FINAL REPORT

Mobile Source Emissions New Generation Model: Using A Hybrid Database Prediction Technique

February 6, 2002

Prepared for:
U.S. Environmental Protection Agency
ASD
2000 Traverwood Drive
Ann Arbor, MI 48105

Matthew Barth, Principal Investigator
Theodore Younglove, Co-Principal Investigator
Carrie Malcolm, Assistant Development Engineer
George Scora, Junior Development Engineer
College of Engineering-Center for Environmental Research and Technology
University of California
Riverside, CA 92521
(909) 781-5781
(909) 781-5790 fax

01-TS-26655-02-DFR

Table of Contents

List of Tables

List of Figures

Abstract

The U.S. Environmental Protection Agency (EPA) is developing a New Generation Model (NGM) to more accurately predict in-use vehicle emissions at the micro-, meso-, and macro-scales. One of the characteristics of the NGM is that it should be able to predict emissions based on data collected from in-use vehicles under actual operating conditions. By contrast, today's regulatory models are based primarily on data only from dynamometer laboratories. This report describes activities conducted by the University of California, Riverside, College of Engineering-Center for Environmental Research and Technology (CE-CERT) under a data analysis "shootout" conducted by the EPA. EPA provided driving and emissions data from twelve spark ignition (SI) light-duty vehicles (LDVS), twelve compression ignition (CI) heavy-duty vehicles (HDDVs), and three CI off-road vehicles. The data were collected using the EPA's new Portable Emissions Measurement System (PEMS). Using these data, CE-CERT's objective was to estimate emissions from three similar vehicles under actual operating conditions determined by EPA.

CE-CERT chose a hybrid database model for its approach. In the hybrid database model, emissions are predicted by searching a second-by-second emissions database for the most similar vehicle and driving pattern, then using the previously observed emission rate in the database as the estimated emission rate for the vehicle to be predicted. In this hybrid approach the vehicle activity data are pre-processed to improve the speed and accuracy of the matching process. The methodology for this hybrid database model was developed for the micro-, meso-, and macro-scale levels. Predictions for the three on-road LDVs and three HDDVs were produced using the methodology for each level of the model. In addition, microscale emissions estimates were produced for the three off-road test vehicles.

The ability of the hybrid database model to easily incorporate new data, including existing laboratory data, was demonstrated by the microscale prediction of one of the LDVs using a combination of the NGM data and data from one additional comparable vehicle from CE-CERT's existing database. Preliminary sampling plans for the data collection of the NGM were also developed.

After presentation of the results to EPA staff, CE-CERT was provided with the actual emissions for the prediction vehicles. The average percent difference between modeled and actual emissions by model implementation level are presented below. The microscale version of the model did very well in predicting the non-road emissions and in general performed quite well on the buses and to a lesser degree on the cars where the CO levels were overpredicted by 84%. The mesoscale and macroscale versions of the model did well overall, with the exception of CO on the cars. The overprediction of CO is due to a lower CO emission rate in the vehicles to be predicted than that observed in many of the vehicles in the modeling database.

Average Percent Difference-Micro					**Average Percent Difference-Meso**					**Average Percent Difference-Macro**				
	HC	**CO**	**CO2**	**NO**		**HC**	**CO**	**CO2**	**NO**		**HC**	**CO**	**CO2**	**NO**
Car	26%	84%	17%	6%	Car	-12%	123%	-16%	-2%	Car	10%	71%	-9%	37%
Bus	2%	8%	-6%	-32%	Bus	-12%	24%	5%	-28%	Bus	14%	-2%	11%	-23%
Off-road			-7%	-2%										

Independent of the NGM program, CE-CERT has been developing a Comprehensive Modal Emissions Model (CMEM) framework [Barth et al., 1996, 1997, 1999 and An, 1997]. Appendix B of this report describes activities conducted by CE-CERT in which the CMEM was used to predict emissions of vehicles from the EPA New Generation Model "shootout." This work was conducted under separate funding and was carried out separately from CE-CERT's NGM modeling work. The CMEM framework was designed to predict vehicle emissions based on operating mode, driving conditions, terrain, driver habits, and other variables. CMEM is fundamentally a load-based model. CMEM is a model suitable for the next generation of mobile source modeling, but was designed to predict emissions of groups of vehicles. However, this data analysis was conducted because of the opportunity that it presented for a blind analysis of real on-road emissions data.

The objective of the work described in Appendix B was to assess the CMEM framework's appropriateness for use in the NGM by testing its ability to predict emissions from a small fleet of test vehicles whose actual emissions EPA had measured under a variety of operating conditions. This work was conducted with the standard laboratory calibration of CMEM. Future work will involve calibration of CMEM to the on-road data. EPA provided data on the vehicles and their operating parameters and CMEM was operated to provide an estimate of their emissions. CE-CERT used two approaches to quantify emissions within the CMEM framework: (1) prediction of the vehicle emissions using the standard CMEM composite vehicle categories; and (2) prediction of the individual vehicles with the most similar individual vehicle parameter set within the NCHRP test fleet. A comparison of the results from the two methods found good agreement for some vehicle types and operating modes, and poorer agreement for others. One reason for this variability may be the small population of vehicles and the limited operating conditions for which data were available in this study.

The CMEM results for the category predictions were compared with the actual results using the laboratory calibration of CMEM and the average percent differences results are presented below. In addition, the CMEM results were corrected using the average difference in observed and predicted emissions within the appropriate CMEM categories. This category correction improved the results somewhat; however, the calibration of CMEM to the on-road data is the preferred method and is currently under development under the on-going research. In both the corrected and uncorrected CMEM runs the CO_2 emissions were very close to the measured emissions. CO emissions had the largest percent difference from the measured data, but with the category correction the results were improved.

Average Percent Difference-CMEM Raw					**Average Percent Difference-CMEM Category Corrected**				
	HC	**CO**	**CO2**	**NO**		**HC**	**CO**	**CO2**	**NO**
Car	57%	-157%	-2%	34%	Car	37%	-53%	0.6%	43%

1. Introduction

The United States Environmental Protection Agency (EPA) is in the process of developing a New Generation Model (NGM) for estimation of mobile source emissions [USEPA, 2001]. The NGM is expected to be a system of modeling tools that can be used for the estimation of emissions both for on-road and off-road mobile sources. The EPA has identified four broad objectives:

1. The model should encompass all pollutants including CO, CO_2, HC, NOx, PM, air toxics, and greenhouse gases.
2. The model should be developed according to principles of sound science.
3. The software design should be efficient and flexible.
4. The model should be implemented in a coordinated, clear and consistent manner.

On-board emissions data, gathered using on-board emissions measurement devices, are to be an important part of the NGM effort. EPA is working on the development of on-board measurement technology, termed Portable Emissions Measurement System or PEMS [USEPA, 2001]. This report documents the methodology and results of work conducted by CE-CERT in the development of a hybrid database model for predicting emissions rates. In a hybrid database model some or all of the data are preprocessed for use in matching the existing data to the data to be predicted.

In addition to total vehicle miles traveled (VMT), four main factors can significantly influence mobile source emissions:

- Vehicle fleet mix (model year as well as car/truck);
- Proportion and type of high emitting vehicles;
- Soak time distributions;
- Driving behavior.

Because these factors change with both time and location, it is important that the data collection and modeling allow for flexibility in these items. As hot-stabilized emissions decline over the next ten years due to improved automotive technology, these factors will only increase in importance. Understanding these variables, however, is more data-intensive than previous-generation modeling efforts. Design of the NGM should be conducted with due consideration of the sampling burden for users balanced with the need for accuracy of the model. A highly accurate model with nearly impossible data requirements will not serve the user community well.

The University of California, Riverside, College of Engineering-Center for Environmental Research and Technology (CE-CERT) has been researching mobile source emissions modeling for nearly 10 years. In 1992–1995, CE-CERT developed a new framework for integrating transportation and emissions models, the Integrated Transportation/Emissions Modeling (ITEM) framework models [Barth et al., 1995, 1997a]. CE-CERT wrote a proposal to the National

Cooperative Highway Research Program (NCHRP) and was subsequently awarded a multi-million-dollar project to collect a wide variety of second-by-second mobile source emissions data and develop a Comprehensive Modal Emissions Model (CMEM). The overall objective of this research project (carried out from 1995 to 2000 as NCHRP Project 25-11) was to develop and verify a modal emissions and fuel consumption model that accurately reflects Light-Duty Vehicle (LDV, i.e., cars and small trucks) emissions produced as a function of the vehicle's operating mode. Further background on modal emission modeling and this NCHRP project is given in [Barth et al. 1996, 1997b, 1999] and [An, 1997].

The need for a new mobile source model that is capable of predicting emissions in a consistent manner from the microscale to the macroscale has been recognized for several years. Model development and implementation efforts at the EPA and CE-CERT have both been conducted with and eye to the future with on-road data collection and real-world modeling of emissions. The hybrid database model developed as part of this project, as well as CMEM, represents two of the possible approaches to the NGM. The on-going projects at CE-CERT provide synergy in the development of a framework for implementation of a NGM.

2. Model Development and Testing

CE-CERT initially explored three conceptual approaches to this New Generation Model on-board data analysis project.

- **Hybrid GIS/Database approach.** Emissions are estimated directly from data in a database. Hybridization of the database is achieved through pre-processing of the data to facilitate matching of the driving segments to be predicted with the best available driving segment in the database.
- **Multivariate Statistical Equation-Based approach**. Emissions are estimated using statistical relationships between the measured variables such as speed and measured emissions.
- **Driving Summary Statistic approach.** Emissions are estimated by correlating driving summary statistics with emissions. Driving summary statistics are calculated from readily available trip information and are designed to measure important trip characteristics. Average trip speed is a commonly used driving summary statistic.

The multivariate statistical equation approach was dropped from consideration because it was found to have problems with prediction errors when used on vehicles whose driving behavior was at or beyond the range of the behavior observed in the training sample used to develop the model. The statistical summary approach was used in the preprocessing of the macroscale predictions for the hybrid database model; however, it was not used on its own because the precision of the estimates varied considerably between types of vehicles. The hybrid database modeling methodology was selected for further development because it was simple in concept and would provide the greatest ease of expansion and easy incorporation into a Geographical Information System (GIS) framework.

2.1 Model Development Methodology

The database methodology uses existing data to predict emissions. The difficulty with applying this methodology is the "sparse matrix" problem: In general terms, as the number of cells in a matrix increase the amount of randomly collected data necessary to obtain observations in every cell of the matrix expands rapidly. The number of different vehicles, driving behaviors, and road conditions that exist in the real world make for a near infinite number of combinations of conditions that must be matched for accurate emissions prediction if an exact match is required. Our solution to this problem is to conduct a hybridization of the basic approach. This uses preprocessing of the data in combination with statistical "maps" to identify the closest driving data to that to be modeled. In addition, the implementation of the model is conducted differently at the micro-, meso-, and macro- scales because a greater degree of matching can be obtained within the existing data for the smaller time-scale events. It is easier to match a particular modal event than it is a portion of a trip or an entire trip.

The final approach chosen is a modification of Approach 3 described in EPA Solicitation PR-CI-01-12239, in which the NGM comprises a large database of emissions measurements with corresponding driving and location (via GPS) data. A key element in the success of this methodology is the matching of the existing emissions measurements to the operating conditions being modeled. The unique aspect of the CE-CERT methodology is the application of preprocessing of the data as well as the use of the GPS-based location data to identify roadway type and to obtain accurate grade information. A balance must be achieved between properly identifying factors about a driving segment that affect emissions and readily matching the database elements to the desired situation. The GIS aspects are of less use in characterization of the off-road data because of the increased difficulty in identification of geographic features that may influence emission rates.

At this stage of development, the data set used for matching was selected from the vehicles that most closely match the vehicle to be predicted. The optimum situation would be for the database to contain several vehicles having the same mileage and options as the vehicle to be predicted. In this pilot project, vehicles were selected based on the judgment of the research team for those most likely to have similar emission rates and emissions behavior over the observed operating conditions. In an automated implementation the matching methodology likely would vary by vehicle technology type, with different factors used for matching carbureted vehicles than those used for fuel injected vehicles for example.

At the *microscale* level, the driving traces were disaggregated into modal segments encompassing accelerations, decelerations, steady-state cruises, etc. At the *mesoscale* level, the driving traces were disaggregated into roadway/driving-based events. At the *macroscale* level, the driving traces were used in a trip-based manner (see Figure 1). Consistency of emission rates is maintained through the use of the same basic data for each level of the model. Emission rates are estimated by querying the database to find a driving condition similar to the one being estimated based on vehicle, roadway, and driving behavior characteristics. A regression on principal components analysis is used to identify groupings of variables that are correlated with emissions to simplify the search process.

Trip based	Facility specific link based	Mode based

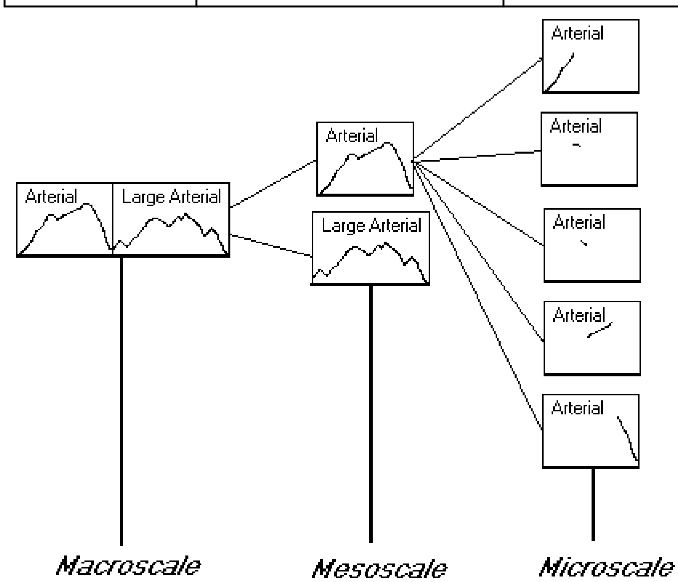


Figure 1. Disaggregation of PEMS driving data for hybrid emissions database/GIS approaches.

In this hybrid approach, data from the PEMS units were used to build up a database of emissions traces in a spatial framework that can be used for on-road based emissions estimates as well as for larger area estimates.

2.1.1 Microscale

At the microscale level, the methodology involves dividing the trip to be predicted into separate modal events. Individual accelerations, decelerations, cruises, and idles are identified visually, and then flagged in the data set (Figure 2).

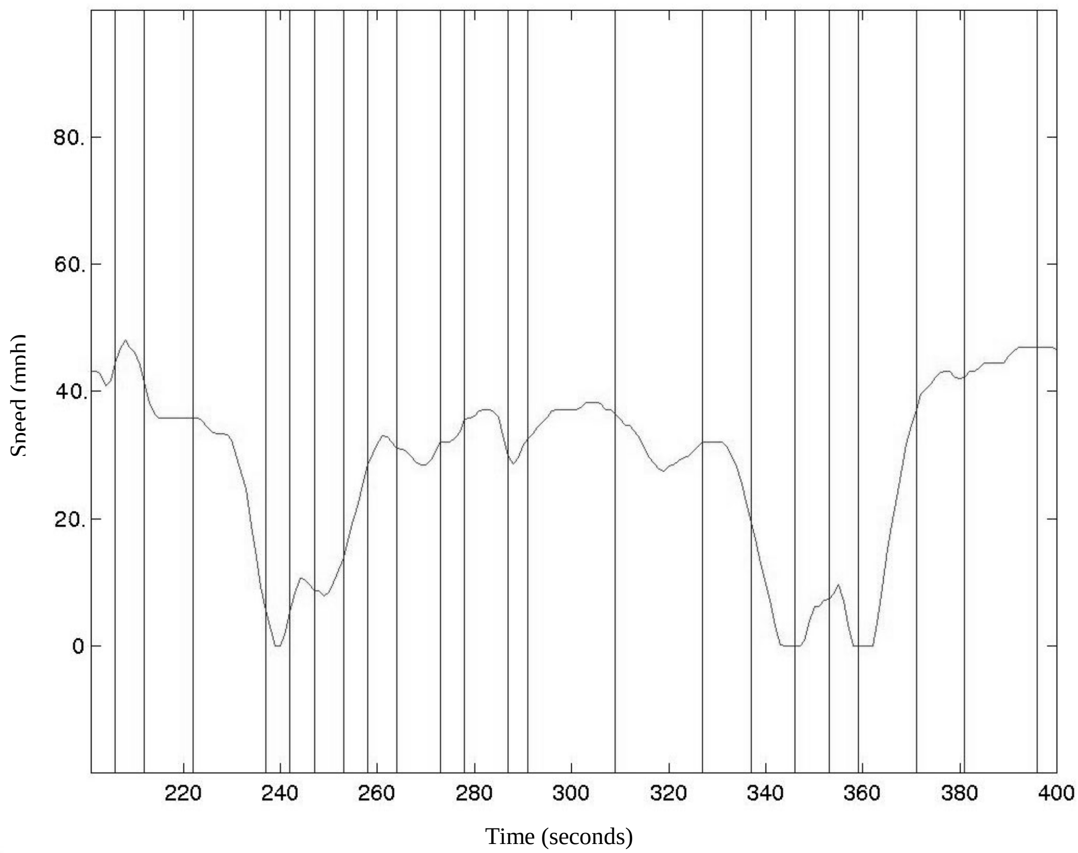


Figure 2. Example speed trace divided into modal segments.

At present, this process is conducted visually using speed plots as shown in Figure 2. In a full implementation of the methodology this step would be automated, both for speed and for consistency of segmentation. Initially the modes were divided at their end points; however, in the case of acceleration events the matching driving trace frequently did not end at the correct speed (Figure 3). Differences in emissions were found between accelerations peaking and similar accelerations that did not peak at the end of the segment. For this reason, acceleration modes included the peak inflection point to ensure that the matching trace was the closest event that ended at the same speed.

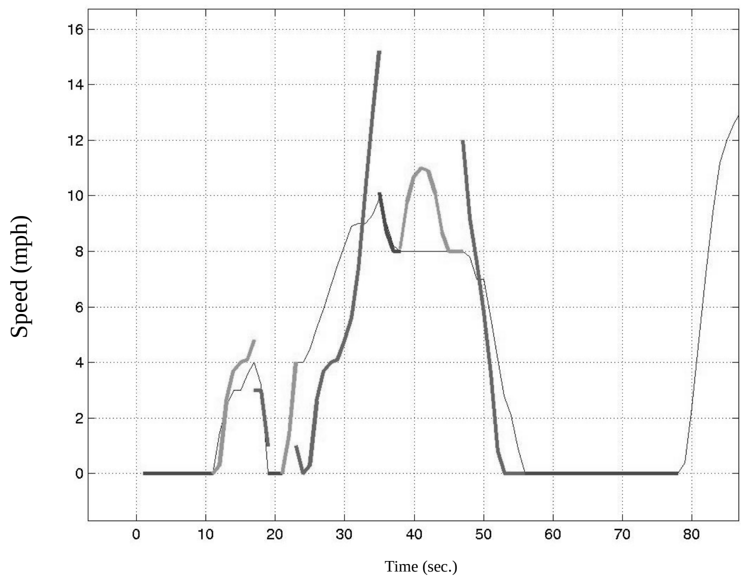


Figure 3. Example speed trace modally divided at the peak with matched speed segments appearing in alternating colors.

Speed matching was chosen in combination with acceleration and power matching to try and keep gear selection effects to a minimum so emissions would be representative of typical driving in the speed under consideration. Each modal segment is then matched to all possible equal length segments within the prediction data set. That is, a moving window of the same number of seconds from the prediction data set is compared with the driving trace to be matched. For example, if a twelve second speed segment were to be matched, it would first be compared with the first twelve seconds of the first trip. The twelve second segment would then be matched with seconds 2 through 13, then 3 through 14, and so on until it is compared with the last twelve seconds of the trip. The twelve second segment would then be compared with the first twelve seconds of the second trip, and so on until it is compared with the last twelve seconds of the last trip in the prediction data set. A match score is calculated for each of the matching segments using three weighted criteria, the sum of the squared difference in speeds for each second, the sum of the squared difference in accelerations, and the sum of the squared difference in grade across the modal event. The current match score uses an 80, 10, 10 weighting of speed, acceleration, and grade that was determined empirically.

While the modal approach increases the ability of the database methodology to find matching driving segments, there are still limitations on the number and type of vehicles that are available for matching. In addition, differences in driver aggressiveness play a role in the ability of the database to match a driving trace. Matching an aggressive driver with a less aggressive driver resulted in consistent mismatches at higher speed accelerations (Figure 4).

