34:19	0:54:31	0:23:43
Day of Week	9/14	9/15	9/15	9/17	9/17	9/17
Number of Seconds of Data	692	1217	1063	2903	416	894

A2. Summary Table for LDGV Vehicles

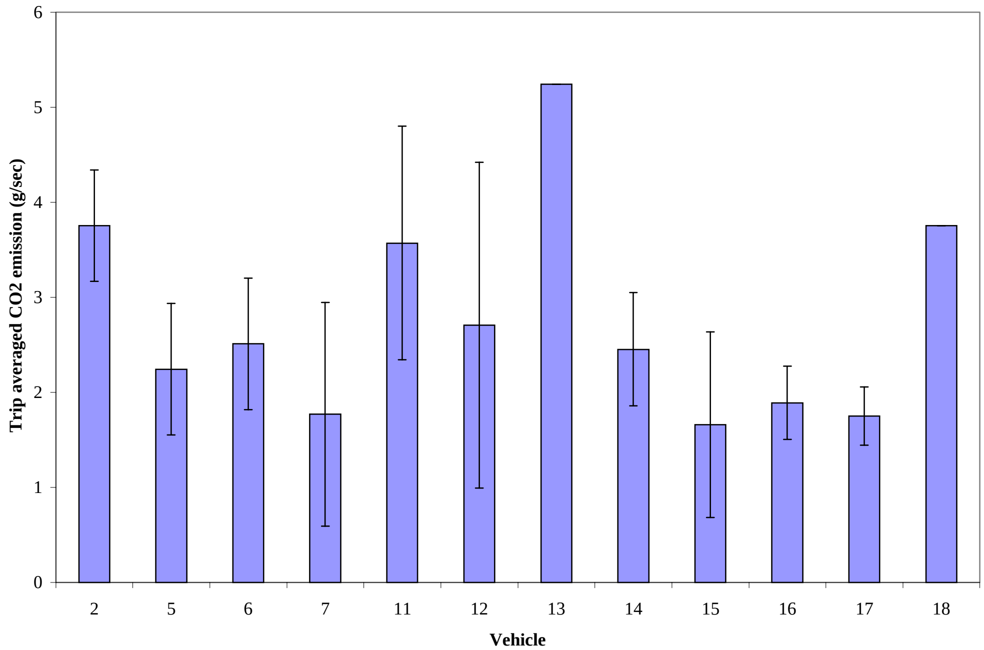
Vehicle No	17					18
Trips	*Trip1*	*Trip2*	*Trip3*	*Trip4*	*Trip5*	*Trip1*
Vehicle Characteristics						
Plate No	5ML10					8BDU58
Vehicle Make	MERCURY					FORD
Vehicle Model	MYSTIQUE SPORT					TAURUS GL
Vehicle Model Year	1998					1996
Engine Displacement	2					3
Transmission Type	MANUAL					AUTO
GVWR	4078					4707
Vehicle Operation						
Average Speed (mph)	7.0	23.9	20.2	21.6	15.4	15.0
Acceleration						
Average Engine Load (%)	22	26	24	23	21	26
Average RPM	1389	1908	1693	1751	1505	1149
Average Torque (ftlbs)	0	0	0	0	0	0
Average Throttle (%)	0	0	0	0	0	0
Average Inlet Air Temperature (F)	N/A	N/A	N/A	N/A	N/A	N/A
Average Coolant Temperature (F)	130	165	194	192	203	202
Average MAF (g/sec)	624	1039	814	834	687	932
Average Exhaust Temp (F)	0	0	0	0	0	0
Average Intake Manifold Absolute Pressure (Hg)	0	0	0	0	0	0
Average Fuel (lb/sec)	0.0010	0.0016	0.0013	0.0013	0.0010	0.0014
Average Power Demand (s*a)	1.04	1.17	0.96	0.83	1.11	0.64
Average KE (s^2*a)	27.4	40.7	32.3	30.1	35.2	22.6
Average HC (g/sec)	0.0035	0.0022	0.0009	0.0004	0.0002	0.0008
Average CO (g/sec)	0.0505	0.0244	0.0109	0.0101	0.0091	0.0154
Average CO2 (g/sec)	1.3407	2.2409	1.8460	1.8253	1.4976	2.0495
AverageNO (g/sec)	0.0030	0.0030	0.0019	0.0013	0.0016	0.0025
Environmental Characteristics						
Average Ambient Temperature (C)	28.0	21.1	21.0	30.2	32.0	27.5
Average Ambient Pressure (kPA)	99.0	99.0	99.0	99.0	99.0	99.0
Average Humidity (%)	27	35	37	32	32	47
Roadway Characteristics						
Average Latitude (degree)	42.30	42.28	42.27	42.27	42.29	42.26
Average Longitude (degree)	-83.71	-83.71	-83.73	-83.70	-83.73	-83.71
Average Altitude (feet)	934	877	896	889	922	887
Average Grade (%)	-0.948	0.058	-0.193	2.506	-0.110	-0.089
Time of Day	16:18:25	21:16:46	21:51:08	14:13:04	14:42:44	14:00:09
Day of Week	9/14	9/14	9/14	9/17	9/17	9/19
Number of Seconds of Data	230	733	695	2075	1216	4249

