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ABSTRACT

The Office of Transportation and Air Quality (OTAQ) of the U.S. Environmental Protection Agency (EPA) has started work on the next generation mobile source emission factor model, termed the "Multi-scale Motor Vehicle and Equipment Emission System" (MOVES).[1] MOVES will be the successor to the MOBILE6 highway vehicle emission factor model and the NONROAD model and include ozone precursors, particulate emissions, toxics and greenhouse gases. In the last few years advances in technology have made it possible to measure vehicle tailpipe emissions during real-world vehicle operation using portable on-board instruments. This on-board emissions data will be the basis for the MOVES model. Because the measurement and interpretation of on-board data is a relatively new area, EPA sought input from external experts to provide examples and recommendations of modeling approaches including steps to calibrate and validate their models. Each of the three organizations worked simultaneously and independently under the same scope of work and each prepared its own report. The three organizations were North Carolina State University (NCSU), the University of California at Riverside (UCR), and Environ. EPA also worked simultaneously on another approach. This paper shows each approach as well as the results of the shootout and then discusses how EPA will proceed with the exhaust emissions calculation methodology in the MOVES model.

INTRODUCTION

Under the Clean Air Act, EPA's Office of Transportation and Air Quality (OTAQ) is charged with developing emission factors for on-road sources such as light and heavy-duty vehicles and trucks, and off-road sources such as construction and agricultural equipment. This has led to the development of a number of emission factor estimation tools such as MOBILE (for on-road VOC, CO and NOx), PART (on-road particulate matter and SOx), MOBTOX (on-road toxics), and NONROAD (all off-road pollutants). These tools have been focused on the estimation of mobile source emissions based on average operating characteristics over broad geographical areas. Examples of this scale of analysis are the development of SIP inventories for urban nonattainment areas and the estimation of nationwide emissions to assess overall trends. In recent years, however, analysis needs have expanded in response to statutory requirements that demand the development of finer-scale modeling approaches to support more localized emission assessments. Examples include "hot-spot" analyses for transportation conformity, and the evaluation of the impact of specific changes in a transportation system (e.g. signalization and lane additions) on emissions.

In response to the acknowledged limitations of the MOBILE5 model in addressing these modeling needs, separate modeling initiatives have been undertaken to develop tools which provide a better assessment of finer scale emissions. Three notable efforts are the Comprehensive Modal Emissions Model (CMEM) developed by UC Riverside under NCHRP Project 25-11[2]; TRANSIMS, under development by Los Alamos National Laboratory through the U.S. Department of Transportation[3]; and MEASURE, developed by Georgia Tech under cooperative agreement with EPA's Office of Research and Development[4].

The increasing requirements of model users as well as external recommendations from a variety of sources have indicated the need for more emission research and improved modeling methodologies. A comprehensive review of EPA's mobile source modeling program was published by the National Research Council (NRC) in May 2000[5]. It recommended that EPA develop a mobile source emission modeling system that is capable of supporting the expanding range of mobile source emissions analyses. EPA has just released the latest on-road emission factor model MOBILE6, which represents a substantial improvement from MOBILE5, particularly for finer-scale modeling. We view the development of the "Multi-scale Motor Vehicle and Equipment Emission System" (MOVES)[1] as a logical next step in the continual effort to improve mobile source emissions models to keep pace with new analysis needs, new modeling approaches, and new data.

MOVES as proposed would employ three analysis scales termed macroscale, mesoscale and microscale[6,1], and a primary goal of the model will be to use a common set of emission rates for each scale to enable consistent results from MOVES across analysis scales. An initial issue paper was published in April 2001[6] which proposed the concept of an "Emission Rate Estimator" which would process the same set of instantaneous exhaust emissions data into modal emission rates for use in all scales of analysis. The issue paper outlined three possible approaches to developing this Emission Rate Estimator: 1) develop a physical instantaneous emission model which takes microscopic vehicle trajectory information and produces emissions aggregated to the desired level; 2) generate modal emission rates directly by processing a database of instantaneous emissions into modal bins (e.g., acceleration, deceleration, cruise, idle), applying these rates directly for finer scales analyses and aggregating as necessary for macroscale analysis; and 3) link directly to a database of raw instantaneous emission measurements, so that the emission rate estimator would essentially query a database of these raw data.