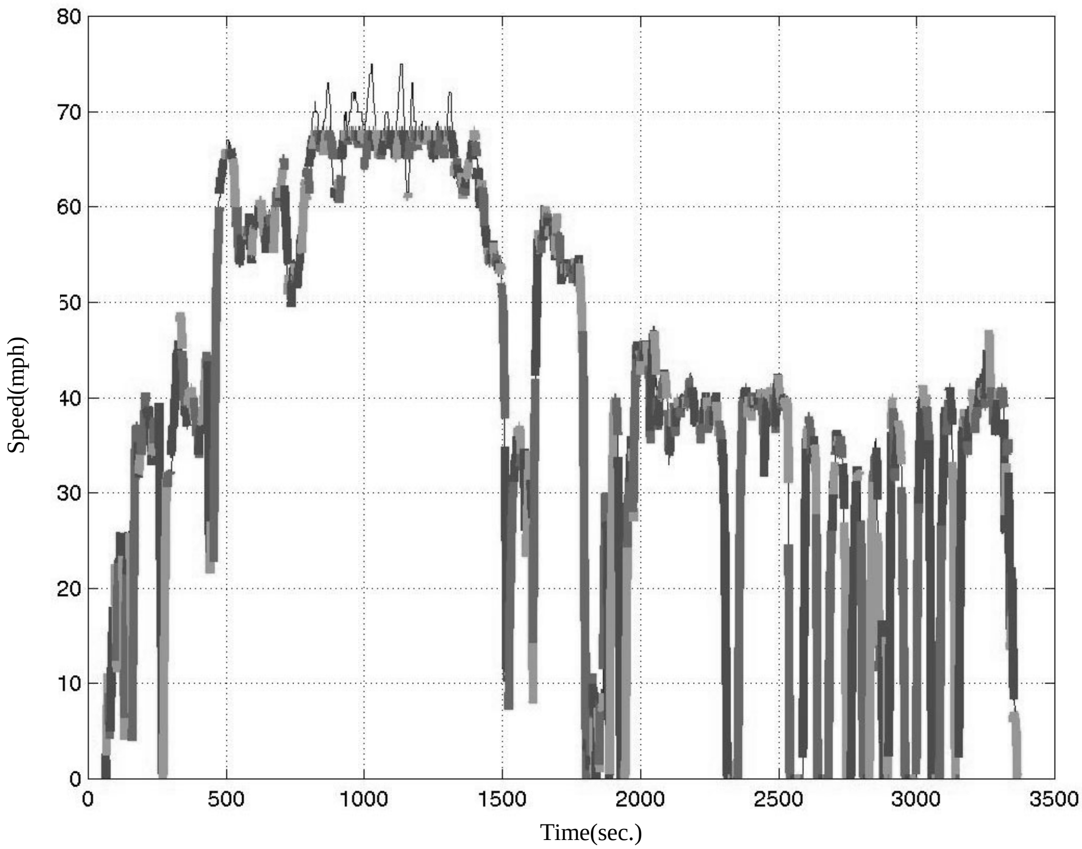


Figure 4. Driving trace match of an aggressive driver (blue line) with a less aggressive driver (alternating green, pink, and red segments).

Catalyst temperature and efficiency play a critical role in the emissions characteristics of modern automobiles. Because of the large effect catalysts have on emissions, matching of driving behavior alone is not likely to produce accurate emissions estimates. For this pilot demonstration, the trips were divided into cold operation and hot operation sections. Driving behavior in cold sections was then matched to cold sections within the data set, and hot operation segments were matched to hot operation segments in the prediction data set. With the relatively small number of trips and vehicles in this study, it was decided to break the trips into only two parts because of the need for finding similar driving behavior. Implementation of this methodology will require sufficiently large numbers of trips so that the full range of vehicle operation from cold to hot can be matched to a variety of modal behaviors at the second-by-second level. Table 1 summarizes the approach to microscale modeling.

Table 1. Microscale model development requirements.

Database preparation	**Prediction data preparation**
• Division of trips into hot and cold driving segments.	• Select matching vehicle or vehicles in prediction data set. • Divide trips to be predicted into modal segments. • Estimate Cold and Hot modal segments. • Run matching program to identify closest driving trace for each modal segment to be predicted. • Use grams/second emission rates from prediction data set for matching segments of the segment to be predicted. • Sum g/s for the trip and calculate g/mi.

2.1.2 Mesoscale

The methodology at the mesoscale level involves matching of driving segments on individual road links to similar links in the prediction data set. This link-based approach introduces greater variability in the driving behavior and terrain covered, and the limitations of the "sparse matrix" are magnified. Therefore, with the small data set used in this project, we would expect less accuracy at the mesoscale than at the microscale level.

Emission estimates for a vehicle on an individual road segment are calculated using similar driving behavior on similar road segments. In this implementation, many of the road segments were modeled using the same road segment. This level of matching would be achievable for individual cities only if they were to have collected large amounts of on-road data. However, it does represent the highest level of development that can be achieved for mesoscale emissions modeling with this modeling methodology. The more typical application would involve the identification of the most similar driving segment in the database to the link being modeled. The key element of this mesoscale implementation is the identification of characteristics that can be used to identify driving segments that have similar emission rates.

In the general implementation, roadway characteristics would be used to classify each driving event, resulting in a multivariate classification for each event based on the characteristics of the roadway. Within each roadway the driving behavior would be classified using driving summary statistics to enable matching of driving as well as roadway. Examples of possible variables for roadway classification are physical characteristics such as type, length, average grade, maximum grade, posted speed, etc., and traffic characteristics since driving behavior greatly affects emissions. This multivariate classification of the driving events is a critical component of implementation of this methodology. It is not possible to collect multiple sets of PEMS data for multiple vehicles on even a small proportion of the roads in a particular area. However, for the prediction of the emissions rate on a given roadway section, it should be sufficient to find a similar set of driving conditions in the PEMS database that does have sufficient emissions estimates for characterization. Future implementation will be based on identifying similar links with similar driving conditions to those being modeled.

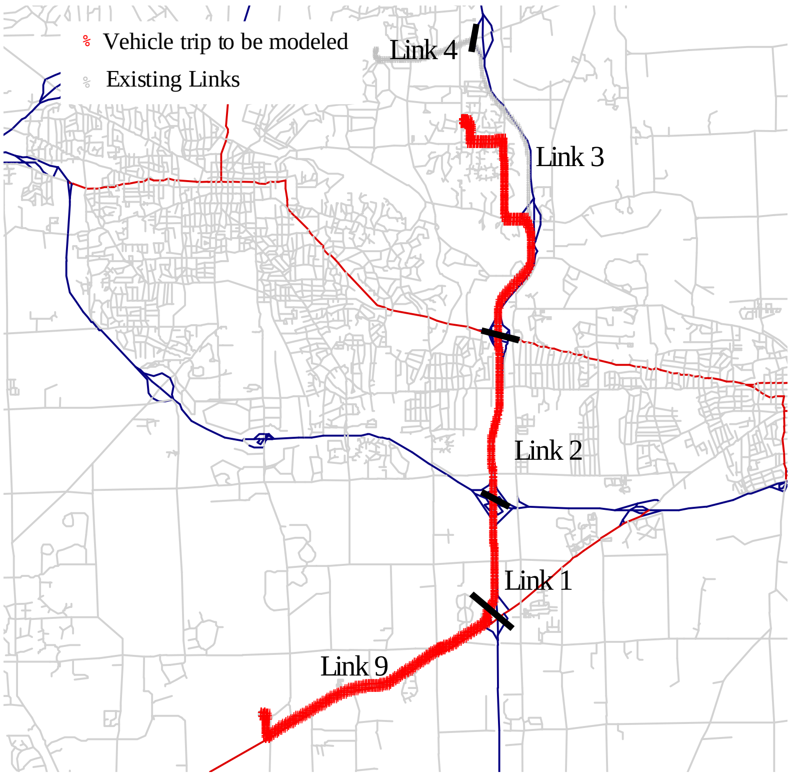


Figure 5. Example of link based mesoscale methodology, see text for details.

Best case scenario is that the emissions to be predicted are on a specific road link that occurs within the database. This requires matching the appropriate vehicles and matching the appropriate driving behavior for those vehicles on the correct links. However, in the typical case the emissions that are to be predicted are on a specific road links that does not exist within the database. This requires matching the road link characteristics, the appropriate vehicles, and the appropriate driving behavior for those vehicles on the correct links. An example of this is shown in Figure 5. The gray line represents links with existing data and the red line is the trip to be predicted. The emissions for portion of the trip that overlaps Links 9, 1 and 2 will be predicted by using the values from a similar vehicle in the database with similar driving behavior over each link. The remaining section of the trip would be divided by roadway type, and the database would be searched to find a link that best matches the characteristics of each section with a similar vehicle. Table 2 summarizes the approach to mesoscale modeling.

Table 2. Mesoscale model development requirements.

Database preparation	**Prediction data preparation**
• Divide trips in prediction database into road links. • Calculate driving summary statistics for each road link. (Not done for this project because of data limitations).	• Select matching vehicle or vehicles in prediction data set. • Identify links in the trip to be predicted. • Estimate matching road link emissions using corresponding emissions from the database. • Estimate unmatched road links using the most similar road link (and traffic conditions in the full implementation).

2.1.3 Macroscale

At the macroscale, the hybrid database model predicts the emission rate of the target trip by using the emission rate of the most similar trip in the database. In this implementation, preprocessing of the driving characteristics and roadway characteristics are used to overcome the sparse matrix problem. At the trip level, it is unlikely that a matching trip will be found for most if not all of the trips to be predicted. It is thus essential that the methodology include statistical means of identifying the best trip possible for use in the prediction of the emission rates.

A four step process was used to identify the "best" trip matches:

- Calculation of driving summary statistics for all trips
- A stepwise regression was then used to identify the best trip summary statistics
- A principal components analysis (PCA) [Dunteman, 1989] was then run on the selected driving statistics, driving conditions, and vehicle condition statistics
- A regression on principal components was then used to select the principal components with the best correlation to emissions.

The *driving summary statistics* are statistical summaries of second-by-second driving and roadway information that were used to characterize each trip in the database. The summary statistics were designed to capture different aspects of driving using easily measurable variables that would be readily available. In some of the initial work on developing a statistical second-by-second model, speed and acceleration were identified as significant predictors of emissions. The summary statistics are listed in Table 3. Average speed is a common driving summary statistic used in modeling of on-road emissions. Many of the driving summary statistics were calculated with increasing and/or decreasing thresholds. This was done in order to identify the optimum statistic based on the data, rather than a predetermined fixed level.

Table 3. Trip Driving Summary Statistics.

Mean (velocity)	Average trip speed
Mean (grade)	Average trip road grade
Mean (sp)	Average trip specific power (sp = 2*v*a)
Sum velocity > X	Sum of all speeds > X, where X = 0, 5,10,…80mph.
Sum acceleration < X	Sum of all decelerations < X where X = -10, -9, -8,…-1mph/s
Sum acceleration > X	Sum of all accelerations > X, where X = 0, 1,2,3,….10mph/s
Sum sp > X	Sum of trip specific power > X, where X = 0, 50, 100,…400
Sum grade related power	Sum of sp as a function of road grade
Sum grade > 0	Sum of all positive grade values
Sum grade < 0	Sum of all negative grade values

The *stepwise regression* is a linear regression procedure in which variables are added into the regression equation based on their ability to improve the regression predictions. In this case, the stepwise regression was used to screen the large number of driving summary statistics to identify those which had the strongest predictive ability for emissions associated with the trips. In a stepwise regression, the first variable added to the regression is the single variable having the highest correlation with the dependent variable (CO_2, CO, HC, or NO). After adding in the single best variable, the next variable added is the one that statistically improves the regression the most. The procedure continues in a stepwise fashion until no variables significantly improve the regression.

The *principal components analysis* is a statistical procedure that reduces a large number of possibly correlated variables into a smaller number of independent variables that are linear combinations of the original variables. These "principal components" represent most of the variability found in the original variables, but simplify presentation and analysis. In this case, the principal components were constructed to identify trips having similar driving and emissions behavior that could then be used to identify the appropriate trips for use in predicting the emissions of the test trips.

The *regression on principal components* is a statistical procedure in which dependent variables are regressed on the new composite variables in a stepwise fashion. In this analysis, the principal components are independent, eliminating the problems with co-linearity in the driving summary statistics. The primary goal of the regression on principal components was to identify the correct principal components for use in plotting the trips to identify groupings of trips whose emissions behavior would be similar. Table 4 summarizes the approach to macroscale modeling.

Table 4. Macroscale model development requirements.

Database preparation	**Prediction data preparation**
• Preprocess trip data to calculate trip summary statistics (Table 3). • Perform stepwise regression of trip summary statistics against trip CO_2, CO, HC, and NO. • Select best trip summary statistics for characterization of driving effects on emissions.	• Run principal components analysis on all trips summary statistics. • Regress principal component scores against trip CO_2, CO, HC, and NO. • Plot all trips on best two principal components and identify matching trips to the trips to be predicted. • Estimate grams/second for trips to be predicted from matching trips grams/ second. • Apply estimated emission rate to trip and calculate cumulative trip CO_2, CO, HC, and NO.

2.2 Pilot Data Demonstration

2.2.1 On-Road Spark Ignition

The EPA provided a total of twelve data sets for on-road spark ignition light-duty vehicles for testing the modeling approach (Table 5). Vehicle 13 was eliminated from the prediction database because of problems in the collection of NO data. These vehicles were driven a total of 55 trips with a variety of distances and soak times with a total of 50 trips available after removal of vehicle 13. The database model requires a large amount of data to function well, including vehicle types and operating conditions. The model will be very sensitive to differences in emission rates between the individual vehicles in cases where the sample size is small.

Additional study that is beyond the scope of this current project will be required to determine what size datasets will be required for optimum performance.

Table 5. Vehicles included in the training database.

Vehicle Number	Make	Model	Model Year	Odometer	Number of Trips
2	FORD	TAURUS GL	1997	79984	7
5	SATURN	SATURN	1998	37278	3
6	CHEVROLET	MALIBU LS	1999	26288	3
7	SATURN	SATURN	1999	43242	3
11	FORD	TAURUS SE	1998	78187	4
12	FORD	ESCORT	1997	71446	3
14	CHEVROLET	CAVALIER	1996	86999	9
15	CHEVROLET	CAVALIER	1998	56803	3
16	MERCURY	MYSTIQUE SPORT	1998	29233	9
17	FORD	TAURUS SE	1998	41319	5
18	FORD	TAURUS GL	1996	94321	1

From the activity and emissions data provided for each of the 50 trips in the training database, CE-CERT’s task was to predict emissions from three additional vehicles over a total of six trips, as summarized in Table 6. All three vehicles have at least one similar vehicle in the prediction set. However, vehicle-to-vehicle differences in emission rates are likely to cause bias problems in the predictions with this limited data set. In a full implementation of the hybrid database model a larger sample of vehicles for each vehicle to be predicted should average out vehicle variability effects.

Table 6. Vehicles included in the prediction database.

Vehicle Number	Make	Model	Model Year	Odometer	Number of Trips
1	CHEVROLET	LUMINA LS	1998	44362	1
2	MERCURY	SABLE LS	1996	96099	2
3	FORD	ESCORT	1999	39429	3

Microscale

The first step in the application of the microscale level was to select the closest vehicle in the training database for each of the vehicles to be predicted. In this implementation, because of the small number of available vehicles, selection of the matching vehicles was done manually. In the full implementation vehicles likely would be assigned to equivalent groups based on emissions behavior and technology. For the 1998 Chevrolet Lumina, we selected the 1999 Chevrolet Malibu and the 1998 Ford Taurus SE. The Taurus was added to the prediction data because the Lumina driver was more aggressive than the Malibu driver, making for poor fits at the higher power events. The 1996 Mercury Sable was fit with the 1996 Chevrolet Cavalier to keep a similar power to weight ratio with the same model year and similar mileage. Differences in emissions behavior were observed in analysis of the NCHRP vehicle test fleet between some early Tier 1 vehicles and later models so the match was based on similar mileage and model year instead of matching the make and model [Scora et al., 2000]. The 1999 Ford Escort was modeled using the 1997 Ford Escort in the model database.

The six trips to be predicted were then manually divided into modal events. The third step in the microscale modeling was to estimate the warm up time period for the vehicles to be predicted. The soak time from each of the vehicles in the training data set was regressed against the estimated warm up time for the trip (Figure 6) where warm up time was estimated from the data using emissions on similar driving events. For this implementation soaks greater than 200 minutes were assigned a warm up time of 150 seconds. In some cases this was difficult because of the driving patterns observed during the warm up period. The modal matching program was then run to find the best match for each segment of each trip. The output for the 1998 Chevrolet Lumina is presented in Figure 7. All output figures are presented in Appendix A.

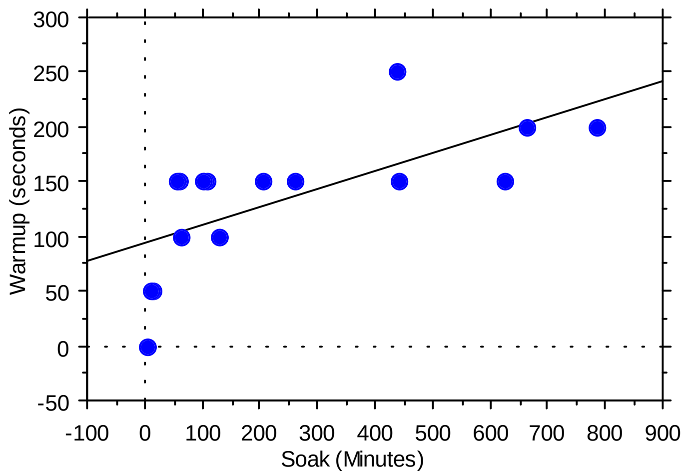


Figure 6. Soak time regression.

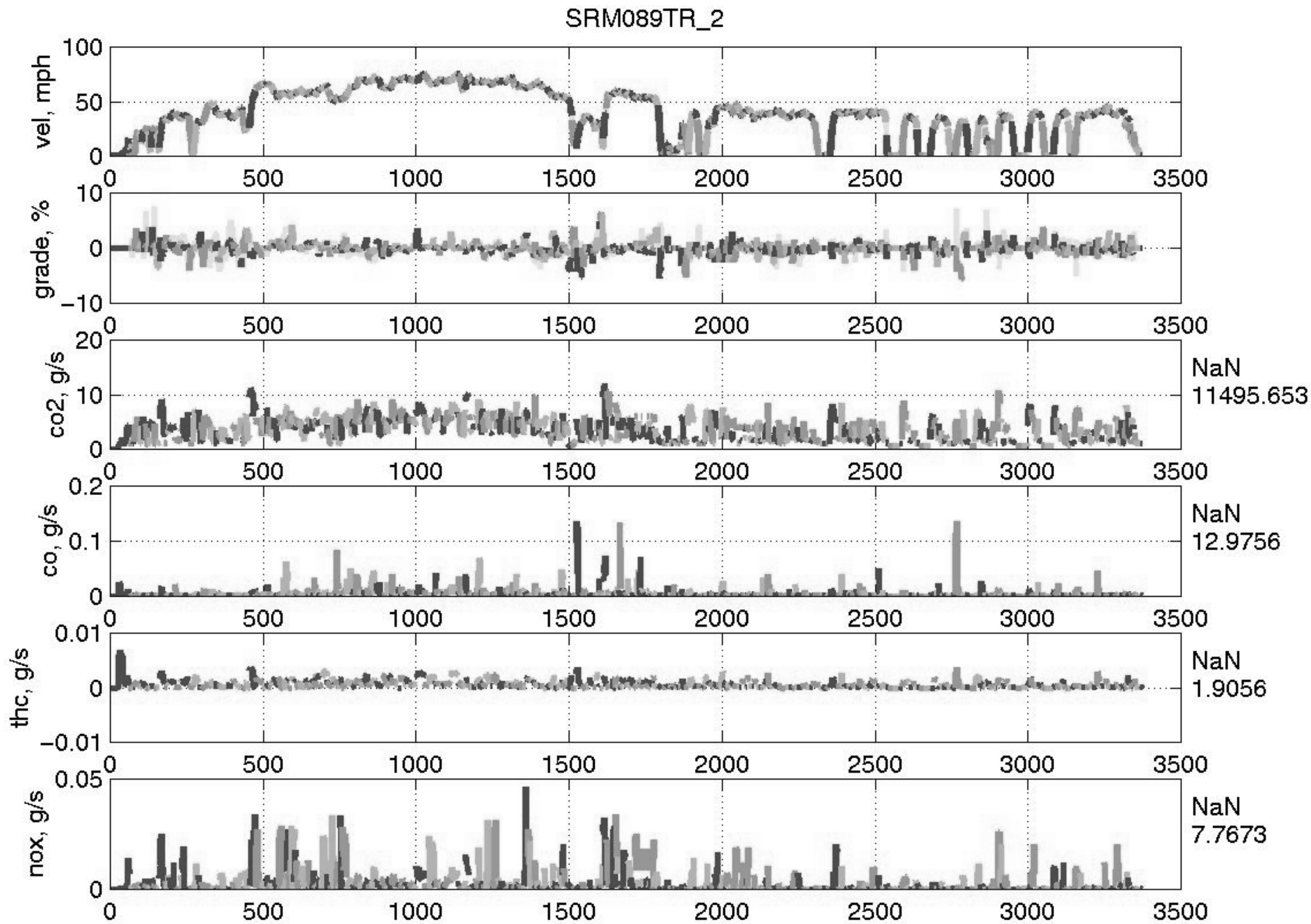


Figure 7. Example microscale model output for 1998 Chevrolet Lumina.