A3. Inter-Vehicle Variability for HC, NO, and CO_2 Emissions

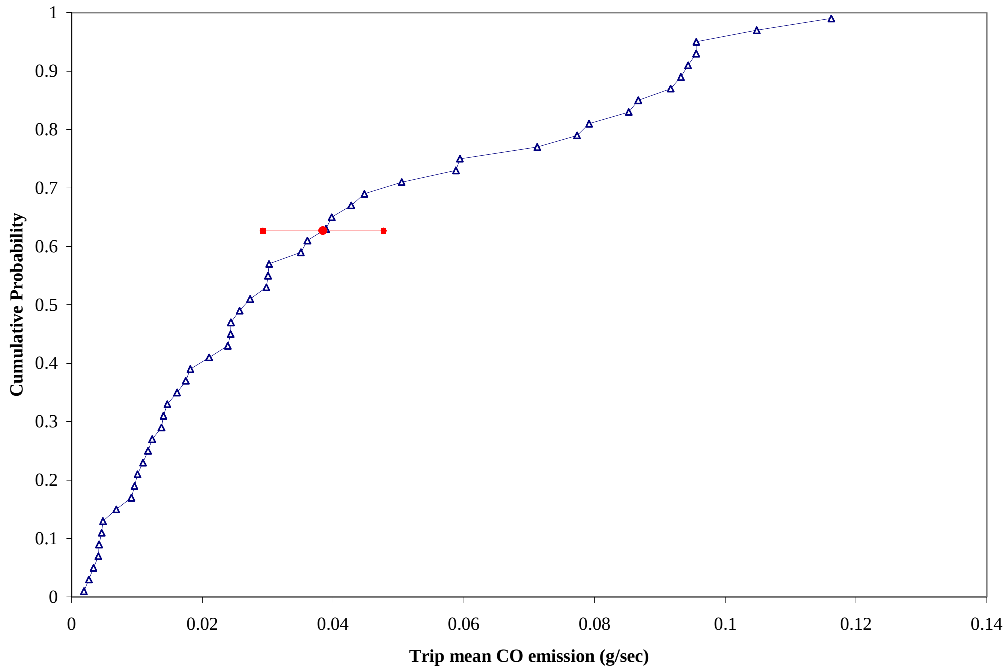


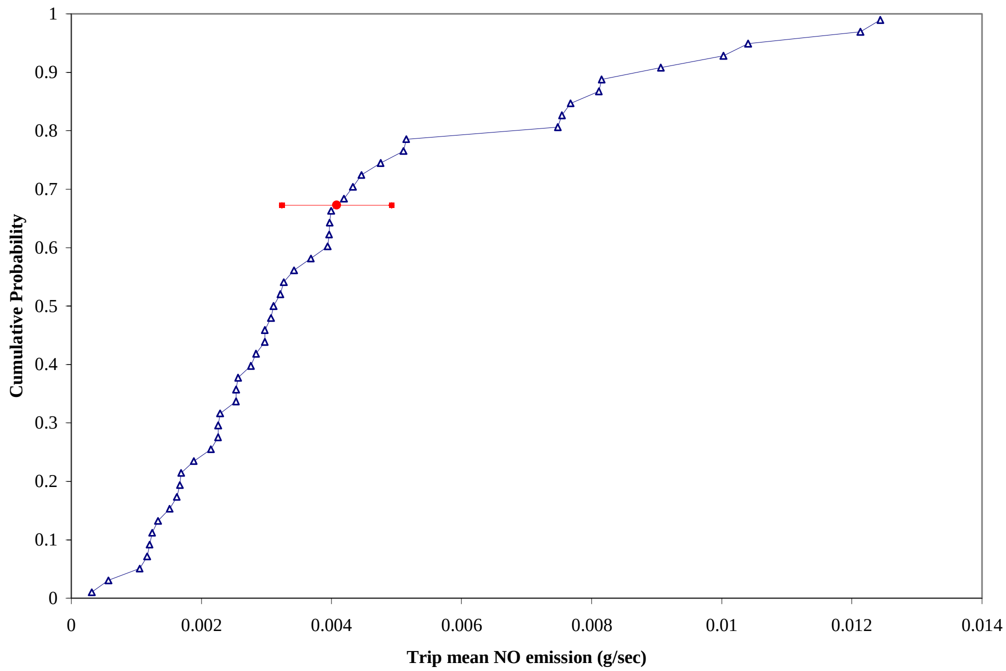


A3. Inter-Vehicle Variability for HC, NO, and CO_2 Emissions

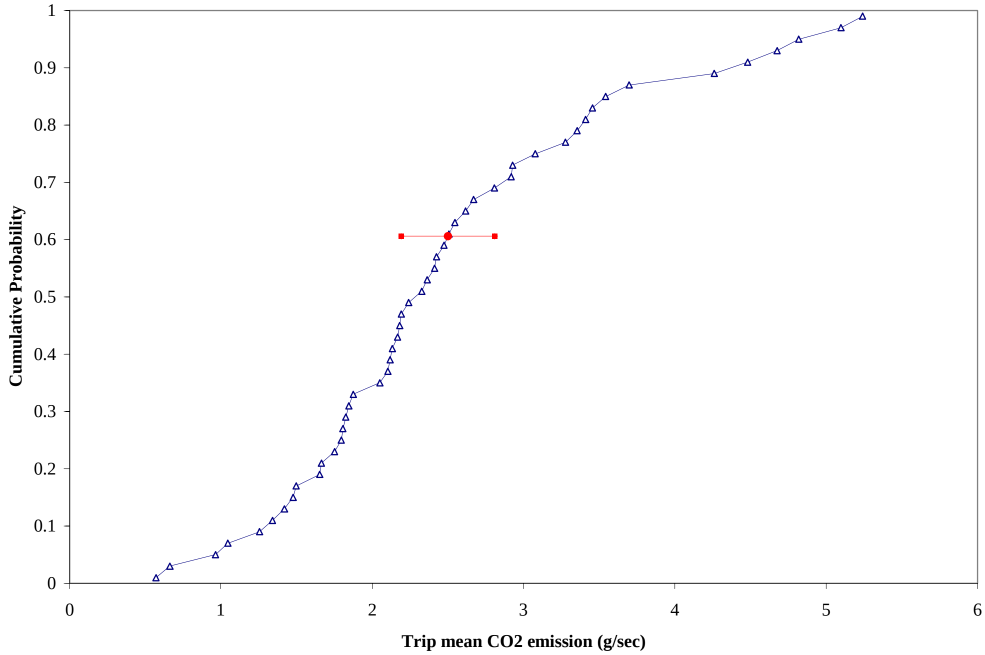


A4. Inter-Trip Variability for CO, NO, and CO_2 Emissions

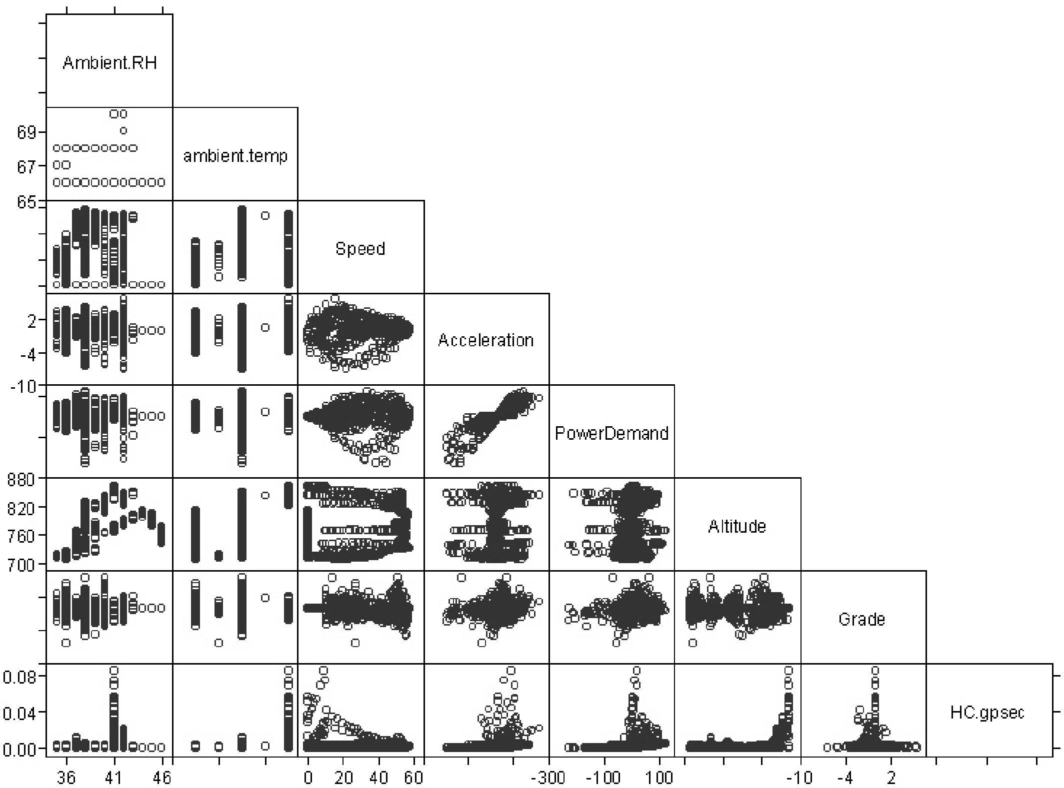




A4. Inter-Trip Variability for CO, NO, and CO_2 Emissions

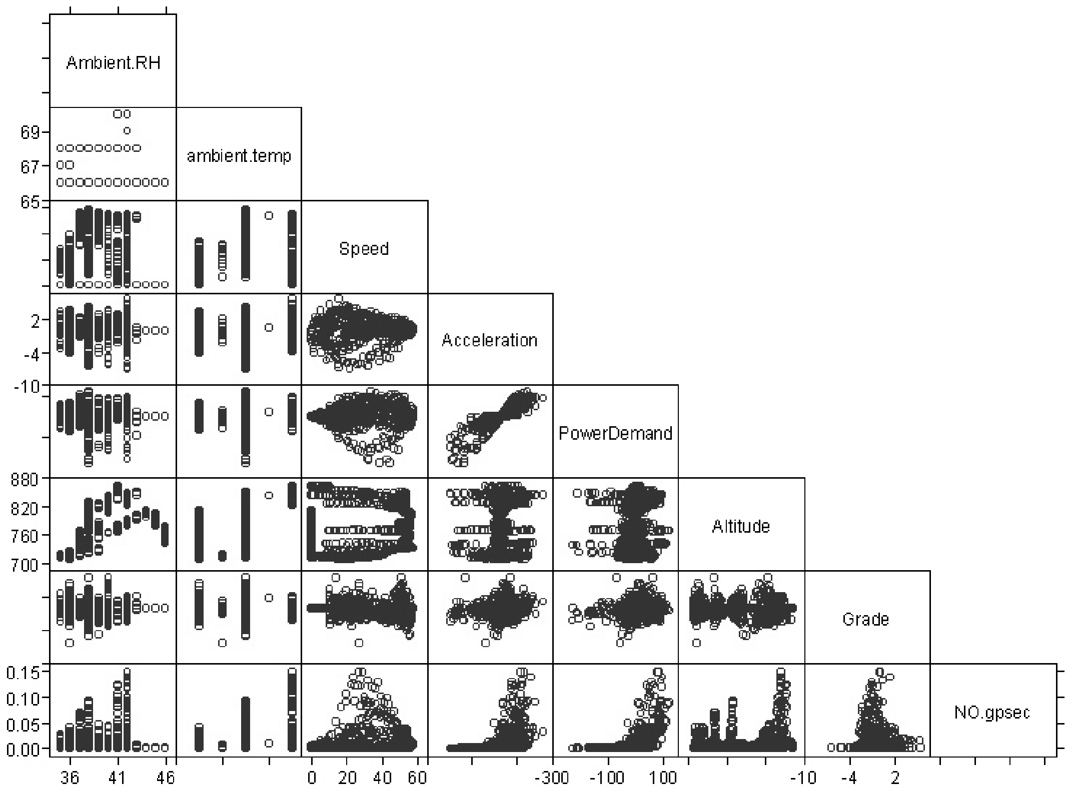


A5. Scatter Matrices for CO, NO, and CO_2 for Vehicle 2



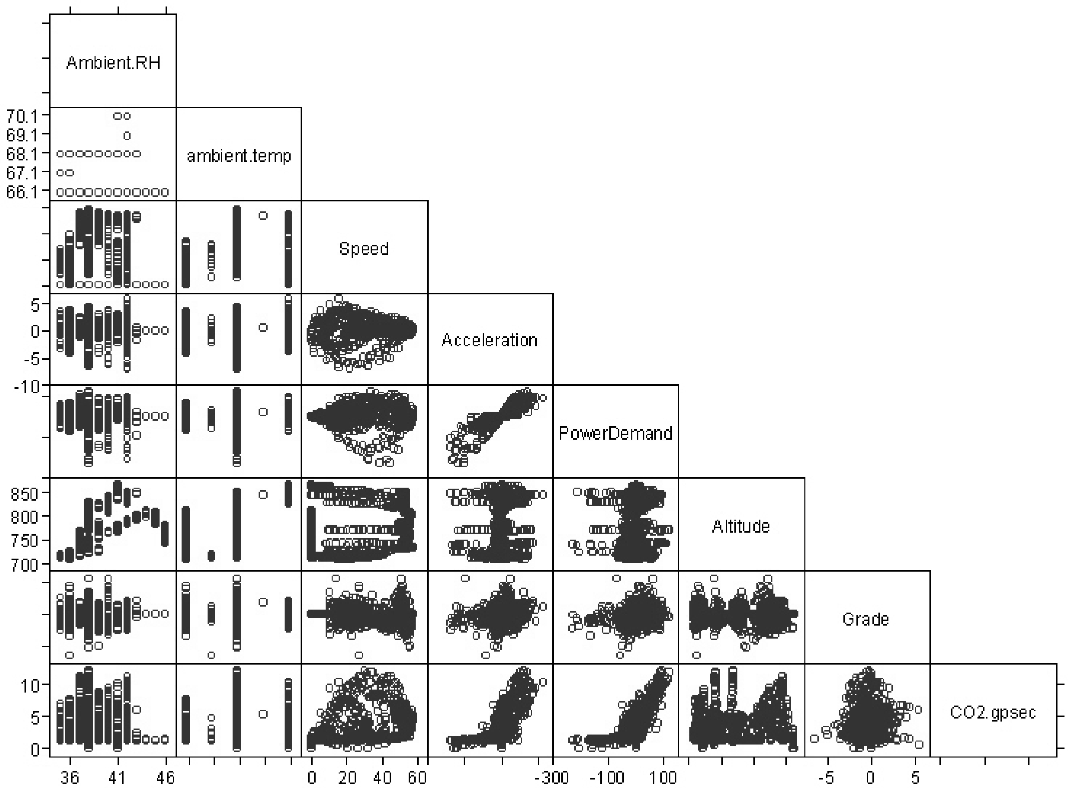
Example Scatter Matrix for HC Emissions for Data Collected with Vehicle 2

A5. Scatter Matrices for CO, NO, and CO_2 for Vehicle 2



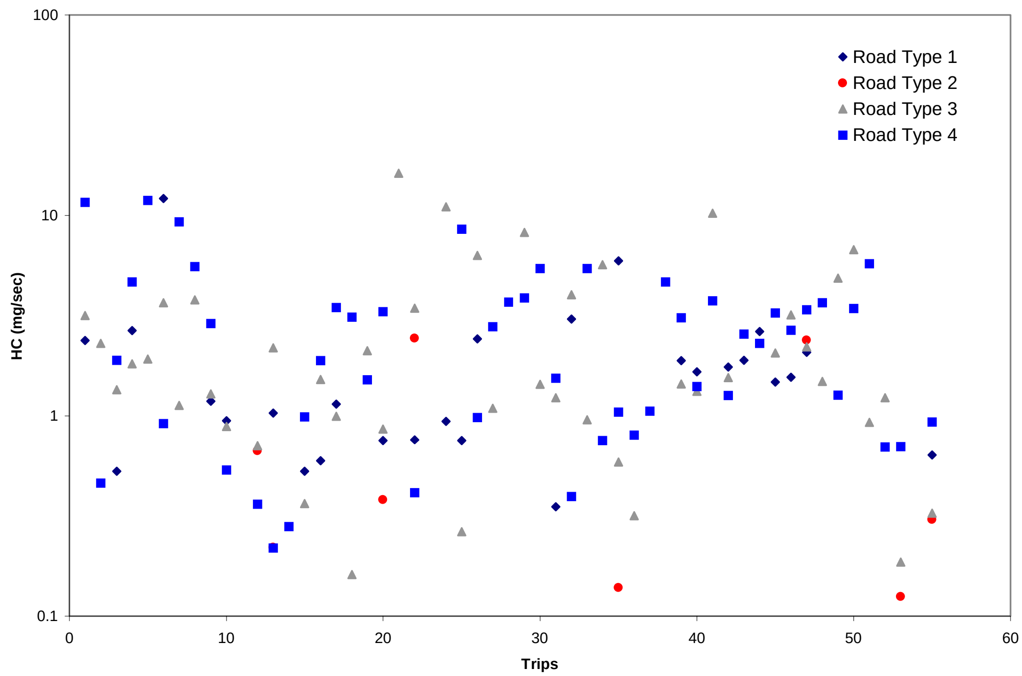
Example Scatter Matrix for NO Emissions for Data Collected with Vehicle 2

A5. Scatter Matrices for CO, NO, and CO_2 for Vehicle 2

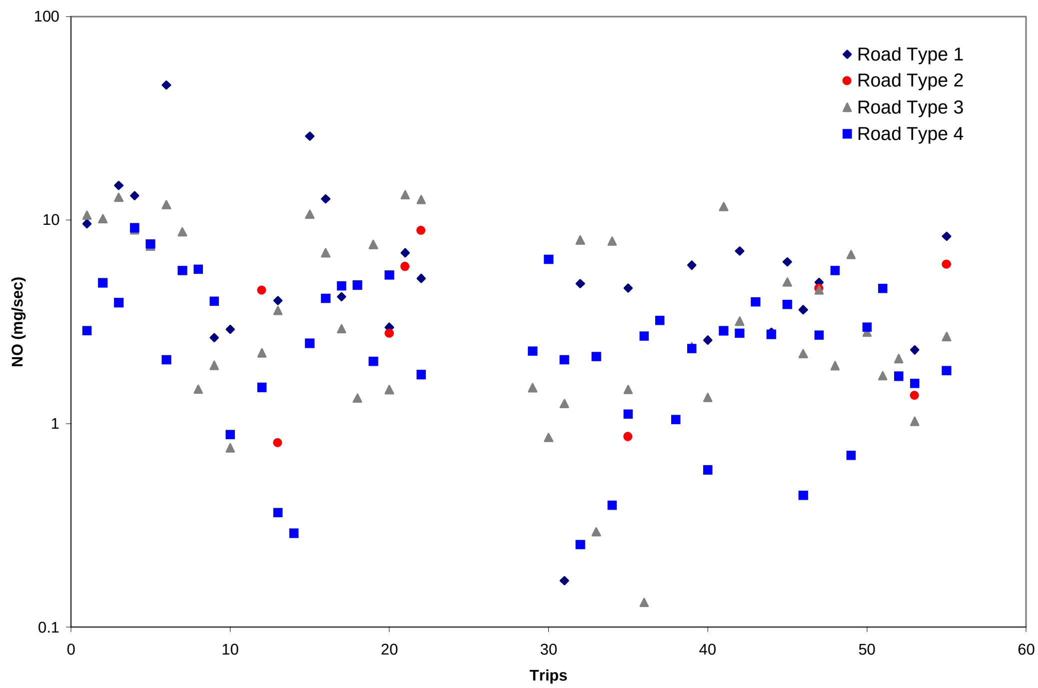


Example Scatter Matrix for CO_2 Emissions for Data Collected with Vehicle 2

A6. Spatial Analysis for NO and HC Emissions

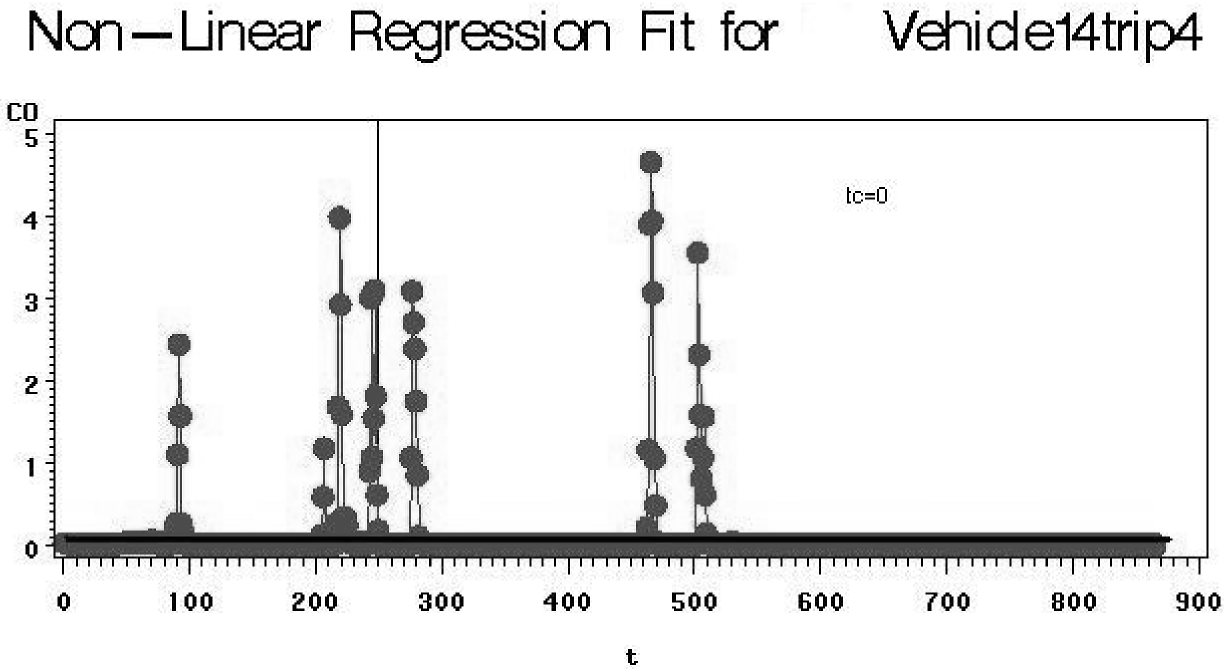


Summary for Average HC Emission Rate for Different Roadway Types



Summary for Average NO Emission Rate for Different Roadway Types

A7. Cold-Start Identification Example



Non-Linear Regression Fit for Vehicle14trip4
CO
5
4
3
2
1
0
tc=0
0
100
200
300
400
500
600
700
800
900
t