The results for the microscale modeling runs for all six on-road light-duty SI vehicle trips are summarized in Table 7.

Table 7. Microscale model results for on-road spark ignition vehicles.

Car	Trip	CO2 (g)	CO (g)	NOx (g)	HC (g)
SRM089	2	11495.65	12.98	7.77	1.91
Subtotal		11495.65	12.98	7.77	1.91
3DAU86	3	6640.00	45.56	3.94	2.75
3DAU86	5	9144.49	40.75	3.80	4.97
Subtotal		15784.49	86.32	7.74	7.73
RAK416	2	3596.94	137.80	11.15	5.27
RAK416	4	4252.84	98.41	10.82	4.68
RAK416	5	4398.59	32.88	6.39	2.02
Subtotal		12248.37	269.09	28.35	11.96
Total		39528.51	368.38	43.86	21.60

Mesoscale

The first step in the mesoscale level is to divide the database into road links. A link is defined as a unique section of roadway, typically between major intersections. The vehicles provided in the pilot study were separated by trip and were plotted in ArcView (Figure 8).

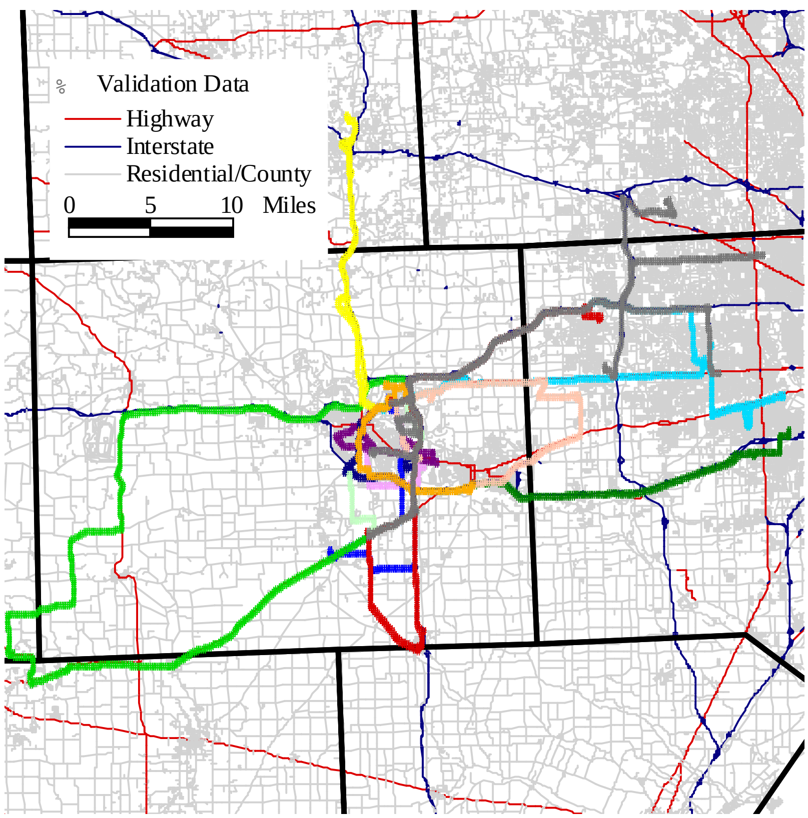


Figure 8. Map of vehicle trips.

The vehicle data provided for model prediction data were also broken into trips and plotted in ArcView, (Figure 9).

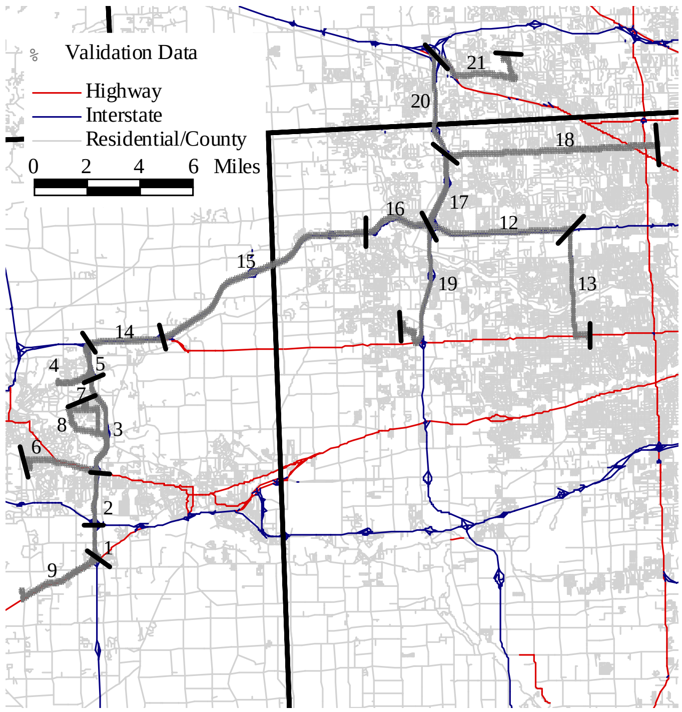


Figure 9. Map of test data and modeled links.

For demonstration purposes, the test data provided by the EPA for modeling were used to determine the location of road links. In a complete model implementation, links will be created throughout the entire designated area. For now, links were broken down into segments by roadway type and, to some extent, availability of the pilot data. If a link contained a small portion of a different roadway type, then that section was included to reduce the overall number of links in the analysis. For example, Link 13 (see Figure 9) is primarily on a residential/county road but contains a small section of highway driving.

The first approach explored for this level consisted of creating an Avenue model in ArcView [ESRI, 2001]. The model looked at two trips at a time and searched for overlapping points. If overlapping points were found, then a new table was created for each trip of just the overlapping sections. These new tables were then summarized. The process was repeated for each possible pair of trips. The resulting summary table summarized each pair and contained statistics for speed, length of trip, time, grade, and emissions.

This method worked, but it limited the number of individual links that could be compared. This approach might be better suited for a situation where large amounts of data existed and the user was trying to match a few vehicles. The only preparation that is required in this modeling method is to plot the unmatched data over the existing data and run the program. For the pilot study, a better methodology was to create a database of links where the links could be combined in any manner to form a trip. The new approach takes longer to set up initially because for each link all the vehicle trips that pass over that link need to be summarized and entered into a database. However, the new approach allows for more data to be incorporated, an important factor with the limited amount of available data.

An analysis of link emissions showed that vehicle trip emission rates vary over the same links, even when the vehicle is the same. This is due to differences in driving that would be included in the matching for the full implementation. With the limits on the available data for this project matching of driving behavior within links was not done. A sample of the link database is given in Table 8. This variability shows that driving behavior is important factor in determining emissions as well as vehicle type.

Table 8. Sample of link database.

Link	Direction	Car	Avg. Speed	HC (g)	CO (g)	CO2 (g)	NOx (g)
2	N	02t03	69.91	0.03	3.32	503.31	0.90
2	N	06t03	55.67	0.05	0.40	392.10	0.49
2	N	11t04	66.87	0.07	1.12	592.32	0.27
2	N	14t04	62.06	0.27	13.38	625.58	0.38
2	N	RAKt05	66.68				
2	S	02t01	71.05	0.34	4.22	612.55	1.36
2	S	02t04	67.59	0.28	2.60	589.55	0.75
2	S	05t02	55.89	0.11	0.23	435.76	0.26
2	S	11t01	62.94	0.06	0.88	501.65	0.22
2	S	14t07	65.64	0.20	5.24	495.37	0.25
2	S	15t02	62.78	0.14	4.38	411.79	0.59
2	S	RAKt02	75.98				
2	S	RAKt04	75.45				

A database of average speed, average grade, and average total emissions in grams was created by direction for each link. Each trip was plotted individually and a separate table was created for every link that the trip encompassed. These tables were then summarized and added to the database. Because the database is relatively small, each vehicle in the prediction database was included. To determine the emissions for a trip, the sums of the links are calculated. For example, if a vehicle travels on Link 1 North, Link 2 North, and Link 3 North, the emissions for the trip will be the sum of the separate links. If there are no overlapping data for a link, then a similar link with available data was used in its place. As more data become available, vehicle type will be matched as well as links.

The results of the model validation data for the mesoscale level are shown in Table 9 for each trip, each vehicle, and total emissions.

Table 9. Car validation emission results for the mesocale level.

Car	Trip	CO_2 (g)	CO (g)	NOx (g)	HC (g)
SRM089	2	6977.85	128.66	12.33	2.30
Subtotal		6977.85	128.66	12.33	2.30
3DAU86	3	3396.23	39.78	3.00	2.72
3DAU86	5	7860.86	146.66	15.86	3.63
Subtotal		11257.10	186.44	18.86	6.35
RAK416	2	3784.65	38.76	2.83	2.83
RAK416	4	2912.96	19.04	2.94	1.26
RAK416	5	3175.43	35.45	2.55	0.99
Subtotal		9873.04	93.26	8.32	5.08
Total		28107.99	408.36	39.51	13.73

Modeling the mesoscale level in GIS not only creates a visual representation of where vehicles are driven, as in Figures 8 and 9, but also creates a map of total emissions by link. Emissions were summed by link for all vehicle trips in the pilot study and validation dataset and are shown in Figure 10.

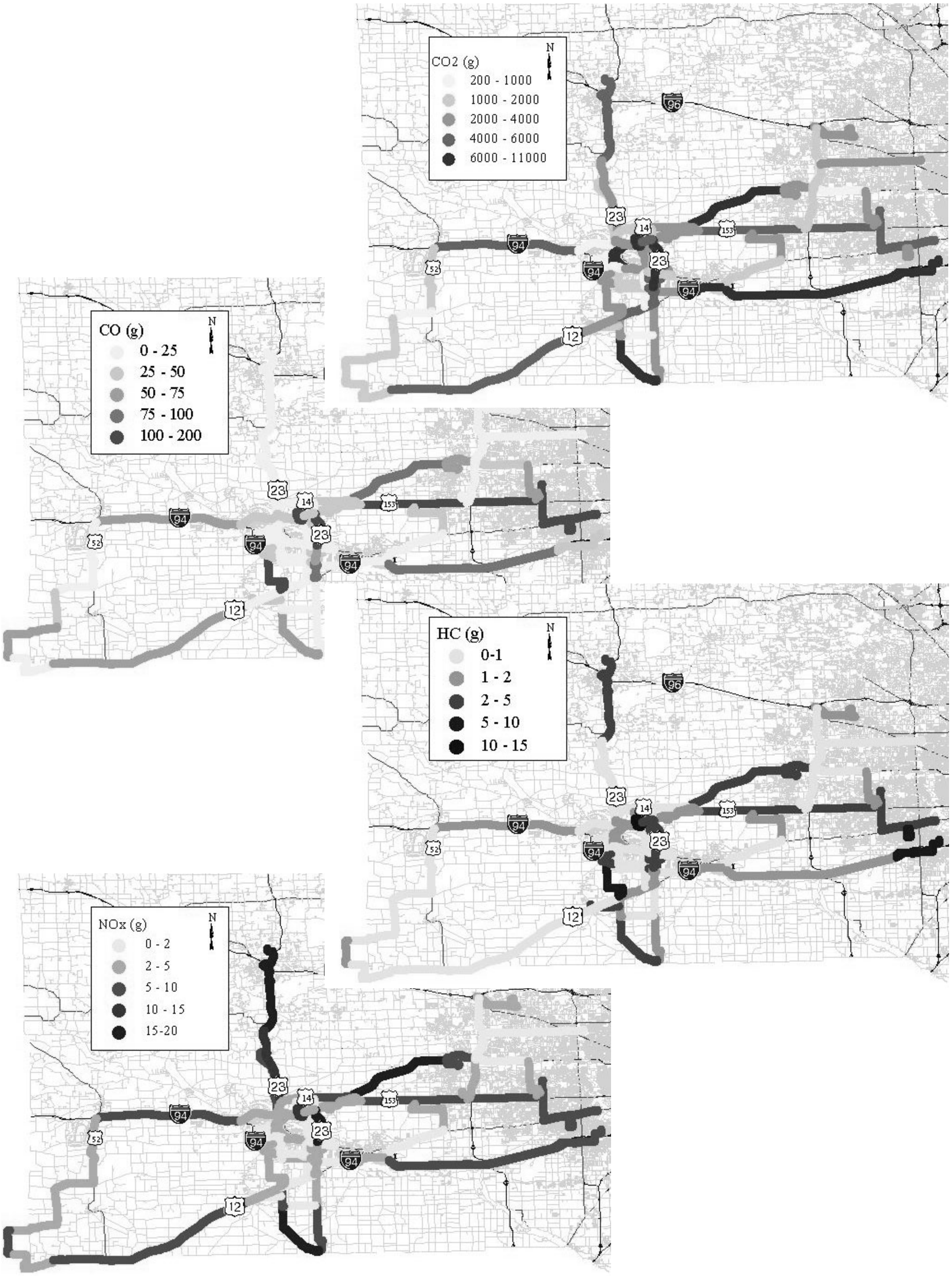


Figure 10. Link CO_2, CO, HC, and NOx emissions for vehicles in the pilot study and validation database.

Macroscale

The first step in the macroscale estimation of trip emissions is to pre-process the vehicle activity data using several trip summary statistics designed to characterize driving behavior. As noted before, the summary statistics were calculated from easily available driving and roadway variables shown to correlate with second-by-second emissions. The trip summary statistics are listed in Table 3 in Section 2.1.3.

The resulting trip summary statistics were then used in a stepwise regression against CO_2, CO, HC, and NO to identify the best trip summary statistics for relating driving behavior to emissions. With the relatively small number of trips available for this project, this pre-screening of the trip summary statistics was necessary for reducing the number of variables that would be included in the principal components analysis. This was done to keep the number of variables in the principal components analysis small compared to the number of degrees of freedom.

Using the emission results from the training data set, the stepwise regression identified ten driving summary statistics that were significant. The statistics are presented in Table 10.

Table 10. Significant driving summary statistics.

Dependent Variable	Significant Driving Statistics
CO_2	Sum velocity > 0 mph
	Sum velocity > 70 mph
	Sum acceleration < -6 mph/sec.
	Sum sp > 400
	Sum grade < 0
CO	Sum acceleration > 5 mph/sec.
	Sum sp > 100
HC	Sum sp > 50
NO	Sum velocity > 45 mph
	Sum velocity > 80

Based on these results, a principal components analysis was conducted on a sub-set of the driving summary statistics for the training trips as well as the six test trips. Soak time, cycle length, and driving distance were added to the set of driving characteristics because of their effects on emissions. The principal components analysis identified five significant factors within the data (Table 11). The factor loadings represent the correlation of the original variables with the five factors. Large (near 1) positive and negative values indicate variables that are strongly associated with the factor.

Table 11. Principal components analysis results for LDV data set showing variables and factor loadings for the five significant factors (eigenvalue >1).

Orthogonal Solution
Inclusion criteria: Criteria 1 from finalstats.csv (imported).svd

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
mean(vel)	.597	-.136	.186	.567	.122
mean(acc)	.080	.072	.691	.077	.149
mean(grade)	.027	.011	.799	-.102	-.092
mean(sp)	-.257	.432	.277	-.029	.716
cycle length	.962	.048	.013	.051	.037
sum vel > 0	.895	-.053	.067	.399	-3.967E-4
sum vel > 45	.745	-.074	.052	.579	-.070
sum vel > 80	.080	.093	-.088	.858	-.013
sum acc < -5	-.549	-.219	-.012	-.020	-.619
sum acc > 5	.364	.559	-.038	.024	.357
sum sp > 0	.893	.206	.018	.293	.217
sum sp > 150	.628	.538	-.064	.272	.312
sum sp > 350	.169	.782	-.085	.039	-.162
sum grade related pow er	.924	.162	.042	.263	.180
soak	.122	-.226	-.041	.017	.765
sum grade < 0	-.929	-.087	.052	.012	-.002
sum grade > 0	.940	.016	.109	-.085	-.034
sum acc > 0	.903	.239	.016	.068	.259

The first factor accounts for 49% of the variability between trips, the second factor accounts for about 11%, and the other three significant factors account for 6% to 7% of the variability between trips. The first factor is primarily a total trip factor, with weight high for cumulative variables such as Sum velocity >0 and Sum acceleration >0 etc. The second factor is more heavily weighted on the higher power and acceleration variables. The third factor is primarily a function of mean acceleration and mean grade, while the fourth factor loads heavily on the summaries of the higher power events. The fifth factor is a mixture of the deceleration summary, soak time, and mean specific power.

The large number of trip summary statistics were converted to five principal components, and the principal components scores of all training and testing trips were computed. Regressions were then run to identify the principal components that best predicted the total trip emissions of CO_2, CO, HC, and NO using only the principal components scores of the training data. The two best principal components for estimating each of the emissions were then compiled (Table 12) and used to produce plots of all trips, including the test trips. In this manner, the nearest training trips in terms of emissions related driving behavior can be identified by plotting all trips on an XY plot of the corresponding principal components scores. For CO_2 and NO, the two significant principal components were Factor 1 and Factor 4. For CO and HC, the two significant principal components were Factor 1 and Factor 2. The trips are plotted on these factors in Figures 11 and 12.

Table 12. Regression of principal components on emissions of training trips.

Regression	First PC	Second PC	R-square
CO2	Factor 1	Factor 4	.932
CO	Factor 1	Factor 2	.625
HC	Factor 1	Factor 2	.553
NO	Factor 1	Factor 4	.631

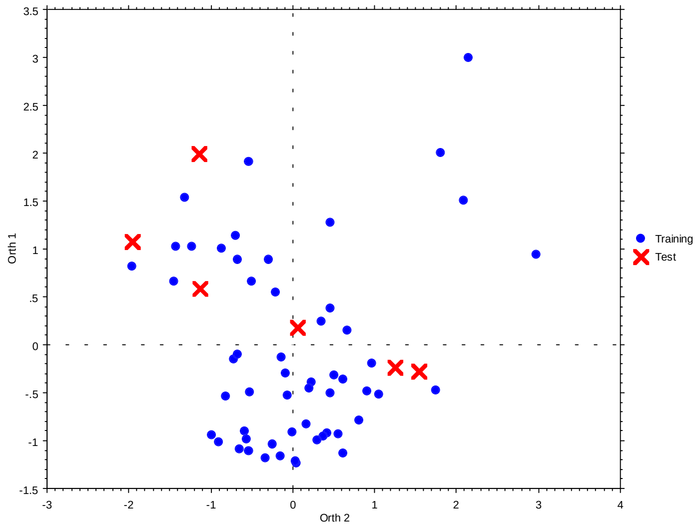


Figure 11. Plot of all light-duty trips against Factor 1 and Factor 2.