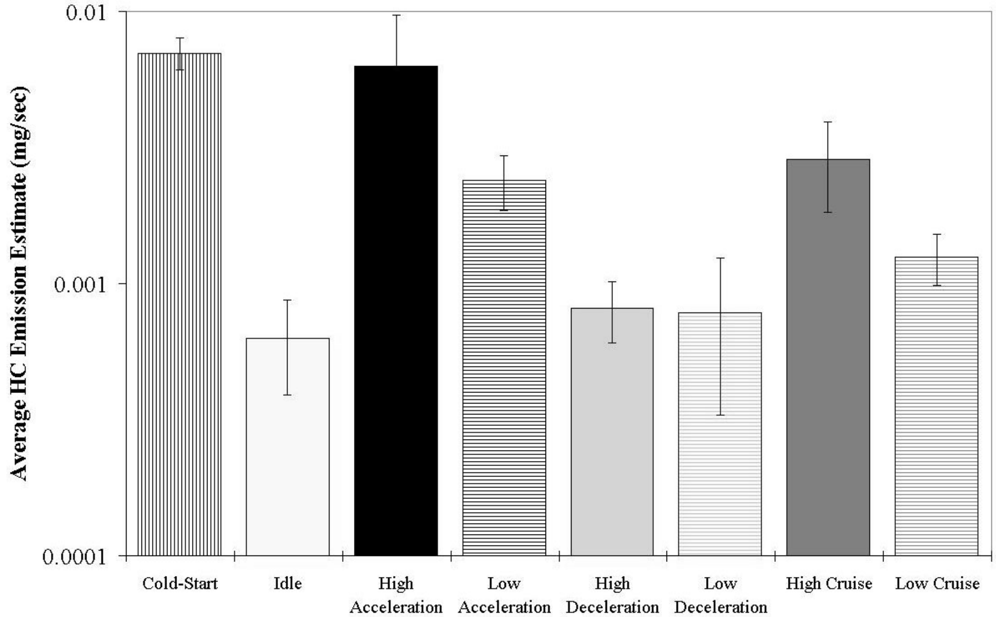
A8. Summary Table for Cold-Start Duration

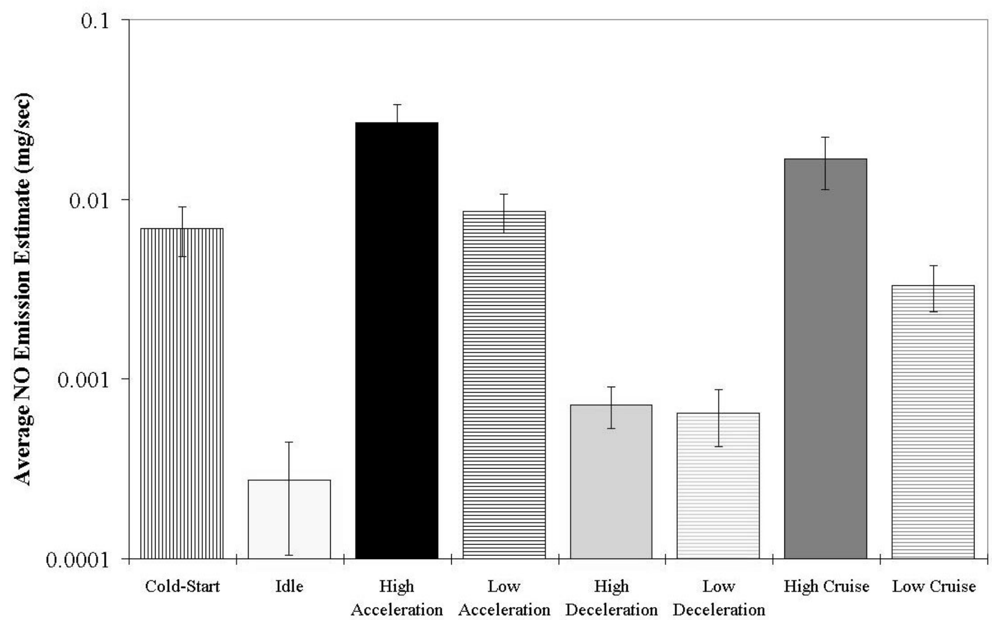
Vehicle	Trip	Cold-Start	Duration (Seconds)
2	1	Yes	199
	2	Yes	200
	3	Yes	85
	4	Yes	118
	5	Yes	188
	6	Yes	75
	7	Yes	233
5	1	No	
	2	Yes	216
	3	No	
6	1	No	
	2	Yes	111
	3	Yes	113
7	1	Yes	135
	2	Yes	329
	3	Yes	214
11	1	Yes	115
	2	Yes	183
	3	Yes	125
	4	Yes	97
12	1	Yes	76
	2	Yes	143
	3	Yes	102
13	1	Yes	109

A8. Summary Table for Cold-Start Duration

Vehicle	Trip	Cold-Start	Duration (Seconds)
14	1	No	
	2	No	
	3	No	
	4	No	
	5	Yes	121
	6	No	
	7	No	
	8	No	
	9	No	
15	1	Yes	137
	2	Yes	221
	3	Yes	228
16	1	Yes	90
	2	No	
	3	No	
	4	Yes	200
	5	Yes	111
	6	No	
	7	No	
	8	Yes	235
	9	No	
17	1	Yes	88
	2	Yes	241
	3	Yes	98
	4	Yes	159
	5	No	
18	1	Yes	391

A9. Improved Modal Rates for HC, NO, and CO_2





A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent of Time spent in each mode							
		Cold start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
2	1	10	13	0	13	10	2	0	53
	2	12	13	1	18	13	2	0	41
	3	0	4	0	9	9	1	1	76
	4	6	2	0	6	4	1	1	80
	5	17	3	0	15	8	2	0	54
	6	6	17	0	15	10	3	0	49
	7	20	6	0	16	10	2	0	46
5	1	0	33	0	19	13	1	0	34
	2	14	9	1	13	11	3	0	50
	3	0	21	1	19	16	1	0	42
6	1	0	31	1	29	22	0	0	17
	2	0	16	0	19	16	2	0	46
	3	4	16	0	18	11	1	0	51
7	1	0	17	0	21	18	0	0	44
	2	0	12	0	18	13	1	0	56
	3	0	10	0	20	15	3	0	52
11	1	5	9	1	11	10	2	2	61
	2	29	16	0	14	13	0	0	27
	3	21	14	0	16	17	1	0	30
	4	3	5	1	10	8	1	2	70
12	1	3	1	1	11	11	1	0	73
	2	3	7	3	18	16	4	1	48
	3	0	44	0	19	7	0	0	30
13	1	12	8	1	13	9	2	0	55
14	1	35	26	0	13	12	1	0	12
	2	7	31	2	20	20	1	0	19
	3	0	25	1	22	22	1	0	29
	4	0	12	3	18	17	3	1	46
	5	29	18	0	16	14	0	0	22
	6	45	2	0	16	15	0	0	22
	7	11	21	2	16	16	1	0	32
	8	0	43	0	21	18	0	0	17
	9	69	14	0	1	1	0	0	16
15	1	63	9	0	1	13	0	0	14
	2	9	21	1	14	13	1	0	41
	3	9	15	0	13	13	0	0	50

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent of Time spent in each mode							
		Cold start	Idle	High Accelera tion	Low Accelera tion	High Decelera tion	Low Decelera tion	High Cruise	Low Cruise
16	1	36	10	0	14	13	1	0	26
	2	4	13	1	17	16	2	1	46
	3	0	15	1	16	17	1	0	51
	4	0	18	0	17	18	0	0	47
	5	7	21	1	19	15	2	0	35
	6	29	6	0	16	13	1	0	35
	7	18	7	0	16	11	2	0	46
	8	0	42	1	11	12	2	0	31
	9	0	49	0	15	16	1	0	20
17	1	38	19	0	15	18	1	0	10
	2	33	2	0	14	12	1	0	38
	3	0	9	0	17	23	0	0	51
	4	0	19	1	19	18	0	0	44
	5	0	26	1	18	21	1	0	33
18	1	0	40	0	14	13	1	0	32

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip CO emissions Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
2	1	7	0	0	30	2	0	2	58
	2	33	0	1	36	3	0	0	27
	3	0	1	0	11	2	0	2	84
	4	8	0	3	12	1	0	1	76
	5	50	0	0	16	1	0	0	33
	6	16	1	2	45	2	0	0	35
	7	37	0	0	23	1	0	0	39
5	1	0	21	0	35	10	0	0	35
	2	78	1	0	5	2	0	0	14
	3	0	5	1	54	9	1	0	30
6	1	0	18	1	59	10	0	0	12
	2	0	2	0	27	6	2	0	63
	3	68	2	0	12	2	0	0	15
7	1	0	2	0	59	4	0	0	35
	2	0	3	0	38	7	0	0	52
	3	0	1	1	32	8	0	0	58
11	1	5	0	2	12	1	0	19	62
	2	86	0	1	8	0	0	0	3
	3	83	0	0	10	1	0	0	5
	4	9	4	16	28	1	0	2	39
12	1	13	0	8	22	3	0	0	54
	2	9	0	28	17	3	2	4	37
	3	0	18	0	50	4	0	0	29
13	1	41	0	29	15	0	0	0	15
14	1	38	2	0	31	26	0	0	3
	2	27	1	50	9	8	0	0	5
	3	0	2	13	65	6	0	0	14
	4	0	0	55	30	0	0	5	10
	5	90	2	0	4	1	0	0	2
	6	96	0	0	1	0	0	0	2
	7	1	0	74	11	1	2	0	11
	8	0	21	0	42	18	0	0	19
	9	0	25	0	3	3	0	0	70
15	1	91	1	0	1	3	0	0	4
	2	24	4	5	26	6	0	0	34
	3	42	4	0	14	5	0	0	36

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip CO emissions							
		Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
16	1	47	5	0	31	5	0	0	12
	2	7	0	7	29	4	1	1	51
	3	0	1	3	38	7	0	0	51
	4	0	2	0	33	3	0	0	62
	5	8	5	3	42	4	0	0	38
	6	38	0	1	26	3	0	0	32
	7	26	0	1	22	3	0	0	47
	8	0	1	16	34	6	1	0	42
	9	0	5	0	58	7	0	0	29
17	1	69	4	0	12	10	0	0	5
	2	66	0	0	7	6	0	0	21
	3	0	2	0	24	29	0	0	45
	4	0	4	2	47	10	0	0	36
	5	0	2	12	55	10	0	0	21
18	1	0	6	9	41	6	0	0	39

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip HC emissions							
		Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
2	1	39	2	2	0	0	39	0	16
	2	59	1	3	0	0	18	1	18
	3	0	13	4	0	1	58	0	24
	4	15	1	1	0	1	73	1	8
	5	62	0	1	0	0	23	0	13
	6	23	5	5	1	0	36	1	30
	7	60	1	2	0	0	22	0	14
5	1	0	30	8	0	0	29	0	33
	2	58	1	7	0	0	26	1	7
	3	0	11	10	1	0	35	2	42
6	1	0	40	4	0	0	20	0	35
	2	0	1	7	2	0	63	1	26
	3	26	2	4	0	0	47	0	20
7	1	0	4	5	0	0	43	0	49
	2	0	1	5	0	1	64	0	28
	3	0	1	8	1	0	60	1	29
11	1	22	1	3	1	6	51	2	13
	2	94	0	0	0	0	2	1	3
	3	93	0	1	0	0	3	0	3
	4	15	7	4	0	2	46	4	23
12	1	78	0	1	0	0	13	2	7
	2	22	1	5	2	2	40	9	19
	3	0	32	6	0	0	28	0	34
13	1	73	0	0	0	0	17	3	6
14	1	47	10	8	0	0	9	0	26
	2	23	5	7	0	0	8	32	25
	3	0	8	12	0	0	29	4	46
	4	0	1	6	1	2	33	28	29
	5	65	9	4	0	0	7	0	15
	6	87	0	2	0	0	7	0	5
	7	17	1	6	6	1	24	32	13
	8	0	37	13	0	0	17	0	33
	9	0	23	3	0	0	72	0	3
15	1	75	4	7	0	0	12	0	1
	2	23	13	9	0	0	31	3	20
	3	34	10	9	0	0	34	0	13

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip HC emissions							
		Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
16	1	41	5	7	0	0	16	0	30
	2	8	1	8	1	1	53	3	25
	3	0	1	9	1	0	50	4	34
	4	0	5	6	0	0	56	0	34
	5	13	16	6	0	0	29	2	33
	6	46	0	6	0	0	26	1	20
	7	31	1	4	0	0	38	1	24
	8	0	6	33	3	0	21	10	26
	9	0	12	16	1	0	28	0	43
17	1	66	6	10	0	0	4	0	14
	2	72	0	5	0	0	15	0	8
	3	0	2	27	0	0	41	1	29
	4	0	9	12	0	0	33	3	44
	5	0	4	18	0	0	33	2	42
18	1	0	26	8	0	0	35	2	29

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip NO emissions							
		Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
2	1	12	0	0	42	1	0	1	43
	2	28	0	3	45	2	0	0	22
	3	0	0	0	17	1	0	2	79
	4	7	0	2	13	0	0	1	76
	5	22	0	0	43	1	0	0	35
	6	14	0	3	51	1	0	0	30
	7	15	0	0	47	1	0	0	36
5	1	0	34	0	34	6	0	0	26
	2	56	0	1	11	2	0	0	30
	3	0	1	5	39	3	0	0	52
6	1	0	2	0	70	14	0	0	13
	2	0	1	0	28	5	0	0	66
	3	12	0	0	25	1	0	0	61
7	1	0	0	0	66	1	0	0	33
	2	0	0	0	20	1	0	1	77
	3	0	0	1	25	3	0	1	70
11	1	3	0	8	25	1	0	7	56
	2	70	0	5	19	0	0	0	6
	3	74	0	0	23	0	0	0	3
	4	7	1	10	33	1	0	3	45
12	1	6	0	2	22	3	0	0	66
	2	6	0	12	24	3	1	3	51
	3	0	60	0	31	0	0	0	9
13	1	0	0	0	0	0	0	0	0
14	1	71	1	0	24	2	0	0	2
	2	5	0	54	34	3	1	0	4
	3	0	0	18	63	4	0	0	14
	4	0	0	30	34	2	0	2	31
	5	75	1	0	21	1	0	0	2
	6	83	0	0	14	0	0	0	3
	7	2	1	31	36	2	0	1	27
	8	0	26	0	43	13	0	0	18
	9	0	16	0	4	2	0	0	79
15	1	81	1	0	1	9	0	0	8
	2	5	1	9	38	3	0	1	42
	3	12	2	0	28	2	0	0	56

A10. Modal Distribution for Time and Emissions for Each Trip

Vehicle	Trip	Percent Contribution of each mode to the total trip NO emissions							
		Cold Start	Idle	High Acceleration	Low Acceleration	High Deceleration	Low Deceleration	High Cruise	Low Cruise
16	1	51	2	0	28	6	0	0	12
	2	3	1	5	24	4	1	3	60
	3	0	0	7	39	4	0	0	50
	4	0	0	0	43	6	0	0	51
	5	1	2	6	59	2	0	0	29
	6	50	0	1	29	1	0	0	18
	7	14	0	1	28	3	0	0	53
	8	0	7	10	56	4	1	0	22
	9	0	2	0	44	7	0	0	47
17	1	49	1	0	37	3	0	0	9
	2	29	0	0	42	2	0	0	26
	3	0	0	2	82	3	0	0	13
	4	0	1	10	63	2	0	0	24
	5	0	1	10	70	4	0	0	15
18	1	0	2	6	55	3	0	0	33

A11. Regression Coefficients for NO, HC, and CO_2

HC (g/sec)	VEHICLE OPERATION MODES						
Variable	Idle	High Accel	Low Accel	High Decel.	Low Decel.	High Cruise	Low Cruise
Intercept	2.7209	5.3221	-3.1842	-1.1931	5.8948	3.3304	2.2967
Engine	-0.6447	0.7530	0.4903	0.1930	0	0	0.5236
Humidity	0	-0.1096	-0.0513	-0.0571	-0.0647	-0.0993	-0.0816
Speed	0	0	0.1704	0.0257	0	0	0
Speed^2	0	0	-0.0050	0	-0.0024	0	0
Speed^3	0	0	0	0	0	0	0
Accel	0	0	0	-0.1809	0	0	-0.2969
Accel^2	0	0	0.0315	0	0	0	0
Accel^3	0	0	0	0	0	0	0
Temperature	-0.1133	-0.1536	-0.0795	-0.1116	-0.1480	-0.1079	-0.1138
Altitude	-0.0018	0	0.0005	0.0022	0	0	-0.0009
Grade	0	-0.0998	-0.1114	-0.0341	0.1009	0	0
AC	-1.3377	-1.8764	0	0.0063	-0.0042	0	0.0179
Power	0	0.0235	0	0.0150	0	0	0.0175
R-square	0.11	0.32	0.13	0.10	0.15	0.09	0.13
Correction Factor	4.9	1.6	5.1	5.4	5.7	2.3	3.1

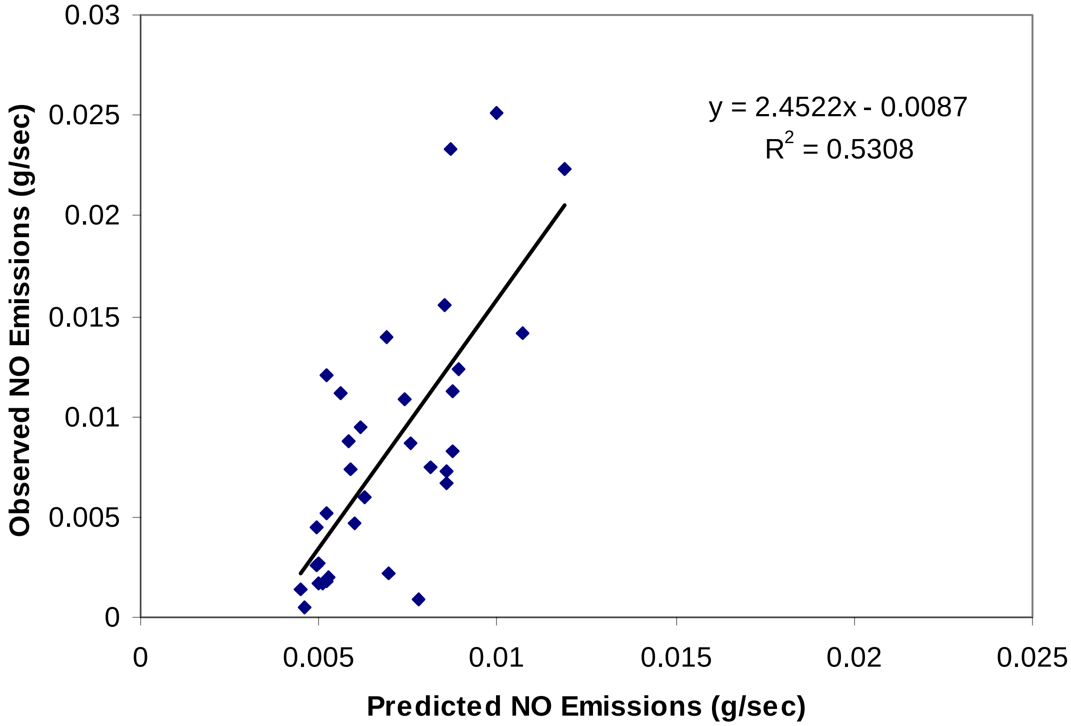
A11. Regression Coefficients for NO, HC, and CO_2