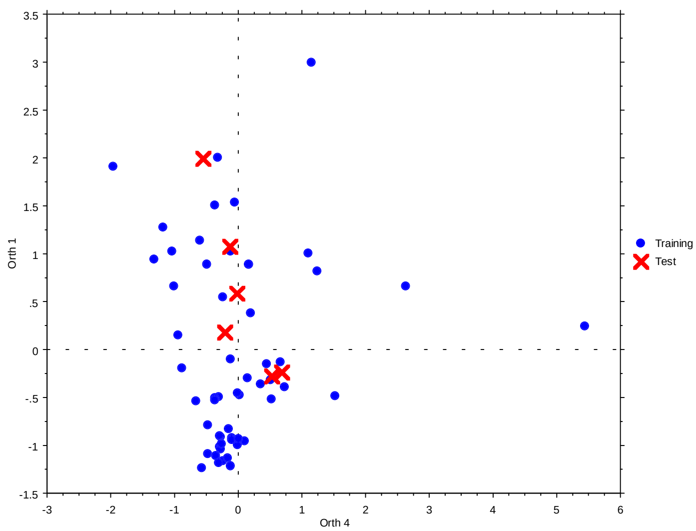


Figure 12. Plot of all light-duty trips against Factor 1 and Factor 4.

It should be noted that two of the test trips in the plot of Factor 1 and 2 are on the outer edge of the driving conditions found in the training trips. This may cause some problems in the estimation of the emissions for these trips because they are at the outer edge of the observed driving behavior.

The emission rates for each of the test trips were then calculated using the average emission rate of the three closest test trips on the appropriate plot (Table 13). In this example, all of the vehicles were used to give a robust data set for the principal components analysis without screening for similarity to the test vehicles. If this methodology were to be implemented it would likely give better predictions if the matching is done only against similar vehicles.

Table 13. Macroscale emission calculations using matching trips.

Trip	SRM089TR_2	3DAU86TR_3	3DAU86TR_5	RAK416TR_2	RAK416TR_4	RAK416TR_5
CO2(1)	2.491951	2.806772	2.412036	3.38824	3.38824	3.410387
CO2(2)	2.67037	2.326812	2.917962	2.927351	2.927351	2.80672
CO2(3)	2.04947		3.698247	4.259898	4.259898	2.616704
Avg. g/s	2.403930333	2.566792	3.009415	3.525163	3.525163	2.944603667
Total seconds	3373	1521	2334	916	1106	1555
Estimated Sum CO2	8108.457014	3904.090632	7023.97461	3229.049308	3898.830278	4578.858702
CO(1)	0.059418	0.036074	0.036074	0.03289	0.03289	0.044808
CO(2)	0.015362	0.004205	0.038925	0.009137	0.009137	0.010087
CO(3)		0.021053	0.021053	0.015362	0.015362	
Avg. g/s	0.03739	0.020444	0.032017333	0.019129667	0.019129667	0.0274475
Total seconds	3373	1521	2334	916	1106	1555
Estimated Sum CO	126.11647	31.095324	74.728456	17.52277467	21.15741133	42.6808625
HC(1)	0.000935	0.000864	0.000864	0.002095	0.002095	0.003462
HC(2)	0.000753	0.00618	0.002945	0.00179	0.00179	0.000369
HC(3)		0.001409	0.001409	0.000753	0.000753	
Avg. g/s	0.000844	0.002817667	0.001739333	0.001546	0.001546	0.0019155
Total seconds	3373	1521	2334	916	1106	1555
Estimated Sum HC	2.846812	4.285671	4.059604	1.416136	1.709876	2.9786025
NO(1)	0.004943	0.002529	0.010405	0.009116	0.009116	0.008112
NO(2)	0.00248	0.009064	0.002841	0.003094	0.003094	0.002529
NO(2)	0.00419		0.007123	0.004461	0.004461	0.001511
Avg. g/s	0.003871	0.0057965	0.006789667	0.005557	0.005557	0.004050667
Total seconds	3373	1521	2334	916	1106	1555
Estimated Sum NO	13.056883	8.8164765	15.847082	5.090212	6.146042	6.298786667

The results from Table 13 are summarized in Table 14.

Table 14. Car modeling emission results for the macroscale level.

Car	Trip	CO2 (g)	CO (g)	NOx (g)	HC (g)
SRM089	2	8108.46	126.12	13.06	2.85
Subtotal		8108.46	126.12	13.06	2.85
3DAU86	3	3904.09	31.10	8.82	4.29
3DAU86	5	7023.97	74.73	15.85	4.06
Subtotal		10928.07	105.82	24.66	8.35
RAK416	2	3229.05	17.52	5.09	1.42
RAK416	4	3898.83	21.16	6.15	1.71
RAK416	5	4578.86	42.68	6.30	2.98
Subtotal		11706.74	81.36	17.54	6.10
Total		30743.26	313.30	55.26	17.30

2.2.2 On-Road Compression Ignition

The EPA provided a total of 12 on-road compression ignition (CI) datasets for use in building the NGM model (Table 15). The on-road CI vehicles were all buses driven over regular bus routes, including stops. These buses were driven a total of 45 trips with a variety of distances and routes. The similarity between buses makes the prediction dataset more robust because all buses can be used for prediction of the testing busses.

Table 15. Vehicles included in the on-road CI prediction database.

Vehicle Number	Make	Model	Model Year	Odometer	Number of Trips
1	NEW FLYER	DETROIT	1996	216502	2
2	NEW FLYER	DETROIT	1996	222245	4
4	NEW FLYER	DETROIT	1996	228770	4
5	NEW FLYER	DETROIT	1996	199188	4
6	NEW FLYER	DETROIT	1996	200459	4
7	NEW FLYER	DETROIT	1996	223471	4
8	NEW FLYER	DETROIT	1996	260594	4
9	NEW FLYER	DETROIT	1996	252253	4
10	NEW FLYER	DETROIT	1995	283708	4
11	NEW FLYER	DETROIT	1995	280484	4
14	NEW FLYER	DETROIT	1995	216278	4
15	NEW FLYER	DETROIT	1995	247379	3

Data from three buses for a total of 6 trips were provided for use in testing the model. The test vehicles and their descriptions are provided in Table 16. All three vehicles match the vehicles in the prediction dataset.

Table 16. Vehicles included in the on-road CI testing database.

Vehicle Number	Make	Model	Number of Trips
385	NEW FLYER	DETROIT	2
375	NEW FLYER	DETROIT	2
360	NEW FLYER	DETROIT	2

Microscale

For the microscale modeling of the busses all trips having good data were used for the matching program because of the similarity of the vehicles. This increased processing time considerably, but improved the fit of the speed traces over those of the on-road spark ignition vehicles. The plots for the on-road compression ignition vehicles are collected in Appendix A. The results are summarized in Table 17 for individual trips, vehicles, and total for the fleet.

Table 17. Microscale model results for on-road spark ignition vehicles.

Bus	Trip	CO2 (g)	CO (g)	NOx (g)	HC (g)
360	2	16911.24	68.96	165.41	2.67
360	3	11577.84	40.99	119.36	1.91
Subtotal		28489.08	109.95	284.77	4.58
375	2	14624.65	46.66	152.69	2.74
375	3	15663.14	46.29	189.38	3.09
Subtotal		30287.79	92.94	342.08	5.82
385	3	17960.83	69.82	211.04	2.78
385	4	10961.88	52.70	127.78	2.23
Subtotal		28922.71	122.52	338.82	5.00
Total		87699.58	325.42	965.66	15.41

Mesoscale

The mesoscale methodology for the bus data is similar than that for the car data. The pilot data were plotted into ArcView along with the prediction data (Figures 13 and 14).

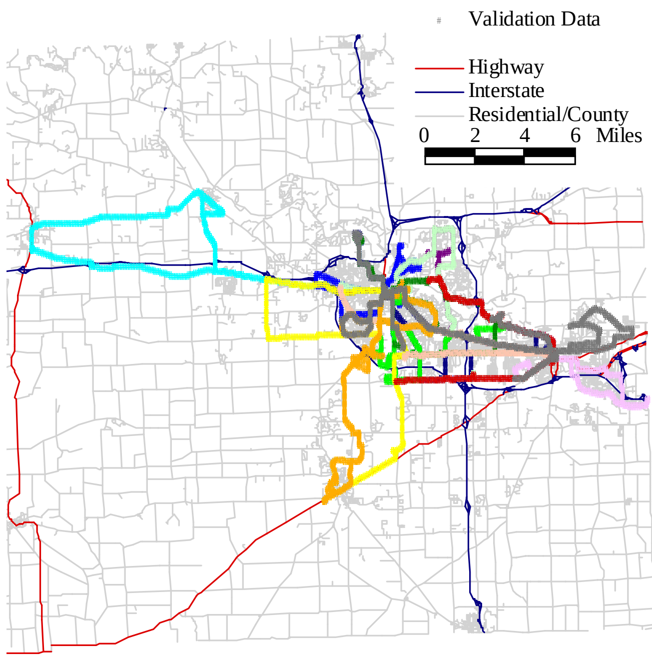


Figure 13. Map of vehicle trips.

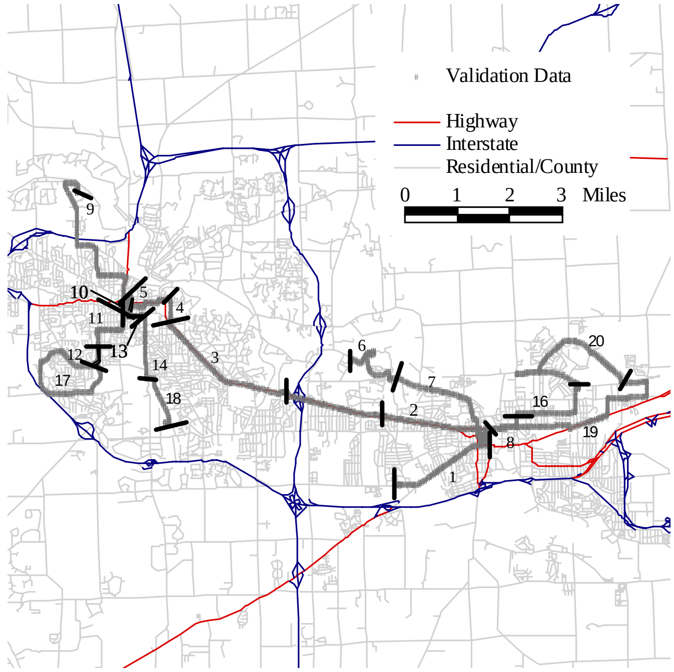


Figure 14. Map of test vehicle data and modeled links.

The resulting emissions are presented in Table 18 for each trip, each bus and total emissions.

Table 18. Bus validation emission results for the mesocale level.

Bus	Trip	CO2 (g)	CO (g)	NOx (g)	HC (g)
360	2	11829.81	47.23	125.65	1.47
360	3	11915.83	39.20	102.88	1.05
Subtotal		23745.64	86.43	228.53	2.52
375	2	20284.77	77.79	216.65	3.16
375	3	24837.01	85.79	254.31	3.13
Subtotal		45121.78	163.58	470.96	6.29
385	3	17412.11	75.43	203.12	2.90
385	4	10983.57	46.34	118.66	1.63
Subtotal		28395.67	121.76	321.77	4.53
Total		97263.09	371.77	1021.26	13.35

Total link emissions for the bus pilot study data and validation data were calculated and plotted into ArcView (Figure 15).

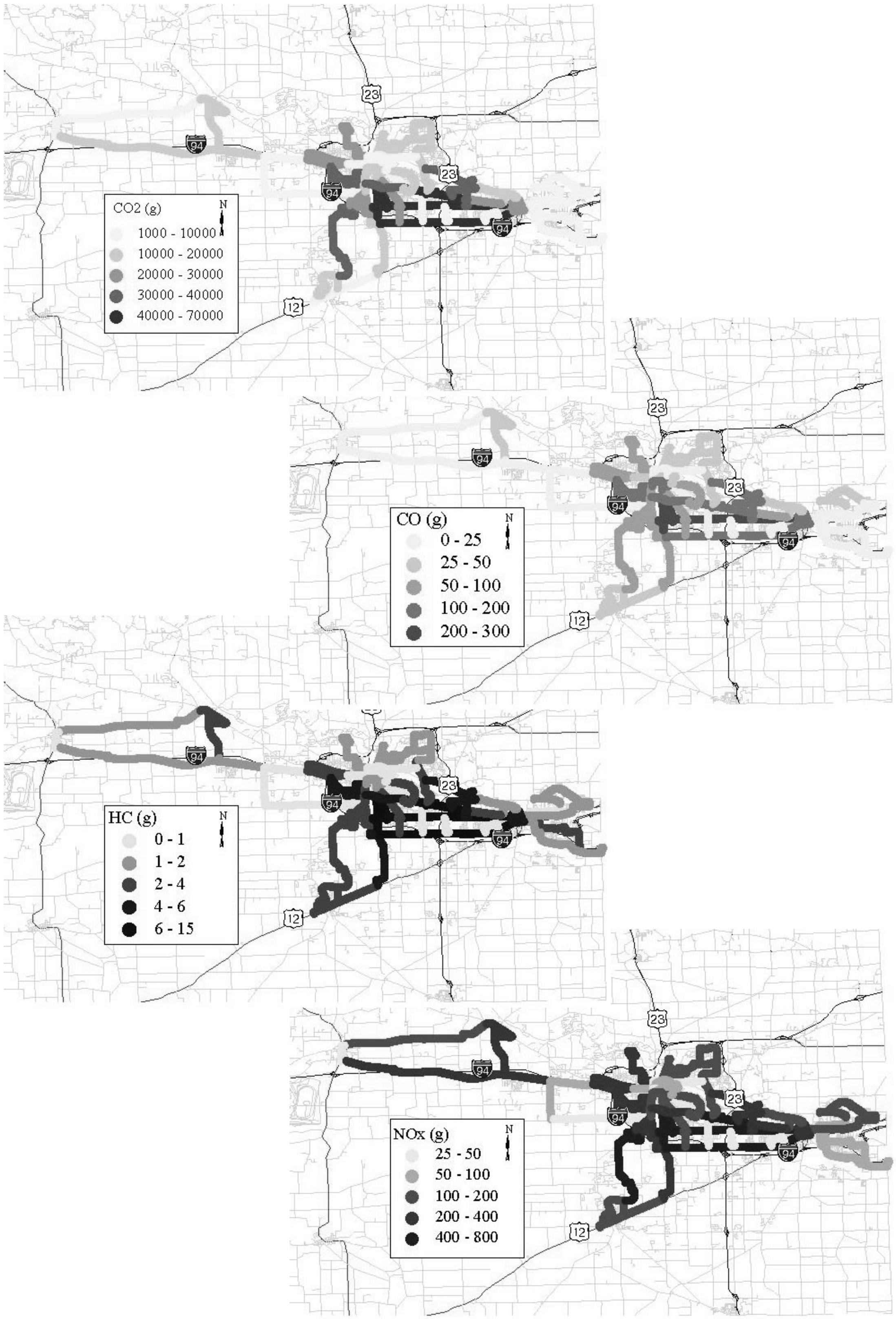


Figure 15. Link CO_2, CO, HC, and NOx emissions for buses in the pilot study and validation database.

Macroscale

The macroscale modeling of the on-road compression ignition vehicles followed the same methodology as that of the on-road spark ignition vehicles. Trip summary statistics were calculated for each trip in the training database and for the trips in the test vehicle data. Regressions were run to identify the best summary statistics for the bus data, then these variables were run in a principal components analysis to reduce the dimensionality of the variable space (Table 19).

Table 19. Principal components results for on-road compression ignition vehicles.

Orthogonal Solution

	Factor 1	Factor 2	Factor 3	Factor 4
mean(vel)	-.247	.871	.170	.224
mean(acc)	-.320	.022	.928	.026
mean(grade)	.286	.238	.042	.540
mean(sp)	-.022	-.049	.994	-.017
sum vel > 55	-.041	.178	-.052	.748
sum acc < -1	-.954	.129	.105	.160
sum acc < 0	-.942	.033	.188	.204
sum acc > 4	.351	.206	-.040	-.622
sum sp > 50	.922	.029	-.072	.177
sum grade related pow er	.949	.192	-.189	.039
Distance	.406	.769	-.411	.020

The emissions for each of the six test vehicle trips were then estimated using the average emission rates of the three best fit trips from the database. The results are summarized in Table 20.

Table 20. On-road compression ignition vehicle results.

Bus	Trip	CO2 (g)	CO (g)	NOx (g)	HC (g)
360	2	19115.51	62.68	226.96	2.87
360	3	12948.18	21.89	142.38	3.12
Subtotal		32063.69	84.57	369.34	5.99
375	2	17022.19	59.56	130.35	1.84
375	3	17706.32	59.02	176.77	2.83
Subtotal		34728.51	118.58	307.13	4.67
385	3	19693.07	65.64	196.61	3.14
385	4	16739.92	25.81	222.89	3.49
Subtotal		36432.99	91.45	419.50	6.63
Total		103225.19	294.59	1095.97	17.29

2.2.3 Off-Road Compression Ignition

The EPA provided a total of three off-road compression ignition (CI) datasets for use in building the NGM model, one scraper, one compactor, and one bulldozer. These pieces of equipment were driven a total of approximately three hours with a variety of distances and routes. An additional hour of operation data were provided for the test data set from the same vehicles. The use of the same equipment makes the prediction dataset more robust.

Data from one additional hour of each of the three off-road vehicles were provided for use in testing the model. This is the optimal case for the database model because each vehicle is predicted with previous data collected on the same vehicle.

For the off-road vehicles there will only be microscale-based predictions because of the lack of road link and trip equivalent events. In addition, the modal events will be matched using exhaust flow instead of speed.

Microscale

The microscale methodology used in the modeling of the on-road data was adapted to the off-road data by using the exhaust flow data in place of vehicle speed to define the operating modes. The exhaust flow data was less smooth than the vehicle speed data, however the differences were not sufficiently large to disrupt the matching of events.

The results are plotted in Figures 16 to 18 and are summarized in Table 21.

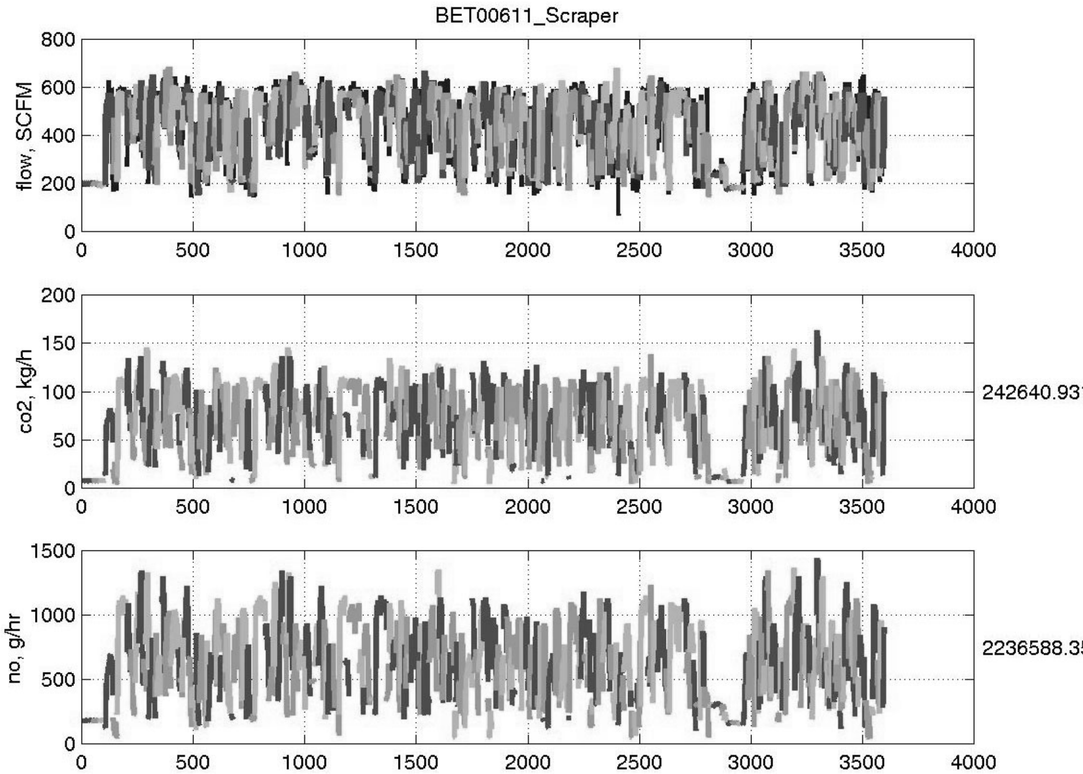


Figure 16. Scraper microscale modeling results.