NO (g/sec)	VEHICLE OPERATION MODES						
Variable	Idle	High Accel.	Low Accel	High Decel	Low Decel	High Cruise	Low Cruise
Intercept	-1.4948	-2.9406	-6.5540	-8.6858	-2.8185	-14.6792	-7.2351
Engine	-0.8238	0.3420	0.1394	-0.1532	-0.6727	0.7794	-0.2111
Humidity	-0.0298	0	-0.0157	-0.0100	-0.0340	-0.0246	-0.0152
Speed	0	0	0.1326	0	0	0.0692	0.0105
Speed^2	0	0	-0.0010	0.0006	0	0	0.0010
Speed^3	0	0	0	0	0	0	0
Accel	0	0	0.2226	0	0	0	0.2233
Accel^2	0	0	0.1886	0	0	0	-0.1633
Accel^3	0	0.0007	-0.0270	-0.0023	0	0	-0.1431
Temperature	-0.0481	-0.0233	-0.0316	0	-0.0516	0	-0.0243
Altitude	-0.0011	0	0	0.0007	0.0013	0.0045	0
Grade	0	-0.1044	-0.1279	0	0.0441	0	0
AC	0.5548	0	0	0	-0.0048	0.0157	0
Power	0	0	0	0.0053	0	0	0
R-square	0.07	0.21	0.34	0.17	0.30	0.40	0.40
Correction Factor	2.4	1.5	1.8	2.4	2.7	1.5	12.0

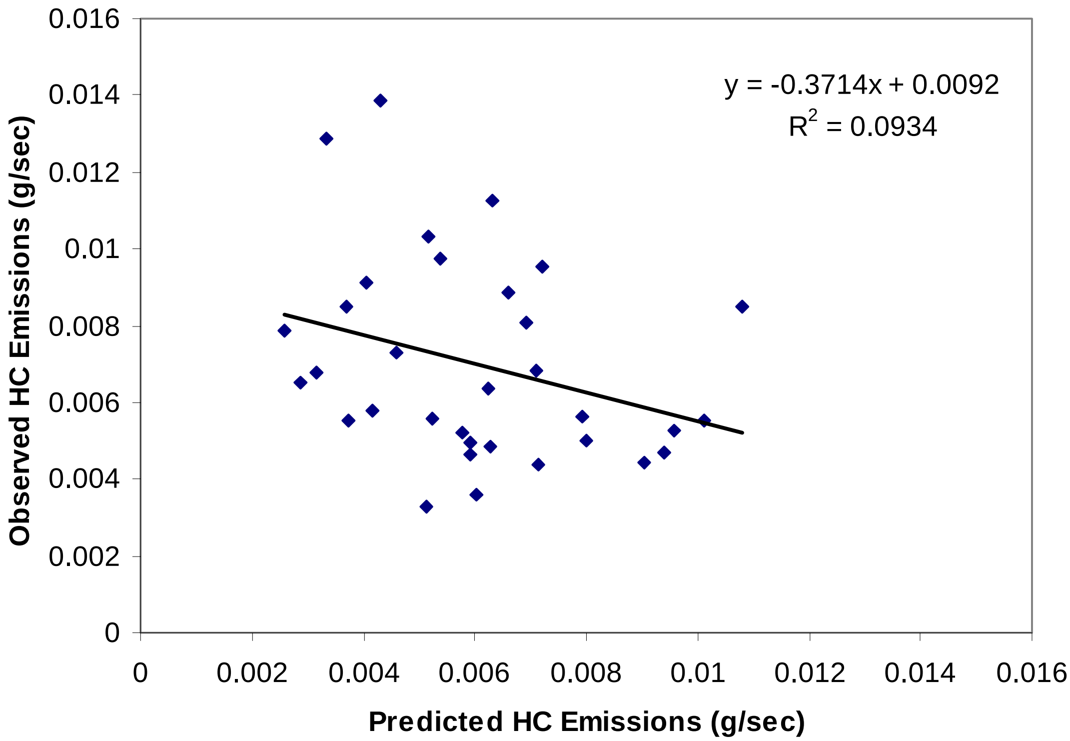
A11. Regression Coefficients for NO, HC, and CO_2

CO_2 (g/sec)	VEHICLE OPERATION MODES			
Variable	Idle	Acceleration	Deceleration	Cruise
Intercept	0.3075	-1.8379	0.6547	-1.4386
Engine	0.3529	1.7448	0.4242	0.6874
Humidity	-0.0021	0	0	-0.0054
Speed	0	0.0197	0.0325	0.0722
Speed^2	0	0.0010	-0.0007	0
Speed^3	0	0	0	0
Accel	0	0.4673	0.3763	0.6337
Accel^2	0	0	0.1046	0.1524
Accel^3	0	0	0.007	-0.4685
Temperature	0	-0.0255	-0.0062	-0.0105
Altitude	-0.0002	0.0006	0	0.0011
Grade	0	-0.2344	-0.0182	0
AC	0.2075	0.2621	0.2236	0.2673
Power	0	0.0532	0.0049	0.0273
R-square	0.48	0.72	0.42	0.71

A12. Comparison of Cold-Start Emissions for NO and HC



y = 2.4522x - 0.0087
R2 = 0.5308
Observed NO Emissions (g/sec)
Predicted NO Emissions (g/sec)
0
0.005
0.01
0.015
0.02
0.025
0.03

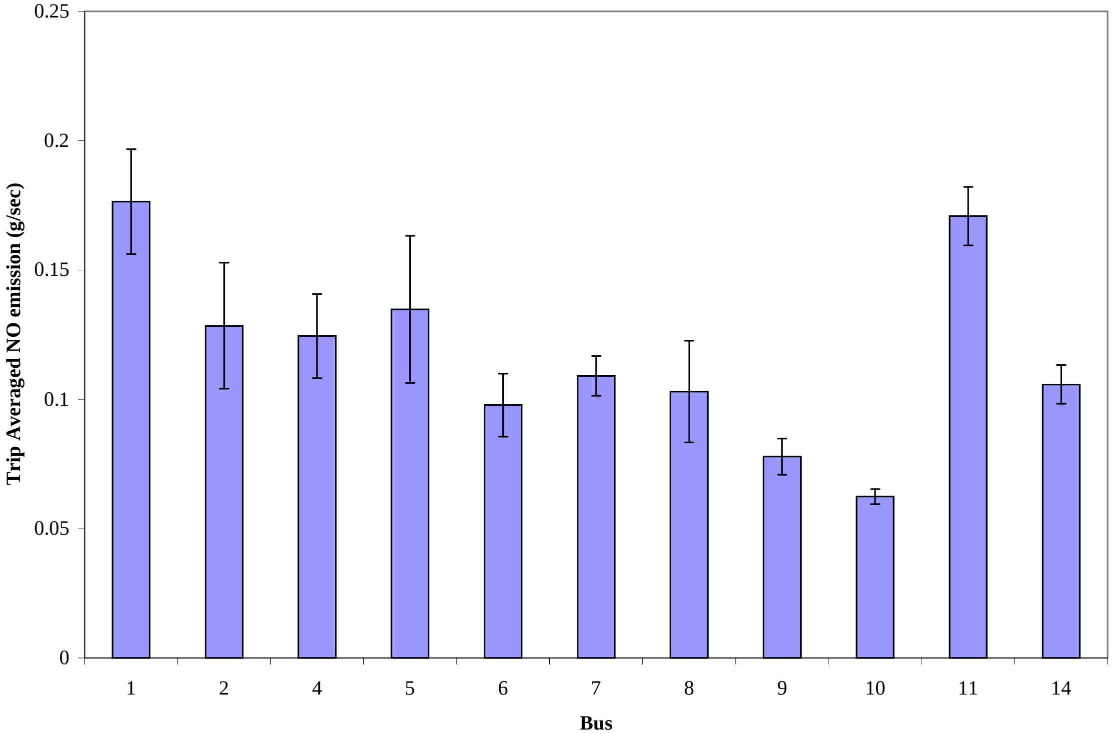


y = -0.3714x + 0.0092
R2 = 0.0934
Observed HC Emissions (g/sec)
Predicted HC Emissions (g/sec)
0
0.002
0.004
0.006
0.008
0.01
0.012
0.014
0.016