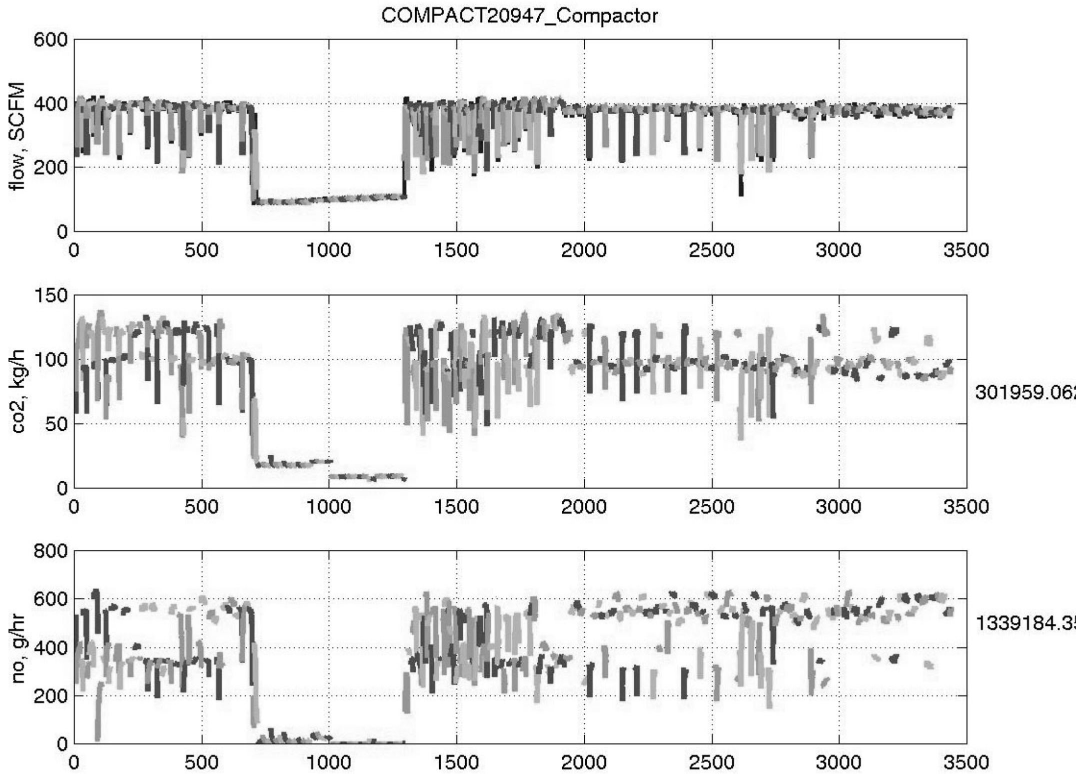


Figure 17. Compactor microscale modeling results.

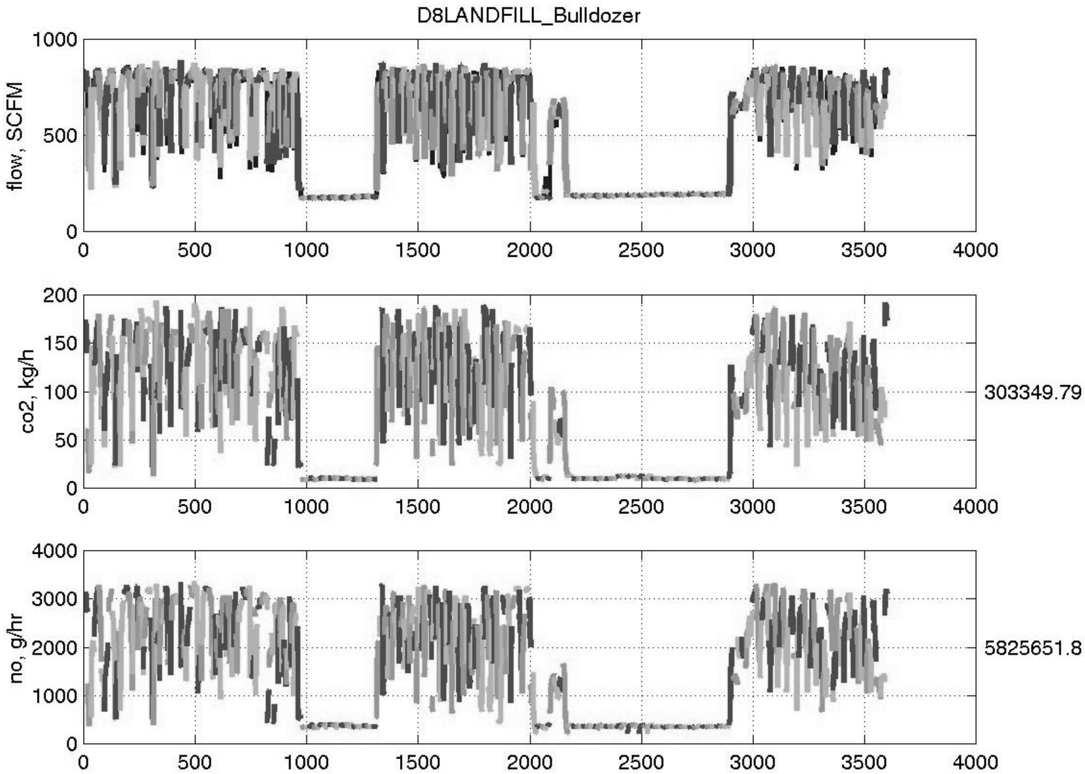


Figure 18. Bulldozer microscale modeling results.

The predicted values for the off-road vehicles are summarized in Table 21. The NO emissions for relative to the CO2 emissions were much higher the Bulldozer than for the Scraper or the Compactor.

Table 21. Nonroad validation emission results for the microscale level.

Vehicle	CO2 (g)	NO (g)
Scraper	67400.26	621.27
Compactor	83877.52	371.99
Bulldozer	84263.83	1618.24

2.3 Results Summary

The results of the model predictions at the micro-, meso-, and macro- scales are summarized in Figures 19 and 20.

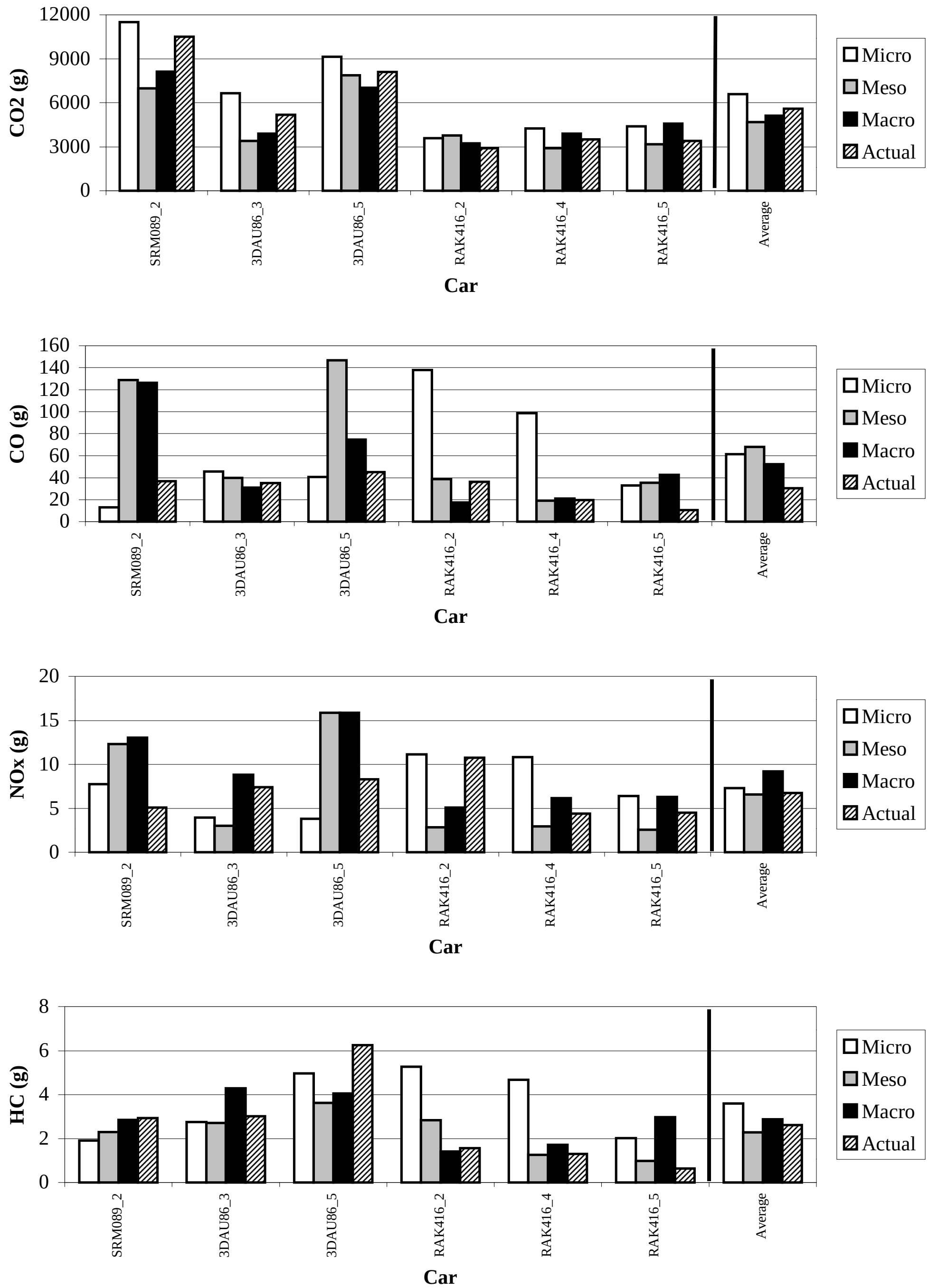


Figure 19. Car emissions for microscale, mesoscale, and macroscale for CO_2, CO, NOx, and HC.

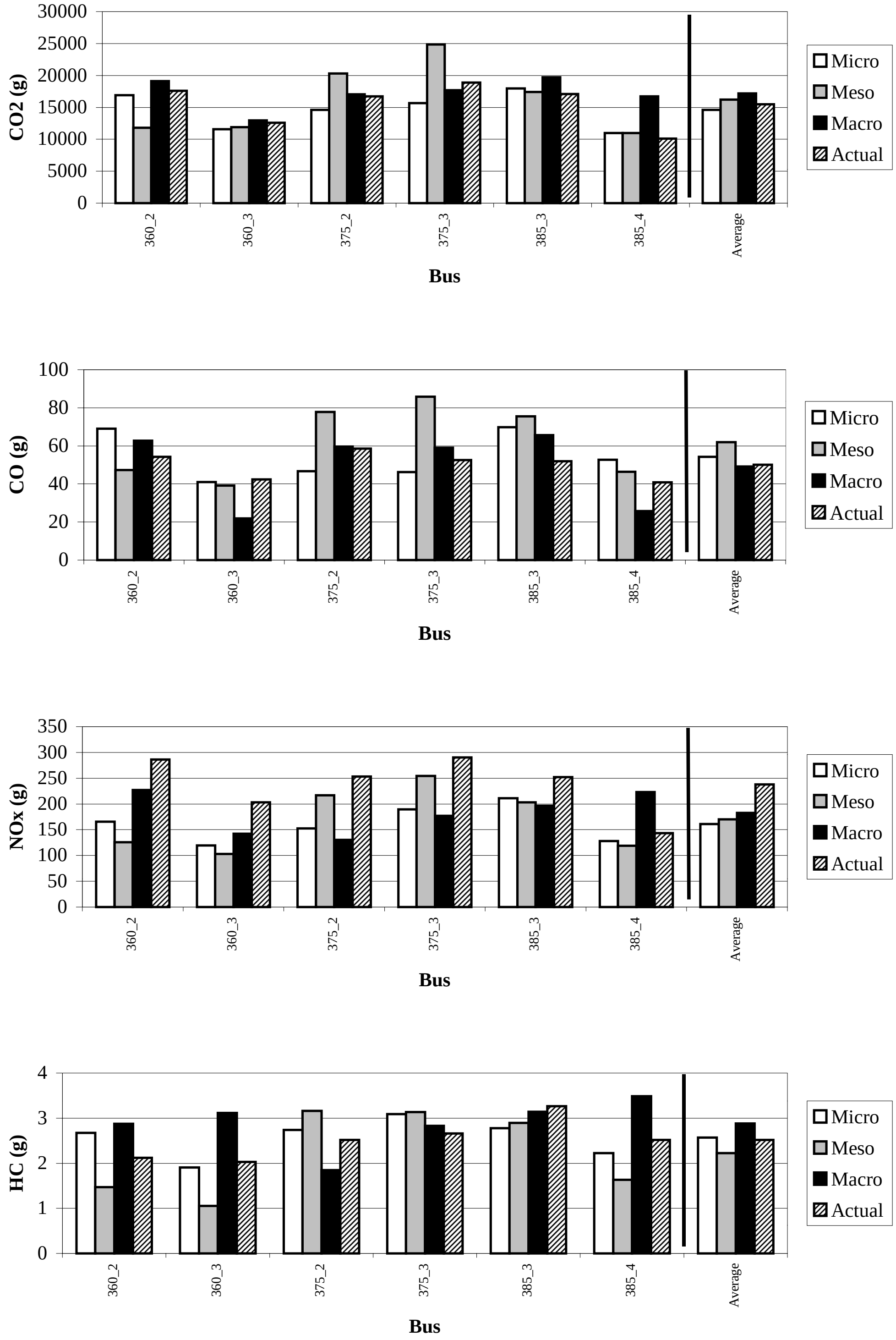


Figure 20. Bus emissions for microscale, mesoscale, and macroscale for CO_2, CO, NOx, and HC.

In general the three levels of the model give similar predictions for the on-road compression ignition vehicles. Some individual vehicles have greater variability between the three predictions, likely due to vehicle to vehicle variability. The difficulty in getting a reasonable match at the mesoscopic level may in part be due to driving differences on the links. In some cases the average emission rate on a link was influenced by a trip on the link that had unusually high or low emission rates and driving behavior. Overall the three levels of the model correspond better on the compression ignition vehicles than on the spark ignition vehicles. This is at least in part due to the greater degree of similarity between the vehicles within the compression ignition class.

After presentation of results to EPA staff, CE-CERT was provided with the actual emissions for the test vehicles. The results are summarized as percent difference for the three levels of the model in Table 22. For the off-road vehicles the results were quite good. In addition, the bus predictions, with the exception of NO at the microscale level, were off by less than 30%. Likewise, the car predictions, with the exception of CO at the microscale level and NO at the macroscale level, were off by less than 30%

Table 22. Percent difference between actual and predicted for microscale, mesoscale, and macroscale model results.

Averge Percent Difference-Micro				
	HC	**CO**	**CO2**	**NO**
Car	26%	84%	17%	6%
Bus	2%	8%	-6%	-32%
Off-road			-7%	-2%

Average Percent Difference-Meso				
	HC	**CO**	**CO2**	**NO**
Car	-12%	123%	-16%	-2%
Bus	-12%	24%	5%	-28%

Average Percent Difference-Macro				
	HC	**CO**	**CO2**	**NO**
Car	10%	71%	-9%	37%
Bus	14%	-2%	11%	-23%

3. Future Data Collection

The PEMS data collection efforts will be a critical part of implementing EPA's NGM. Data collection should follow a test matrix that maximizes the quality and type of data that will make the NGM a robust model. The PEMS unit is on-board equipment, so it is not possible to decide exactly what road types and driving conditions will be measured by any regular in-use installation. Care should be taken to capture true on-road emissions. Specifying the road types and driving conditions needed for the NGM may compromise the data collection process, but targeting recruitment on cities having a preponderance of desired conditions could be done. As an example, Denver could be targeted for recruitment to collect high altitude and high road-grade operation.

The macroscale, mesoscale, and microscale levels have the same goal for data collection, collect as much data as possible while covering the full range of operating conditions. The data can be incorporated easily into all three levels as discussed in the previous section. The deployment of PEMS units will be expensive, so proper statistical design will ensure maximum accuracy for the minimum cost to the EPA. Recruitment should be random in order to obtain an unbiased sample of drivers for data collection.

3.1 Sample size estimates

The bus data were used to estimate the number of vehicles that would be necessary for the characterization of an additional set of vehicles. Predictions of the six bus test trips were run at the microscale level using one randomly chosen bus, two, three, four, and eight busses. Plots of the difference between observed and predicted trip emissions were then produced for CO_2, CO, HC, and NO (Figure 21).

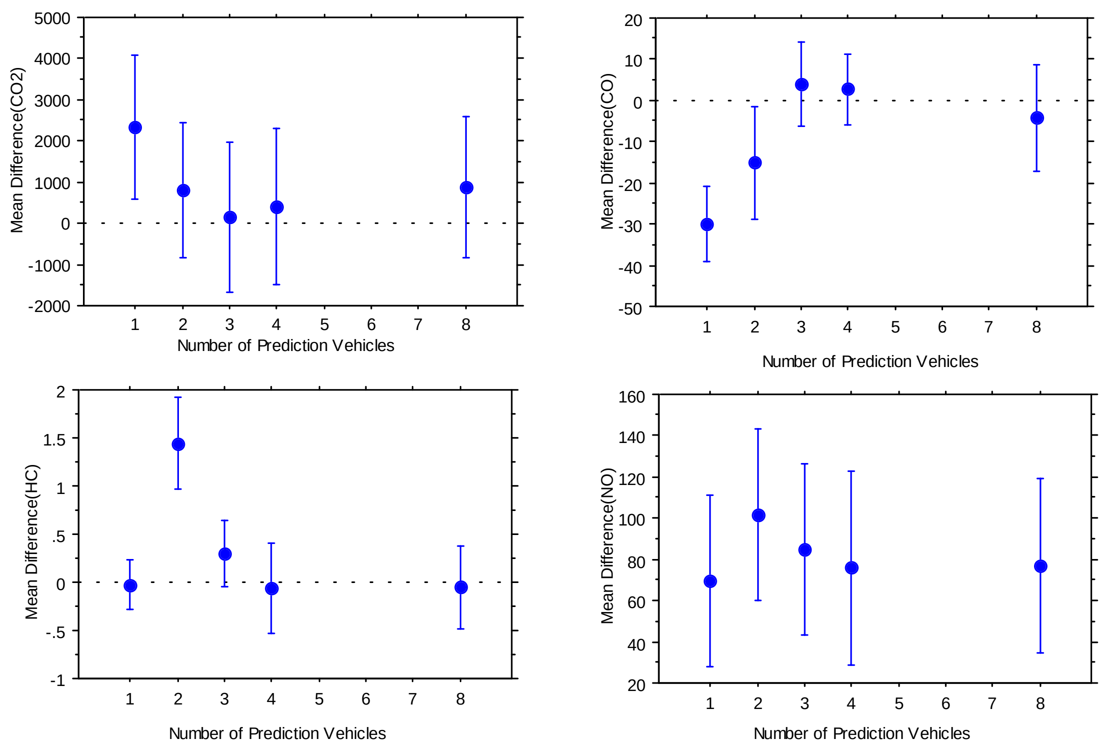


Figure 21. Mean difference (observed-predicted) for CO_2, CO, HC, and NO from bus data.

From these plots it can be seen that in general, there is little improvement in the prediction accuracy after four vehicles. With three to four vehicles, the confidence intervals for the mean difference between actual emissions and predicted emissions includes 0 for CO_2, CO, and HC. It can also be seen that the NO mean difference does not converge to 0. Further examination of the 12 bus prediction database found that the peak NO emission rate for a subset of the buses was lower than that of the other busses and also lower than the peak emission rates for the three prediction busses. In the case of NO, the bus emission predictions are representative of a broader vehicle fleet than was included in the three prediction vehicles.

A similar analysis was conducted on the cars (Figure 22), however the analysis was limited because of the lack of highly similar vehicles as was the case in the bus data. For this analysis the 1999 Ford Escort was predicted with 1) the 1997 Ford Escort in the prediction database, 2) the 1997 Escort and the 1998 Mercury Mystique, and 3) the 1997 Ford Escort, the 1998 Mercury Mystique, and the 1998 Chevrolet Cavalier. This analysis was subject to a greater degree of vehicle bias because the vehicle to be predicted was a single vehicle instead of a group of vehicles, making the target potentially biased relative to the average vehicle in the class. However, the main goal of identifying a rough number of vehicles necessary to characterize an individual vehicles operation is still valid.

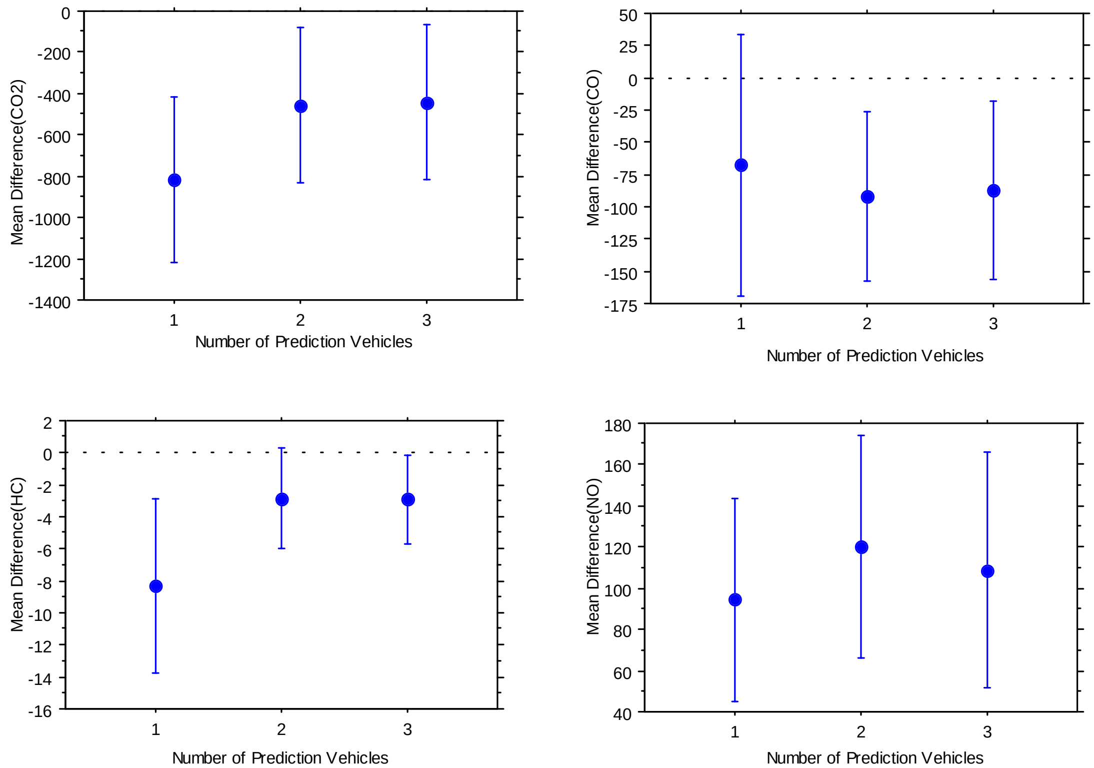


Figure 22. Mean difference (observed-predicted) for CO_2, CO, HC, and NO from car data.

Implementation of this approach in the NGM framework will initially require the collection and categorization of large amounts of PEMS data. However, as more data are collected, the inventory of road/traffic conditions that have been characterized will grow rapidly. As the PEMS units are used, they collect emissions data over various road types and driving situations. Individual cars will drive multiple times on the same roadway in some cases, providing data for estimation on the variability of emissions and driving behaviors associated with a specific road link. The standard application will be dependent upon the degree to which the area where the model is being implemented can be matched to the link database. Individual users such as cities and regional authorities would have the option of collecting area specific PEMS data.

The development of the database for this methodology is primarily a large stratified random sample because the model itself is based on having observed data to match the specific situation that is to be modeled. Understanding vehicle-to-vehicle differences in emissions behavior across a wide variety of driving conditions and road conditions will be critical both for the success of this method and the development of sampling methodology. Our analysis of NCHRP test data have shown significant differences in emissions behavior across technology types even over the relatively limited range of driving conditions experienced in laboratory testing. Thus a key element will be the preprocessing and identification of factors most closely related to emission rates.

From the data available in this study we know that three hours of off-road operation data was sufficient for predicting emissions of one additional hour of operation within 7% for CO2, and within 5% for NO. With the limited off-road data in this study it was not possible to estimate the variability in behavior and emissions within vehicle classes. For this reason, a small pilot study that would include at least five vehicles within the three classes used in this study would be an essential step in the planning of further sampling.

Off-road operation typically has very high engine load because of the type of work that these vehicles do. Therefore, it is expected that the sampling methodology will be more focused on the characterization of the vehicle/technology groups. As with on-road sources, the success of this methodology depends highly upon having an observed emission rate for a similar vehicle and operational conditions to the one being modeled.

3.2 General PEMS Sampling Issues and Needs

Stratified Random Sampling. On-road sampling with PEMS units should follow a stratified random sampling methodology. Sampling to characterize the emissions from an on-road fleet could be achieved with a simple random sample, but sampling for model development has different goals and will require fewer total samples under a stratified methodology. The reason for this is the need to develop accurate modeling of the various sub-fleets within the general on-road vehicle population. Possible stratification factors include:

- emission control technology
- car / truck
- normal emitter / high emitter
- type of high emitter (runs rich, runs lean, misfire, etc.)

Sampling proportional to emissions variability and emissions contribution. An additional factor to be considered in general PEMS sampling is the determination of proper sample allocation based upon emissions variability and emissions contribution. The accuracy of the model for a particular sub fleet, regardless of the final form of the model, is going to be proportional to the emissions variability within the sub fleet and the size of the sample. This includes both vehicle to vehicle variability and variability in modal behavior between vehicles within the sub fleet.

SULEV and other new technology vehicles: Manufacturer to manufacturer variability in emissions control technology is relatively low for the current technology vehicles. Some differences in catalyst warm up behavior exist within the Tier 1 vehicle fleet (Younglove 2000). However the differences are primarily in the speed at which the closed-coupled catalysts warm up relative to the standard configurations. In the SULEV vehicle fleet there are likely to be large differences in behavior from current technology vehicles as well as between manufacturers within the SULEV fleet as they pursue different technological solutions to emissions control. As an example, CO and HC absorber equipped SULEV vehicles would exhibit very different emissions behavior across soak times from vehicles with pre-heated catalysts.

3.3 Database Model – Specific Issues and Needs

Vehicles and operating conditions cannot be modeled well if they are not in the database
This is in contrast to CMEM and other physical parameter based models which use equations that provide smooth calculation of emissions under any operating condition within the calibration range of the model. With the database model it is not possible to extrapolate beyond the on-road data collected for modeling. The use of current lab data to augment the on-road data will provide a wide range of vehicles for modeling, but with a more limited set of operational conditions than that likely to be found in the on-road data. The data specific modeling methodology will also require development of a methodology for characterizing the driving behavior within each vehicle group because if operational "holes" exist in the database they must be identified and corrected. Several factors will need to be estimated prior to development of a sampling design:

- on-road data collection dependent on the degree to which current lab data will be used
- modeling depends upon vehicle-to-vehicle variability in emission rates AND behavior
- modeling also depends upon similarity in emission rates and behavior within vehicle technology groups

Emission correction factors. Smaller conditions that influence emission rates may be modeled through correction factors if effects are consistent within technology groups. The database model could be developed with a much smaller number of samples if some of the factors which influence emissions have a consistent effect within the vehicle sub groups. Uniform effects, or near uniform effects that might be accomplished with correction factors include:

- fuel effects
- AC and other load effects
- temperature and humidity effects

3.4 Specific Recommendations For On-Road Data Collection

Initial scoping study of three to five vehicles. The main goal of this study is to determine the approximate installation time necessary for capturing the warmup and driving/emissions behavior of a typical new LDV. One analysis of this data would be to use the data from each vehicle to predict the trips from that vehicle. Our preliminary analysis using the shootout data indicated that for an individual vehicle, the accuracy of predicting a trip from other trips of the same vehicle ranged from 10% to 40% depending on trip characteristics, particularly soak time. This analysis will help determine the installation time for future studies. Sampled vehicles should be:

- all in the same power/weight and emission technology class

- at least 20 – 30 trips for each vehicle (5 –7 day install)
- keep driver log to differentiate between drivers
- perform limited aggressive driving to capture all events

Follow up vehicle technology study. The main goal of this follow up study is to determine the within group and between group variability in emissions, modal emissions behavior, and activity. This information will be essential in the development of the test matrix for deployment of the PEMS unit. This study will also allow for the estimation of the relative differences in emissions between lab testing and on-road testing across the vehicle technology categories. At least 10 vehicles should be included within each major technology group. The length of installation would depend upon the initial scoping study. Recommended vehicle technology groups:

- Cars
  - Carbureted, no catalyst
  - Carbureted, 2-way catalyst
  - Carbureted, 3-way catalyst
  - Fuel injected, 3-way catalyst, Pre-Tier 1
  - Fuel injected, 3-way catalyst, Tier 1
- Trucks
  - Carbureted, no catalyst
  - Carbureted, 2-way catalyst
  - Carbureted, 3-way catalyst
  - Fuel injected, 3-way catalyst, Pre-Tier 1
  - Fuel injected, 3-way catalyst, Tier 1

This follow up study would provide valid data for the initial stages of modeling of the NGM as well as providing the information necessary for the design of the full scale deployment of the PEMS units. The older vehicle technology groups, while having much higher emission levels, may have more uniformity of emissions behavior across modal events. If this proves to be the case, the 10 sampled vehicles may be sufficient for characterization of the behavior of the older vehicle fleet. After completion and analysis of this follow up study it will be possible to determine the allocation of PEMS units necessary for development of the NGM.

Additional small scale studies. Several additional small scale studies using the PEMS units should be considered. These studies would involve the installation of 15 to 20 PEMS units in randomly selected vehicles either at different times of the year or at different locations having different topography. The studies could include:

- fuel effects
- grade effects
- seasonal effects

3.5 Specific Recommendations For Laboratory Data Collection

Catalyst efficiency study. Catalyst behavior in the first two or three minutes of driving has a large influence on the total emissions for the trip. As vehicle manufacturers continue to lower hot-stabilized emissions the importance of the cold and warm start catalyst behavior will continue to increase in importance. At the present time, catalyst behavior in the first couple of minutes is not well characterized. Laboratory testing with pre- and post- catalyst sampling provides the best source of accurate information for estimation of catalyst efficiency, light off time, and improvements of warm up behavior modeling. A study of 10 – 20 vehicles, with assorted mileage, soak times, and driving patterns at the start of each driving cycle would provide a rich data set for the estimation and modeling of catalyst behavior in the NGM.

Fuel effects study. The small size of fuel effects on emissions of individual vehicles makes the measurement of fuel effects on road difficult. This is an important factor affecting emissions on a regional scale and the inclusion of fuel effects in the NGM is important. For this reason, a replicate of the on-road fuel effects study should be conducted in the lab to try and provide an estimate of the scale of the fuel effects under controlled conditions.

- same fuels in the on-road version
- variable driving/soak times

3.6 Specific recommendations for supplemental data collection

Implementation of the NGM will require accurate data on vehicle fleets as well as specific vehicle driving behavior. While collection of this data is not directly related to the development of the emission rate estimation portion of the model, it is critical for the implementation of the model. The improvements in emissions modeling that can be accomplished through better characterization of vehicle emissions modal behavior are of little use if real-world modal behavior is not accurately characterized. The large differences in emissions rates across vehicle technology groups and vehicle model year make accurate characterization of the on-road fleet at least as important as improvements in the estimation of emissions of individual vehicles. In research conducted at two national parks in the southwestern US, CE-CERT found that both the vehicle fleet and the vehicle driving behavior differed significantly from the local default values [Lents et al., 2001]. The difference in the age and vehicle class distribution of the parks resulted in lower emissions estimates for all pollutants and vehicle classes at all speeds. VOC and CO emissions range from about 34 to 48 percent lower than the baseline case, and NOx emissions are about 53 percent lower than the baseline. The driving behavior within the two parks were significantly different from each other and from the FTP driving cycle, with a variable effect on emissions.

Vehicle activity. While the NGM can certainly be implemented with the current vehicle activity representations used in Mobile6, its greatest value will be achieved if some additional vehicle activity data are collected. Accurate soak time distributions and vehicle class specific driving data would provide significant improvement in emissions predictions. The advent of relatively inexpensive GPS data collection methods makes it possible to collect second-by-second driving trace data in a wide variety of vehicles. A modest vehicle activity study covering 5 to 10 cities would provide adequate data for expansion of the vehicle activity characterization available for the NGM. In addition, the study would serve as a case study for states and other government entities to follow if they chose to improve their emissions modeling with locally specific driving data.

Vehicle fleet data. Accurate characterization of the on-road fleet will improve emissions estimates significantly. The collection of large numbers of license plates for vehicle fleet characterization through digital still and digital video methods has been employed at CE-CERT. Improvements in the NGM emissions estimates could be obtained by conducting a vehicle fleet study in 5 to 10 cities to provide a more robust vehicle fleet profile. Analysis of the data would focus on identification of methods for relating vehicle registration databases to the on-road fleet. It is not anticipated that many states or other government agencies would want to spend the money on locally specific on-road fleet studies so the development of an accurate methodology for estimating the on-road fleet from the vehicle registration records is essential.

4. Integration of New and Old Data

For the NGM to be as, reliable, comparable, and accurate as current emissions models based on dynamometer testing, a large amount of on-board data will need to be collected. Data will need to be gathered for a wide variety of vehicle types and driving conditions. Alternate data can serve to fill voids while more data is collected. The variability of the PEMS will also dictate the amount of alternate data that will be required.

The limitation of on-board emissions data in fulfilling the scope of the NGM is the sheer amount of data that is required to develop a thorough representation of different vehicle categories and driving conditions. For this reason, it is likely that rapid implementation of this methodology will require defaulting to current laboratory testing data when emissions rates are needed for vehicle/operational conditions that do not have PEMS data.

Data from other sources will be necessary in conjunction with on-board emissions data in the NGM to address the limitations. Estimates of trip-to-trip variability and vehicle-to-vehicle variability in emissions will be necessary for calculating the statistical power of the PEMS units for differentiating between effects. In general, the higher the variability the greater the need for laboratory data to estimate differences between fuels and other factors that do not have large-scale differences.

Laboratory dynamometer data will serve both as a short-term step to fill the large data matrix, and as an important tool for the study of fuel effects and catalyst efficiency effects. The PEMS units will do the bulk of the data collection, however, the dynamometer data will fill many essential gaps in the information necessary for accurate modeling.

The role of alternate emission testing will likely be in the evaluation of fuels and other factors that have a small, but significant effect on emissions of individual vehicles. These types of effects require more controlled conditions than that likely to be found in on-board testing. Alternate emissions testing data will also play a significant role in the evaluation and estimation of catalyst efficiency.

As noted above, the database methodology is ideally suited for the combining of laboratory and on-road data for prediction of emissions. An example of incorporating new data into the microscale level is shown in Table 23. CE-CERT's NCHRP database was searched to find a vehicle similar to vehicle SRM089TR_2 from the prediction test set. The new data was added to the searchable database and new emissions results were determined.

Table 23. Comparison of emissions results for one test vehicle with inclusion of lab data.

SRM089TR_2	NGM	NGM/NCHRP
CO_2 (g)	11495.65	11573.04
CO (g)	12.98	10.94
NO_x (g)	7.77	7.00
HC (g)	1.91	1.63

The database methodology allows for easy inclusion of second-by-second laboratory data into the microscale level as the previous example demonstrated. In addition, the current laboratory data on vehicles having results for the FTP, US06, and EPA facility cycles can be included at the mesoscale as well as the macroscale levels of the database model. In these cases, the laboratory data would provide a robust data set for links and trips having similar driving behavior to the driving cycles. The laboratory data provides a starting point for the database model that is tied in to the testing used to develop Mobile6, and allows for rapid expansion of the data matrix.

On-board data are likely too variable to accurately quantify small scale effects such as fuel. At the present time laboratory data provides the best current methodology for measurement of these effects. On-board emissions measurement variability will determine the scope of future laboratory data collection. The greater the improvements in on-road measurement, the smaller the need for laboratory testing. However, it is not likely that on-road emissions measurement will replace laboratory data collection for the measurement of cold/warm start effects or for estimation of catalyst efficiency.

5. Summary and Conclusions

In summary, the hybrid database model was developed and tested at the microscale, mesoscale, and macroscale on both on-road spark ignition and compression ignition vehicles. In addition, it was also tested at the microscale level on off-road compression ignition vehicles.

The hybrid database model approach has advantages and disadvantages:

Advantages
Consistency is maintained from microscale to mesoscale to macroscale by the use of the same data for all three levels. In this study, because of the limited amount of data different prediction sets were used at the different levels of the model. However, in a larger implementation the data for all three levels would be the same, just broken down into smaller and smaller parts.

Emission estimates are based on directly measured “real world” emissions where the vehicles are operated under typical road and environmental conditions. While laboratory dynamometers have sophisticated computer controls to simulate the effects of wind resistance and road load, the on-road data is directly measured under real conditions.

Sub 1-second driving events which may influence emissions are included in the data because the data are directly included without the smoothing effects of modeling. Current computer controlled vehicles monitor vehicle operation at much higher time resolution than current vehicle emissions testing time resolution. Enrichment events and other computer controlled behaviors are likely to be influenced by vehicle operation conditions that are not measured at the lower time resolutions. The database model, by directly including the driving behavior in modal events, includes these events.

The database methodology easily incorporates laboratory dynamometer emissions data as was shown in Section 4. While the laboratory data must be measured at the second-by-second resolution to be included at the microscale level, bag results can still be incorporated at the mesoscale and macroscale levels. Because there is little modeling overhead, resources can be focused more on data collection than on the modeling itself.

The model can also be easily expanded with new on-road data, including toxics and greenhouse gases. Because the model functions entirely on matching driving segments that are to be predicted to driving segments within the database there is little overhead in modeling additional emissions. For example, to predict NH_3 the database search would be restricted to data sets having NH_3 emissions. The ability of the model to match the driving from the reduced data would be hampered by the smaller pool of available vehicle trips, however there would be no additional changes to the model.

Confidence bands can be estimated from the data for modal events, link emissions, and trip emissions by modification of the search routine to identify multiple matches instead of using the single best match to each modal event. At the mesoscale and macroscale levels the emissions confidence bands would be calculted from the set of best link or trip matches.

Disadvantages

The single biggest problem with this methodology is the “sparse matrix” problem in which a vehicle and driving condition must exist within the database to be predicted by the model. This was overcome through the preprocessing of link and trip data to enable matching of driving segments with “best” matches that do exist within the database. However, as was seen in the data analysis, matching of vehicles is subject to considerable variation in emissions rates even within very similar vehicles.

The database methodology is also very data intensive, requiring both good vehicle matches, and good driving matches. The methodology will be somewhat less data intensive if it can be determined that effects such as air conditioning usage can be estimated through correction factors. However, there will still be large amounts of data required on all vehicle types.

The third major disadvantage is that it is difficult to extend predictions beyond range of observed vehicles and driving behavior. Unlike a physical parameter based approach, there is no way for the database model to extrapolate beyond the range of the measured data.

Several areas could be improved with additional research:

The cold start/warmup period for the microscale model could be modeled based on fuel use instead of time. In this implementation of the database model the cold/warm division is based on a regression of soak time on estimated warmup time. Analysis of additional on-road and laboratory data would improve the modeling of this critical portion of the trip. Modification of the methodology to incorporate a fuel based warming estimate would improve the ability of the model to predict emissions under a greater variety of starting driving patterns.

A second area where this methodology could be improved is the automation of the modal division step of the modeling process. Testing of different methods of defining modes on the microscale model would likely improve emission estimates. The short time scale of this project precluded experimentation to identify the optimum methodology for dividing driving traces into modal segments.

The bus trip matching at the macroscale level could be improved with the development of better driving summary statistics for the compression ignition vehicles. The summary statistics for the bus data were statistically significant, however they were not highly correlated with emissions. Improved summary statistics for the on-road compression ignition vehicles would do a better job of relating driving behavior to emissions which will improve trip matching.

6. References

An, F.; Barth, M.; Scora, G.; and Ross, M. (2000) Preliminary Development of a Modal-Based Diesel Vehicle Emissions Model. *10th Annual CRC On-Road Vehicle Emissions Workshop,* San Diego, CA, April.

An, F.; Barth, M.; Ross, M.; and Norbeck, J. (1997) The Development of a Comprehensive Modal Emissions Model: Operating under Hot-stabilized Conditions. *Transportation Research Record*, No. 1587, pp. 52-62, Transportation Research Board, National Academy of Science
.
Barth, M., R. Tadi, and J. Norbeck. 1995. "The development of an integrated transportation/emissions model for estimating emission inventories" pp. 1225-1236. Proc. 1995 American Society of Civil Engineers Annual Conference, San Diego, CA, October 1995.