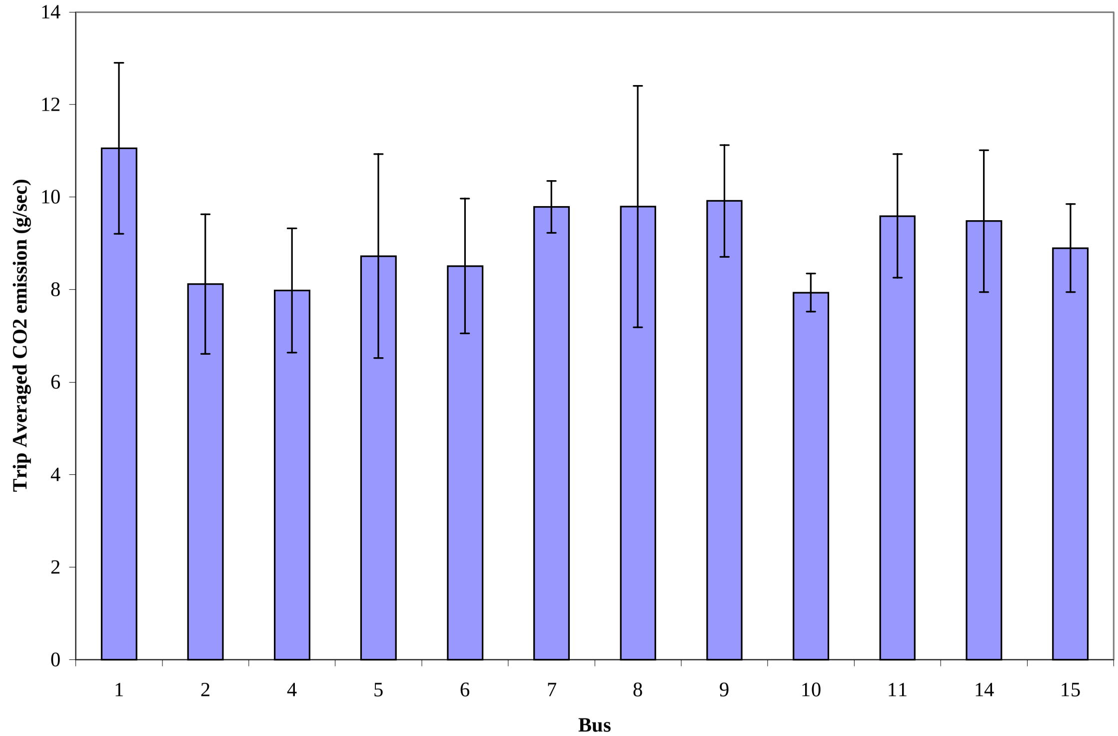
APPENDIX B

- **Inter-Vehicle Variability for NO, HC, and CO_2 Emissions**
- **Inter-Trip Variability for NO, CO, and CO_2 Emissions**
- **Regression Coefficients for CO and CO_2**
- **Mass Balance Equations**

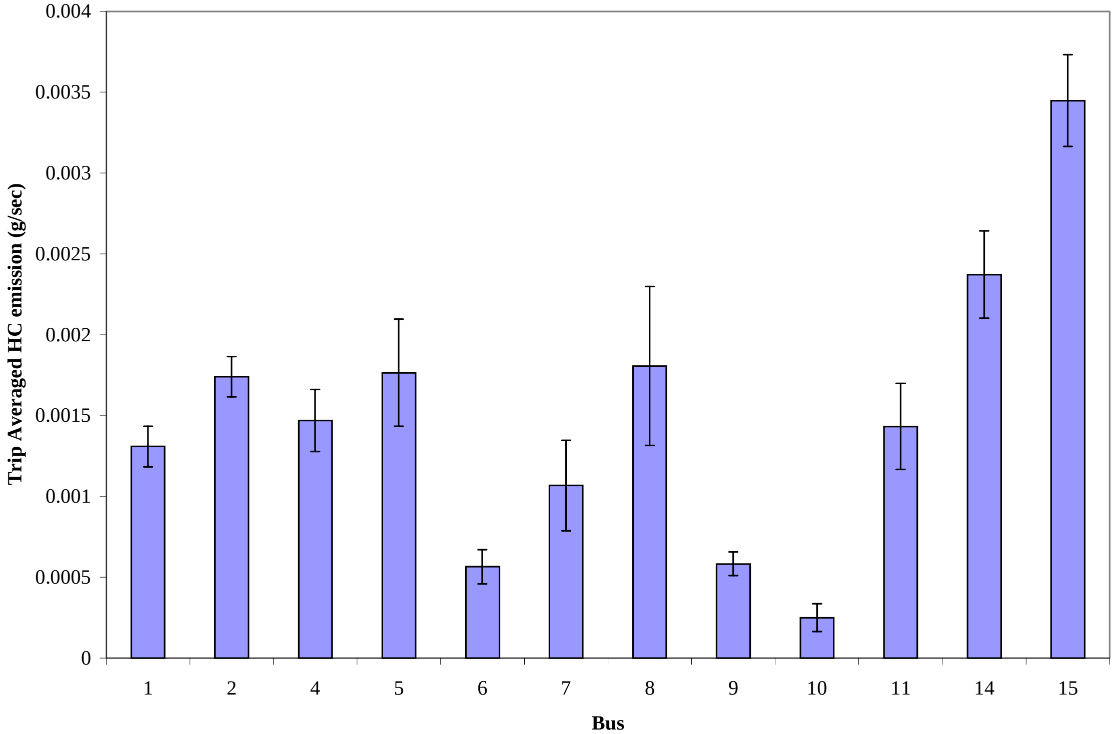
B1. Inter-Vehicle Variability for NO, HC, and CO_2 Emissions



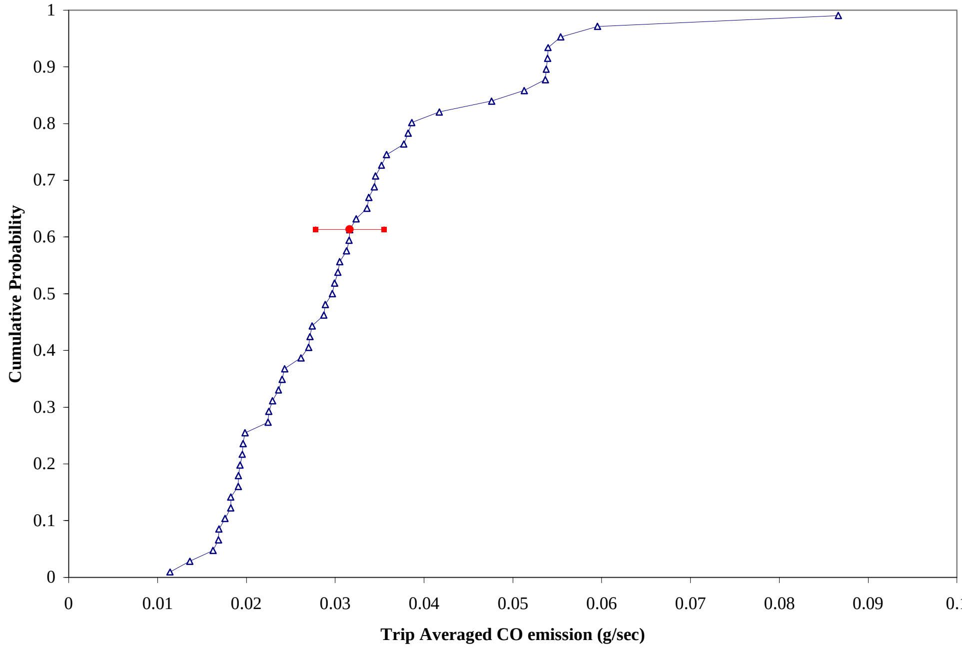
B1. Inter-Vehicle Variability for NO, HC, and CO_2 Emissions

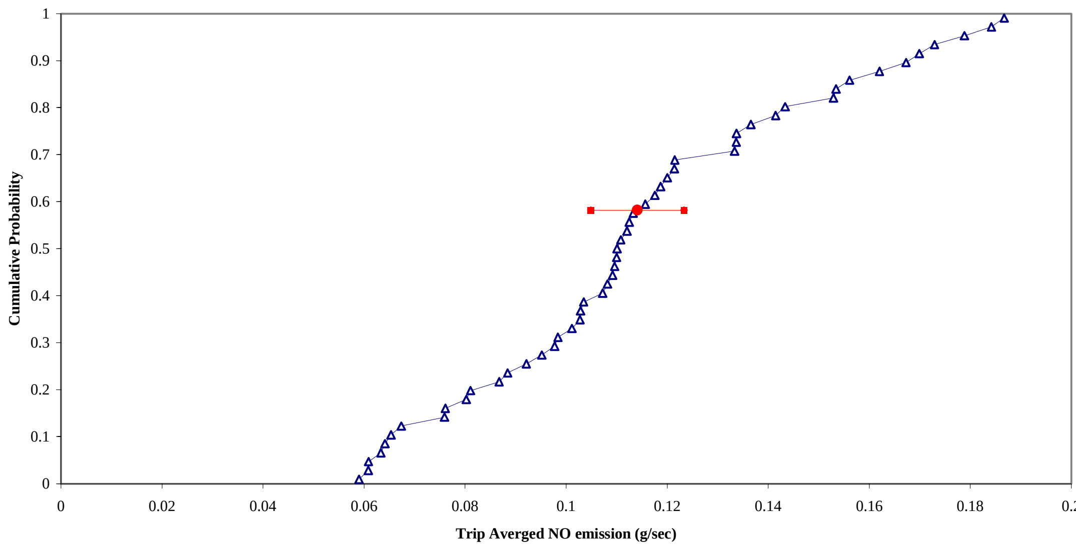

Trip Averaged CO2 emission (g/sec)
0
2
4
6
8
10
12
14
1
2
4
5
6
7
8
9
10
11
14
15
Bus