Barth, M., et al. (1996) Modal Emissions Modeling: A Physical Approach. *Transportation Research Record* No. 1520, pp. 81-88, Transportation Research Board, National Academy of Science, August.

Barth, M.; Younglove, T.; Wenzel, T.; Scora, G.; An, F.; Ross, M.; and Norbeck, J. (1997a) Analysis of Modal Emissions from a Diverse In-use Vehicle Fleet. *Transportation Research Record*, No. 1587, pp. 73-84, Transportation Research Board, National Academy of Science.

M. Barth. (1997a) "Integrating a Modal Emissions Model into Various Transportation Modeling Frameworks", proceedings of the ASCE Transportation and Air Quality III Conference, Lake Tahoe, CA, 8/97.

Barth, M. (1997b) Preliminary Emissions and Fuel Consumption Evaluation of Automated Highway Systems. National Automated Highway System Consortium Final Report Appendix.

Barth, M. (1997c) The Effects of AHS on the Environment. *In* Ioannou, P. (ed.), *Automated Highway Systems*, pp. 265-291. Plenum Publishing Corp., NY.

Barth, M.; An, F.; Younglove, T.; Levine, C.; Scora, G.; Ross, M.; and Wenzel, T. (1999) The Development of a Comprehensive Modal Emissions Model. Final report submitted to the National Cooperative Highway Research Program, November, 255 pp.

Dunteman, G. H. (1989) Principal Components Analysis. Quantitative Applications in the Social Sciences. Sage Publications, Newbury Park.

ESRI (2001) http://gisstore.esri.com/

Lents, James, Nick Nikkila, Nicole Davis, and Theodore Younglove, (2001) Mobile Source Emissions Inventory For Zion And Arches National Parks,Proceedings of The 11th CRC On-Road Vehicle Emissions Workshop, San Diego, California. March 26-28, 2001

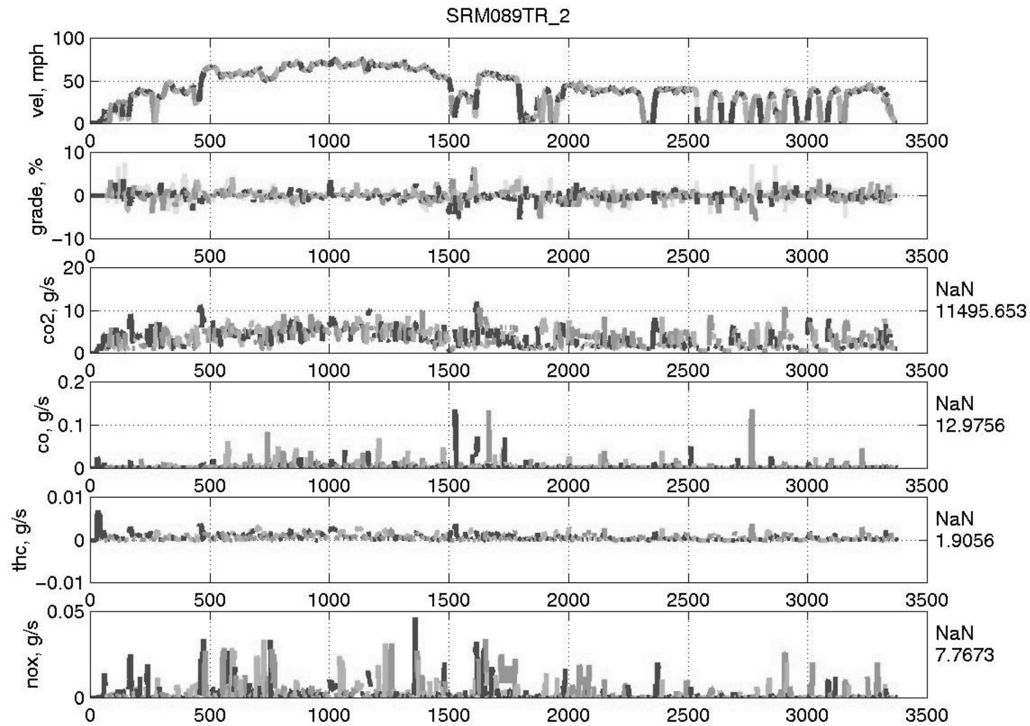
Scora, George, Carrie Levine, Theodore Younglove, and Matthew Barth (2000) Second-by-Second Analysis of Catalyst and Fuel Enrichment Behavior in an In-Use Light-Duty Vehicle Fleet, Proceedings of the 10th CRC On-Road Vehicle Emission Workshop. San Diego, CA, 2000.

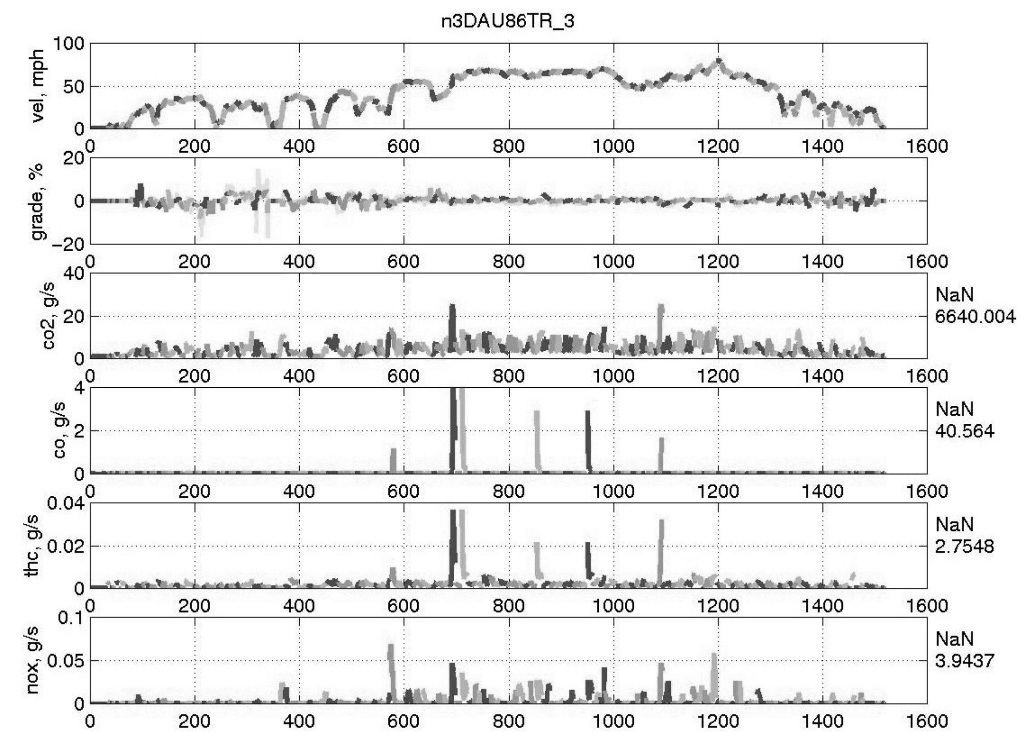
USEPA, (2001) EPA's New Generation Mobile Source Emissions Model: Initial Proposal and Issues. United States Environmental Protection Agency, EPA Mobile Source Emissions Modeling Workgroup, EPA420-R-01-007, April 2001

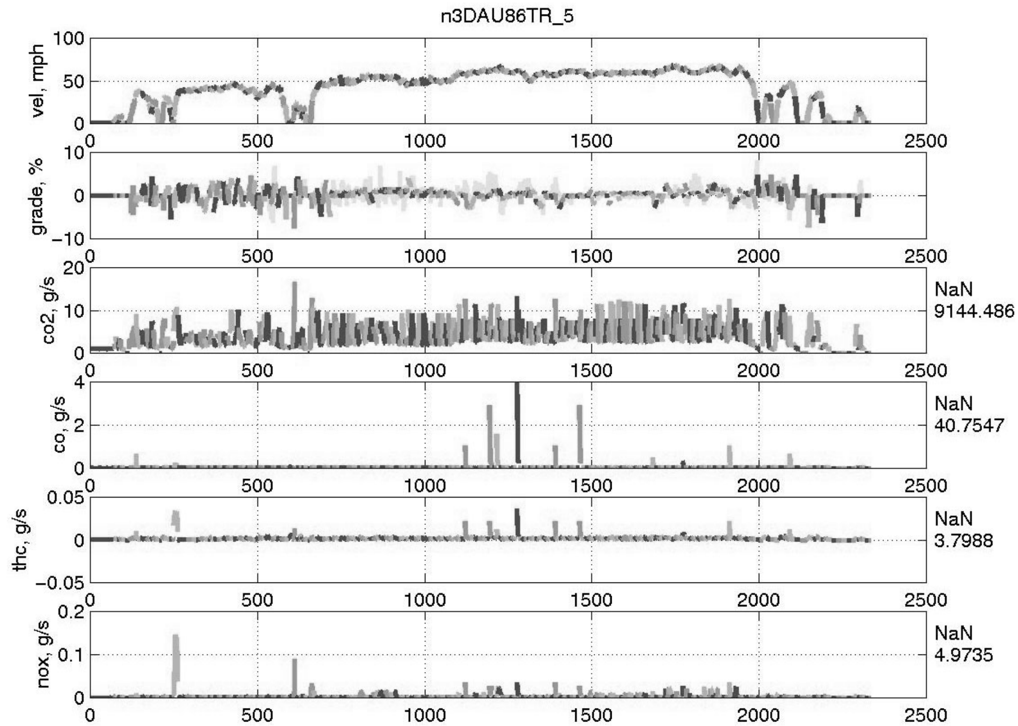
Appendix A

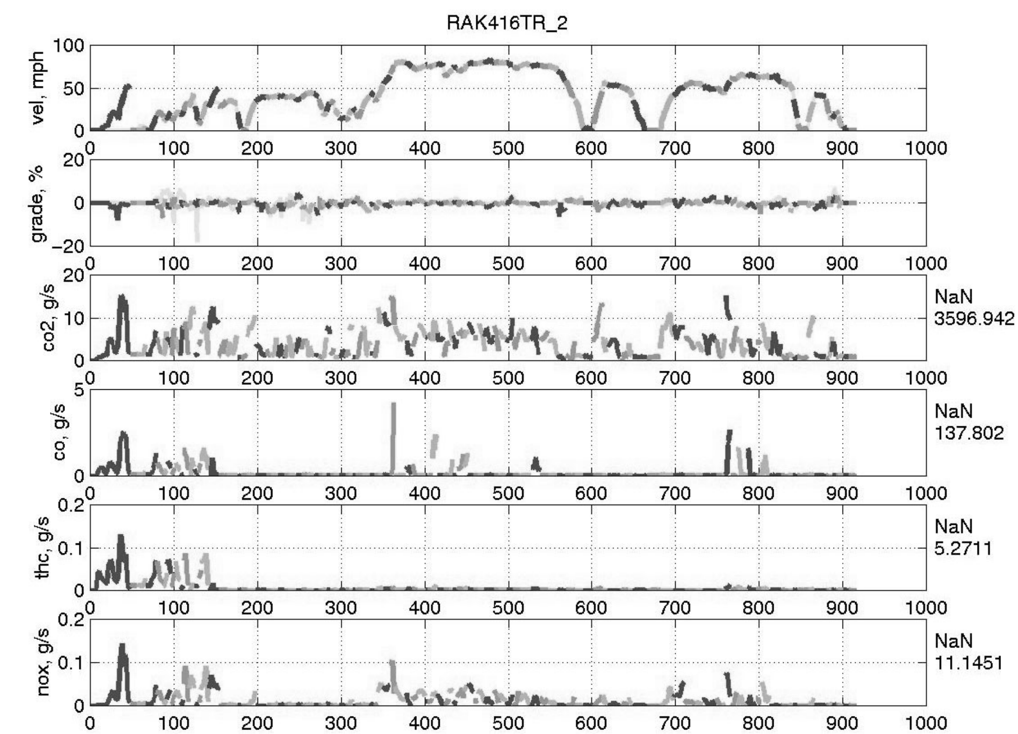
Micro-scale Emissions Plots

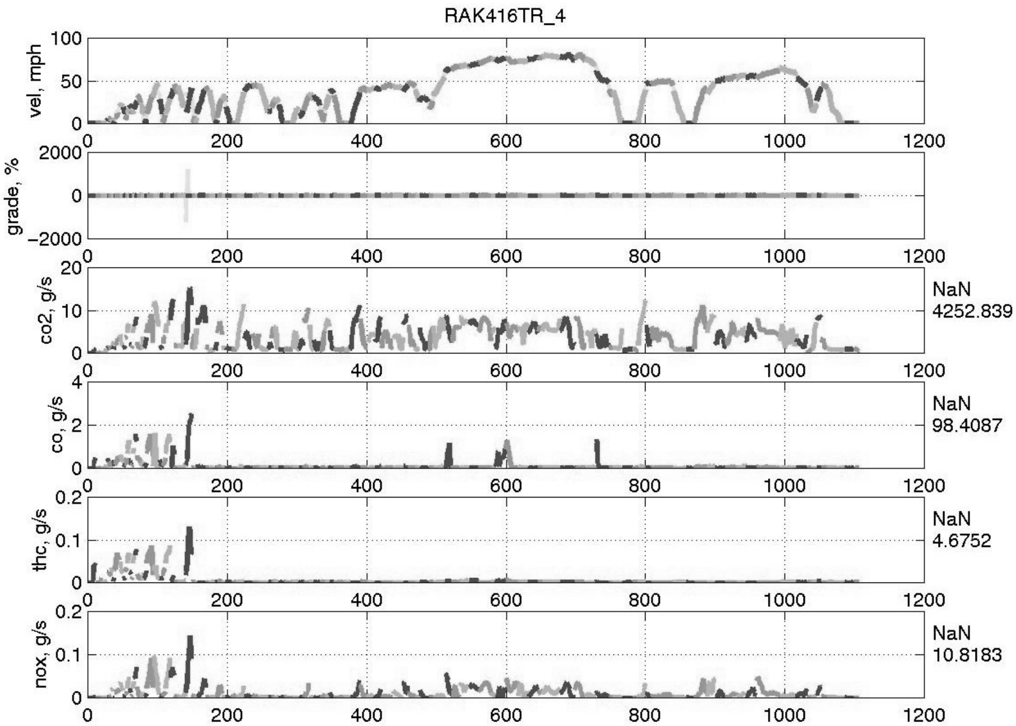
ON-ROAD SPARK IGNITION

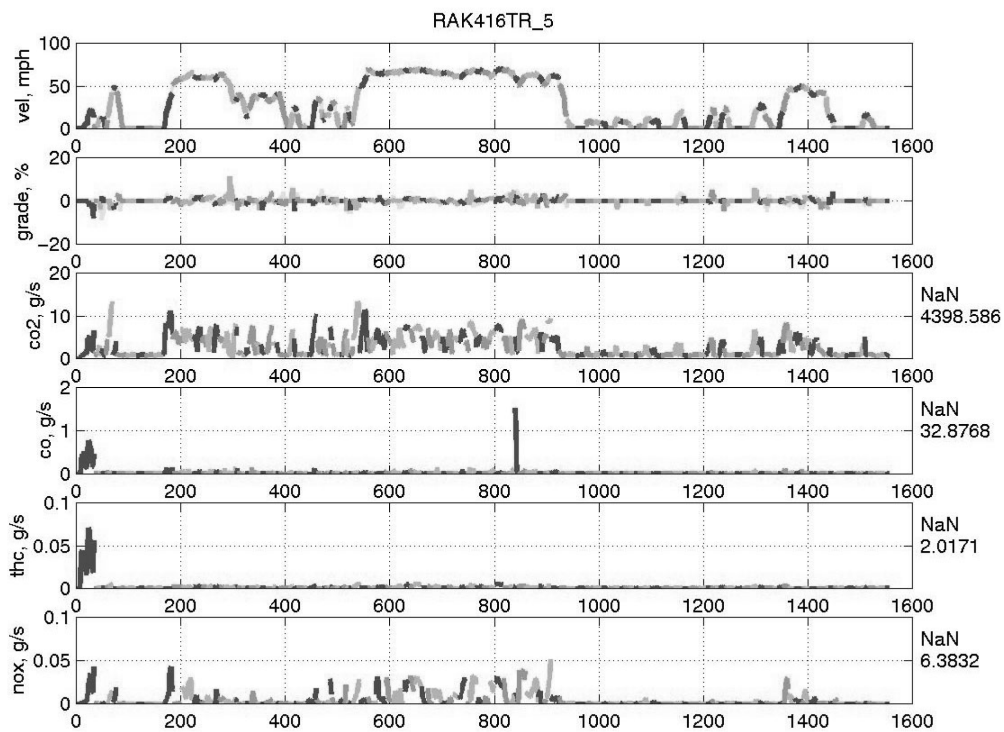

SRM089TR_2
vel, mph
grade, %
co2, g/s
co, g/s
thc, g/s
nox, g/s
NaN
11495.653
NaN
12.9756
NaN
1.9056
NaN
7.7673


n3DAU86TR_3
vel, mph
grade, %
co2, g/s
co, g/s
thc, g/s
nox, g/s
NaN
6640.004
NaN
40.564
NaN
2.7548
NaN
3.9437

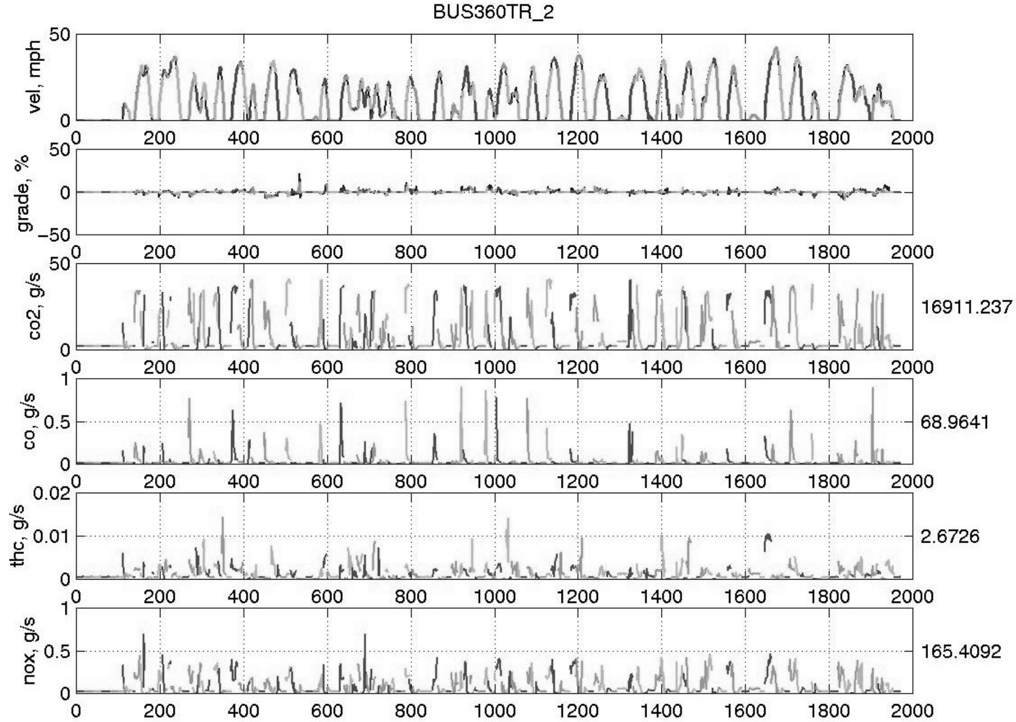

n3DAU86TR_5
vel, mph
grade, %
co2, g/s
NaN
9144.486
co, g/s
NaN
40.7547
thc, g/s
NaN
3.7988
nox, g/s
NaN
4.9735