B1. Inter-Vehicle Variability for NO, HC, and CO_2 Emissions

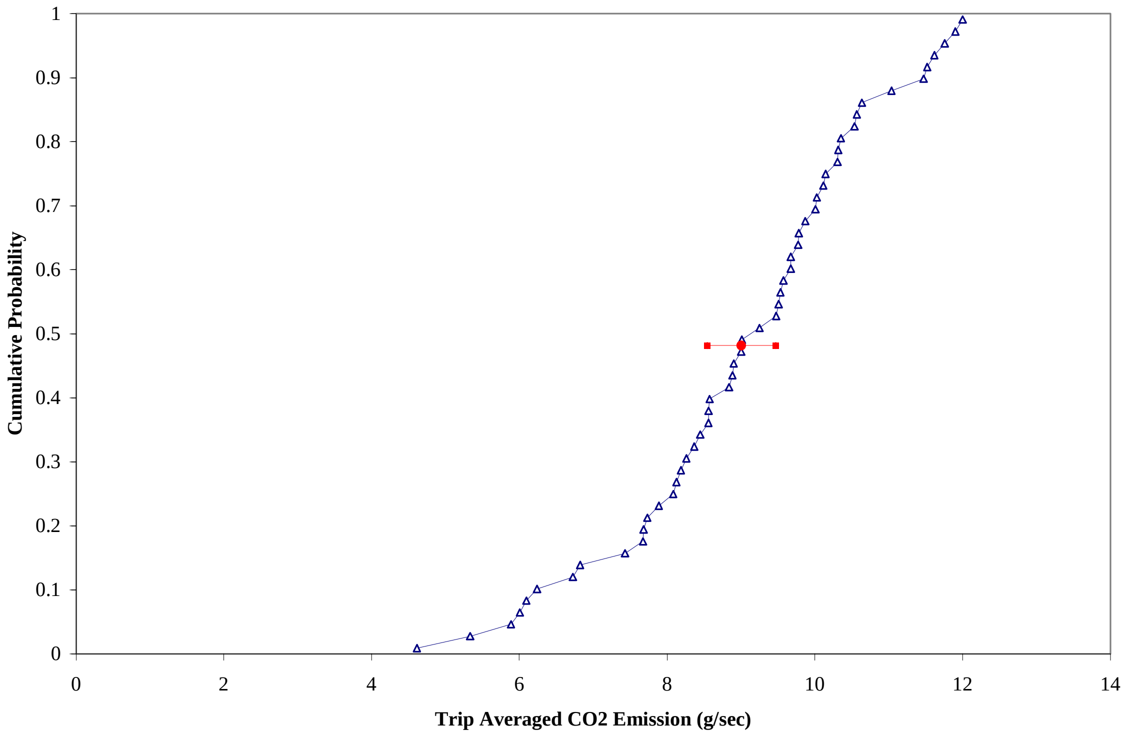


B2. Inter-Trip Variability for NO, CO, and CO_2 Emissions





B2. Inter-Trip Variability for NO, CO, and CO_2 Emissions



B3 Regression Coefficients for CO and CO_2

CO (g/sec)	**VEHICLE OPERATION MODES**				
Variable	Idle	High Acceleration	Low Acceleration	Deceleration	Low Cruise
Intercept	984.7	-2552.4	-957.2	999.4	-280.2
Model Year	-0.4934	1.2802	0.4746	-0.5220	0.1356
Humidity	-0.0288	0	0	0	-0.0186
Speed	0	0.0997	-0.0736	0.0339	0.0538
Speed^2	0	-0.0096	0.0022	0.0000	-0.0014
Speed^3	0	0.0002	0.0000	0.0000	0.0000
Accel	0	0.2107	-0.8894	0.1375	0.9994
Accel^2	0	0.0003	1.8879	0.0000	0.1313
Accel^3	0	0.0000	-0.5834	0.0000	-0.1441
Temperature	0.0306	-0.0637	0	0.0724	0.0203
Altitude	-0.0025	-0.0013	0	-0.0027	-0.0005
Grade	0	-0.0613	-0.1025	-0.0595	-0.0698
Pressure	-0.0051	-0.0036	0.0064	0.0361	0.0047
Power	0	0	0.0000	0.0036	-0.0121
R-square	0.13	0.42	0.15	0.06	0.08
Correction Factor	2.8	1.4	2.0	3.5	2.1

CO_2 (g/sec)	**VEHICLE OPERATION MODES**			
Variable	Idle	Acceleration	Deceleration	Low Cruise
Intercept	3206.9	-6242.3	786.3	878.5
Model Year	-1.6056	3.1311	-0.3920	-0.4384
Humidity	0.0109	0.0615	0.0155	0.0181
Speed	0	1.1410	-0.0270	0.1883
Speed^2	0	-0.0344	0	-0.0066
Speed^3	0	0.0004	0.0000	0.0001
Accel	0	4.2854	0.5099	6.5063
Accel^2	0	0	0.0145	1.0686
Accel^3	0	0	0.0000	-3.2870
Temperature	0.0000	-0.1647	-0.0529	-0.0449
Altitude	-0.0029	-0.0052	0	0.0040
Grade	0	-0.9499	-0.1449	-0.1055
Power	0	0	0.0149	0.0784
R-square	0.06	0.28	0.10	0.33

B4. Mass Balance Equations

$$Q_f \times [C_f] = Q_e \times \{[CO_{2e}] + [CO_e] + 6 \times [C_6H_{14e}]\} \quad (1)$$

$$Q_f \times [H_f] = (Q_e \times 14 \times [C_6H_{14_e}]) + (Q_w \times 2 \times [H_2O_w]) \quad (2)$$

$$Q_f \times [O_f] + (Q_a \times 2 \times [O_{2a}]) = Q_e \times \{(2 \times [O_{2e}]) + [CO_e] + (2 \times [CO_{2e}] + [NO_e]\} + Q_w \times [H_2O_w] \quad (3)$$

Combining these equations:

$$\text{Numerator} = \{(2\times[O_{2e}] + [CO_e] + (2\times[CO_{2e}] + [NO_e] - (7\times[C_6H_{14e}])\} - \left\{([CO_e] + [CO_{2e}] + 6[C_6H_{14e}]) \times \left([O_f] - \frac{1}{2}[H_f]\right)\right\} \quad (4)$$

$$\text{Denominator} = 2 \times [C_f] \times [O_{2a}] \quad (5)$$

$$Q_a = Q_e [C_f] \frac{\text{Numerator}}{\text{Denominator}} \text{ gram moles/second} \quad (6)$$

$$Q_e = \frac{1.013 \times 10^6 \times V_e \times 0.0283}{8.31 \times 273.15 \times 60} \text{ gram moles/second} \quad (7)$$

$$M_{air} = 28.8 \times Q_a \text{ grams/second}$$
(8)

$$\phi = \frac{M_{air}/M_{fuel}}{14.7} \quad (9)$$

Where:
$[X_f]$ denotes: the mole fraction of element X in the fuel, X can be C, O, H;
$[X_a]$ denotes: the mole fraction of species X in the air, X can be O_2;
$[X_e]$ denotes: the mole fraction of species X in the exhaust flow, X can be CO, O_2, NO, CO_2, C_6H_{14};
$[X_w]$ denotes: the mole fraction of species X in the exhaust water, X can be H_2O;
Q_a, Q_e denotes the mole flow rate of the Intake Air and the Exhaust Flow;
V_e denotes the standard volumetric flow rate of the exhaust;
M_{air}, M_{fuel} denotes the mass rate of Intake Air and Exhaust Flow;
Φ denotes the Equivalence Ratio (14.7 represents stoichiometric fuel-to-air ratio).

APPENDIX C

Coefficients of Regression for CO_2

C1. Coefficients of Regression for CO_2

Bulldozer CO_2		
Parameter	Estimate	Pr > |t|
Intercept	0.0001	0.009238
AR (1)	0.3207	<.0001
AR (2)	-0.0681	<.0001
AR (3)	-0.0132	0.2092
AR (4)	-0.0362	0.0003
amb_temp	0.0133	<.0001
bar_press	-0.2327	<.0001
RPM	0.0005	<.0001
Exh. Flow	0.0019	<.0001

Compactor CO_2		
Parameter	Estimate	Pr > |t|
Intercept	0.0000	0.008995
AR (1)	-0.2361	<.0001
AR (2)	-0.1650	<.0001
AR (3)	-0.0587	0.026
AR (4)	-0.1399	<.0001
RPM	0.0002	<.0001
Exh. Flow	0.0037	<.0001

Scraper CO_2		
Parameter	Estimate	Pr > |t|
Intercept	0.0000	0.009895
AR(1)	0.3382	<.0001
AR(2)	-0.0837	<.0001
RPM	0.0003	<.0001
Exh. Flow	0.0025	<.0001

Scraper NO_X		
Parameter	Estimate	Pr > |t|
Intercept	0.0001	0.0997
AR (1)	0.5319	<.0001
AR (2)	-0.0739	<.0001
RPM	0.0002	<.0001
Exh. Flow	0.0021	<.0001

Compactor NO_X		
Parameter	Estimate	Pr > |t|
Intercept	0.0000	0.009627
AR (1)	0.2843	<.0001
AR (2)	0.0502	0.0589
AR (3)	-0.0846	0.0014
AR (4)	-0.1534	<.0001
RPM	0.0001	<.0001
Exh. Flow	0.0032	<.0001