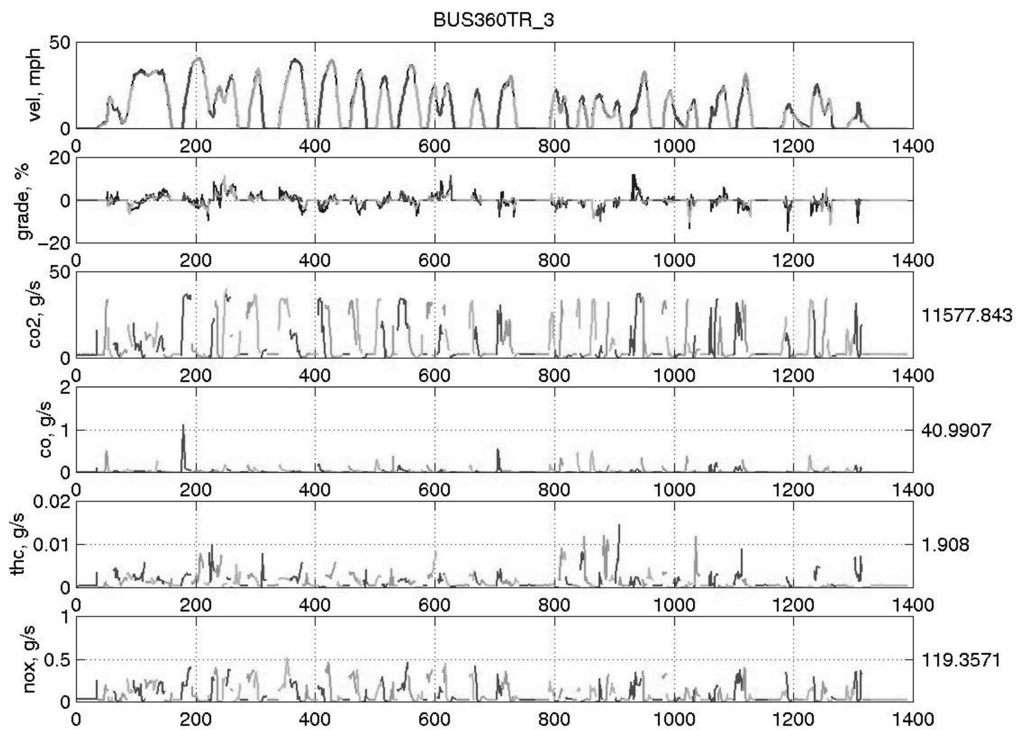

RAK416TR_2
vel, mph
grade, %
co2, g/s
NaN
3596.942
co, g/s
NaN
137.802
thc, g/s
NaN
5.2711
nox, g/s
NaN
11.1451

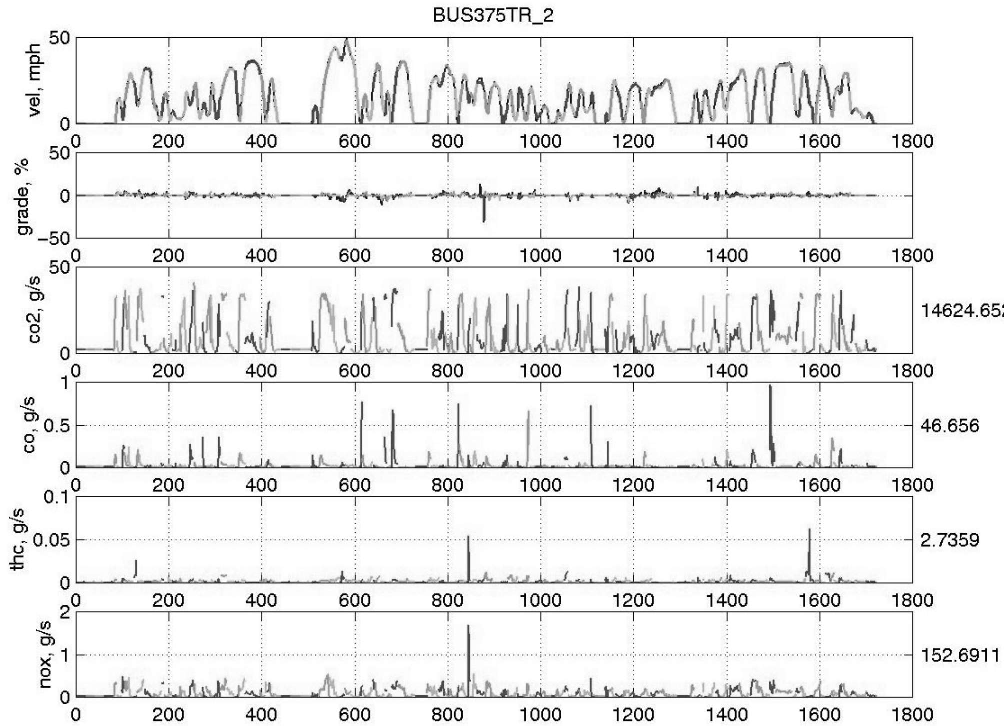

RAK416TR_4
vel, mph
grade, %
co2, g/s
NaN
4252.839
co, g/s
NaN
98.4087
thc, g/s
NaN
4.6752
nox, g/s
NaN
10.8183

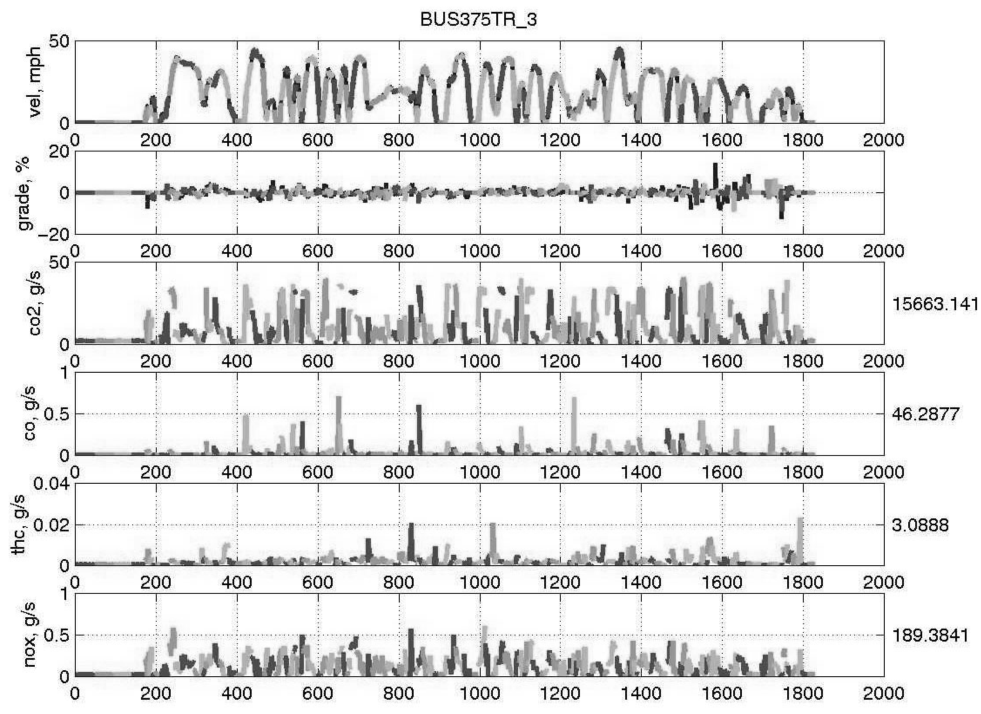

RAK416TR_5
vel, mph
grade, %
co2, g/s
NaN
4398.586
co, g/s
NaN
32.8768
thc, g/s
NaN
2.0171
nox, g/s
NaN
6.3832

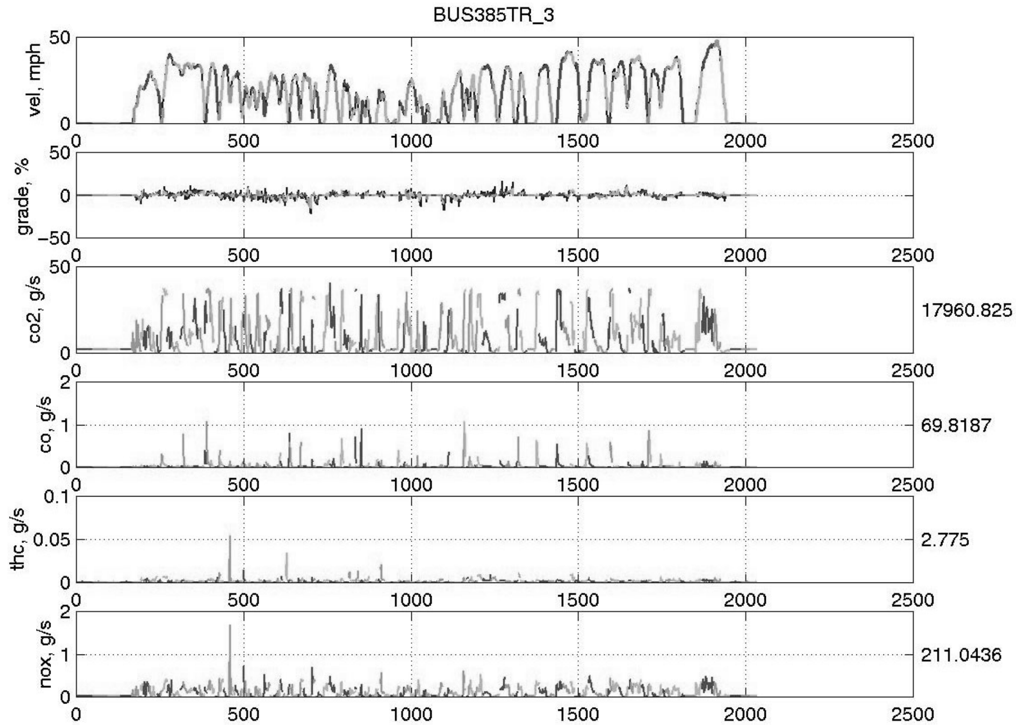
ON-ROAD COMPRESSION IGNITION

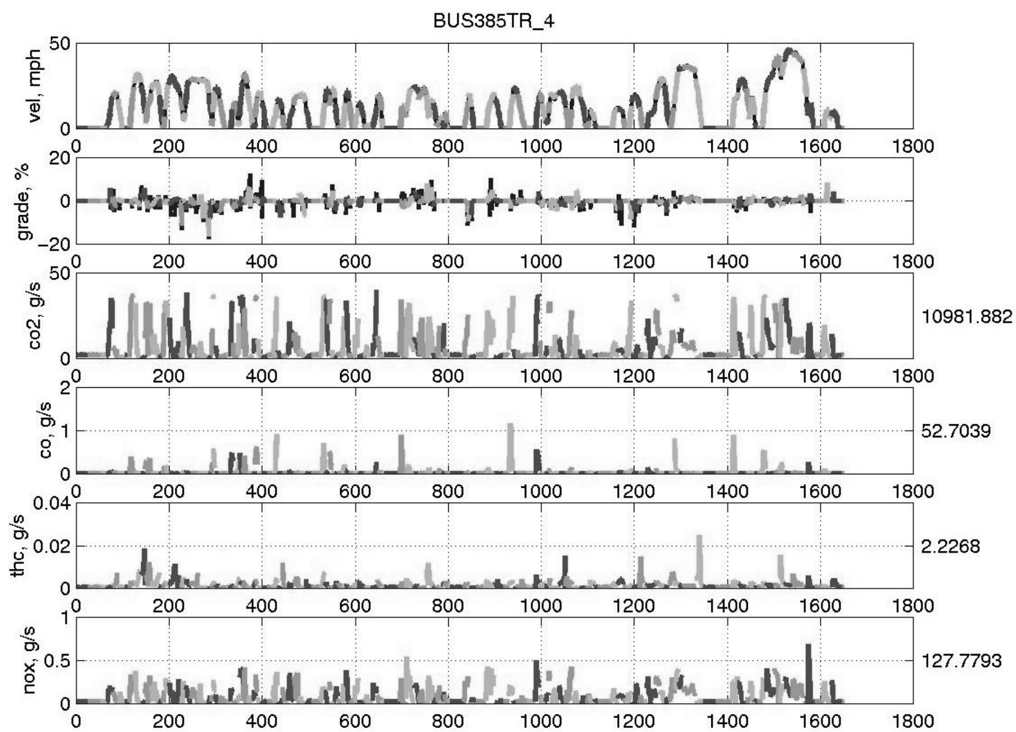

BUS360TR_2
vel, mph
grade, %
co2, g/s
16911.237
co, g/s
68.9641
thc, g/s
2.6726
nox, g/s
165.4092


BUS360TR_3
vel, mph
grade, %
co2, g/s
11577.843
co, g/s
40.9907
thc, g/s
1.908
nox, g/s
119.3571

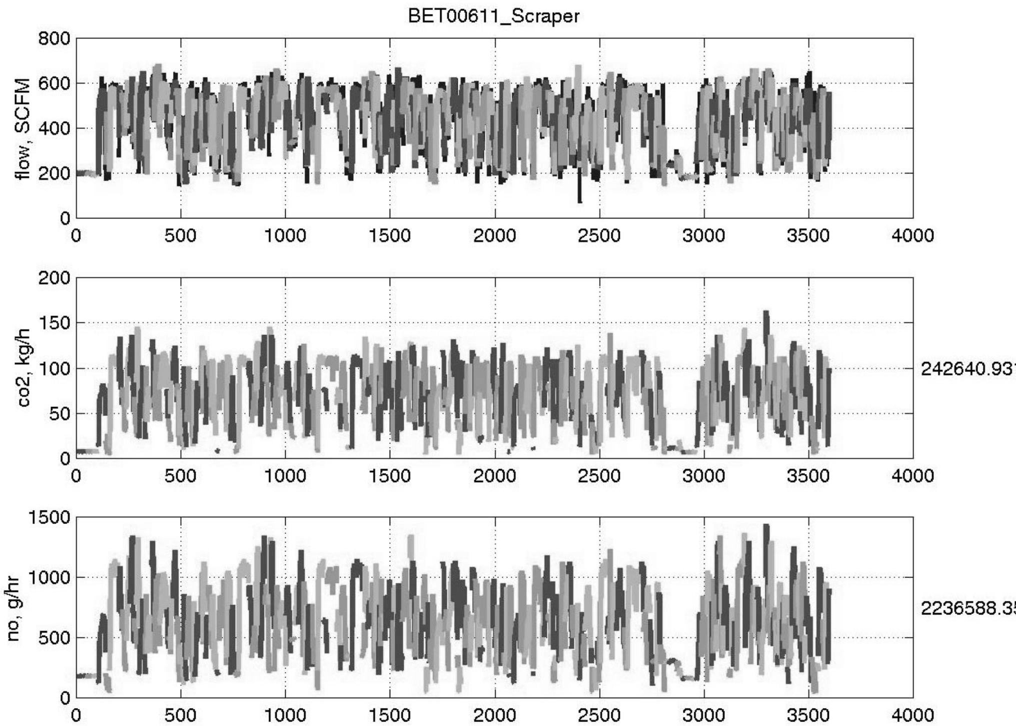

BUS375TR_2
vel, mph
grade, %
co2, g/s
14624.652
co, g/s
46.656
thc, g/s
2.7359
nox, g/s
152.6911

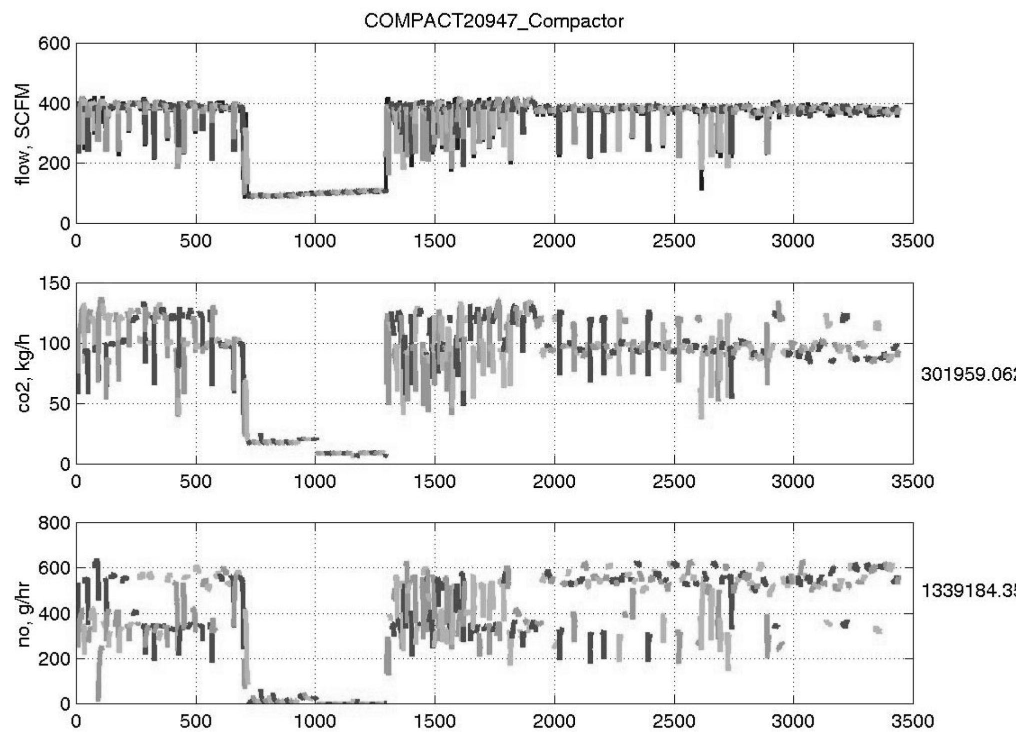

BUS375TR_3
vel, mph
grade, %
co2, g/s
15663.141
co, g/s
46.2877
thc, g/s
3.0888
nox, g/s
189.3841

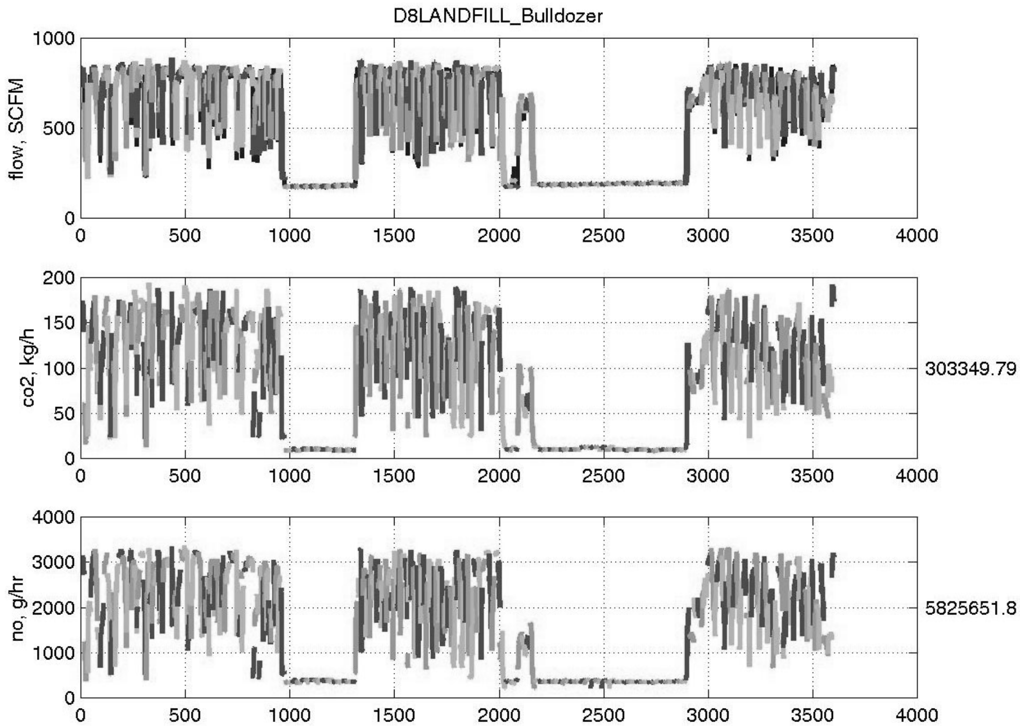

BUS385TR_3
vel, mph
grade, %
co2, g/s
17960.825
co, g/s
69.8187
thc, g/s
2.775
nox, g/s
211.0436


BUS385TR_4
vel, mph
grade, %
co2, g/s
10981.882
co, g/s
52.7039
thc, g/s
2.2268
nox, g/s
127.7793

OFF-ROAD COMPRESSION IGNITION


BET00611_Scraper
flow, SCFM
co2, kg/h
242640.93
no, g/hr
2236588.3


COMPACT20947_Compactor
flow, SCFM
co2, kg/h
301959.06
no, g/hr
1339184.3



D8LANDFILL_Bulldozer
flow, SCFM
co2, kg/h
303349.79
no, g/hr
5825651.8