The NRC recommendations also address the need for improved model science and improved model structure, two key objectives of MOVES. An improved modeling structure will allow better responsiveness to new data and enable model validation, which in turn will facilitate improved science. Improved science is also a direct function of the quality of information feeding the model. The recent emergence of on-board emissions measurement devices is revolutionizing how emissions data are collected for on-road and off-road mobile sources. Several commercial applications of this technology have begun to enter the marketplace or are under development. In addition, EPA is undertaking a major effort to advance the development of on-board emissions analysis equipment, termed Portable Emissions Measurement System (PEMS). PEMS will ultimately allow the gathering of instantaneous exhaust emissions data for HC, CO, NOx, particulate matter, toxics and greenhouse gases. It will also include a global positioning system (GPS) to allow linkage of emission measurements with the location and speed of the vehicle. Vehicle operating information will be monitored and for vehicles equipped with on-board diagnostics systems (OBD), the OBD stream will provide engine and vehicle operation information. This system will enable the gathering of in-situ emissions across all mobile sources in several geographic locations, for relatively low cost. We envision that this technology will become the focus of EPA's emissions factor testing program and will provide the opportunity for a significant shift in how emissions modeling is approached.

While on-board emission measurement represents a significant shift in the ability to collect real-world data, incorporating these data into emission factor models poses a challenge, particularly at multiple scales as proposed for MOVES. Data collected with on-board emission measurement systems would depart from traditional laboratory data in many ways. Whereas nearly all elements of vehicle activity (speed, acceleration, soak time, etc.) and ambient conditions (temperature, humidity, road load, road grade) are controlled in the laboratory, all of these factors will vary from trip to trip in the real world. A method which develops emission rates from on-board data therefore must contend with far more variation in parameters which typically do not come into play with lab data, or are varied "one at a time" to specifically gauge the effect of a particular factor.

The "On-Board Emissions Analysis Shootout" was devised to evaluate potential methods for using on-board emissions data to generate emission rates for MOVES. The participants were supplied with on-board emission data gathered on light-duty vehicles, transit buses and nonroad equipment. They were then required to develop a model calibrated with this data which could predict total HC, CO, CO_2 and NO_x emissions from a separate sample of independent data. The predictions from the various methods were then validated with measured emissions in order to provide an initial sense for the promise of different approaches to applying on-board emission data in MOVES. This was considered a pilot study in the sense that not all possible factors which will ultimately need to be addressed in MOVES were included in the analysis; the study was designed to hold certain parameters constant, such as fuel effects and vehicle technology. The purpose of the study was to provide an initial sense of how different approaches could be used to develop models from on-board emission data, based on a limited sample of on-board data.

The participants in the shootout were selected through a competitive process, based on evaluation of solicited proposals: North Carolina State University (NCSU), University of California at Riverside (UCR), and Environ Corporation. EPA also participated according to the same parameters as these contractors. The three contractors provided full reports to EPA on their analysis methods and results, which are merely summarized here [7, 8, 9]; the EPA methodology, developed by the authors, is presented in full in this report.

DATA COLLECTION

On-Road Vehicles. On-board emission data was gathered on a sample of 18 light-duty vehicles in the summer of 2001, and 15 heavy-duty diesel transit buses in Fall 2001 in the Ann Arbor, Michigan area. The light-duty vehicles were selected from employees of EPA, and of Sensors Incorporated, and rental vehicles. Sensors provided testing and data processing for the project[10]. Because of the small sample size and pilot nature of the project, an attempt was made to limit the number of vehicle-related variables in the vehicle sample. Thus, all vehicles used were certified to Federal Tier 1 tailpipe standards, with a model year range of 1996 through 2000, and had either 4 or 6 cylinder engines. The transit buses were all from the in-use fleet of the Ann Arbor Transportation Authority (AATA)*;* as such, all of the buses had the identical engine and after-treatment system, with a model year range of 1995 through 1997, and had similar mileage accumulation. Overall the bus sample was much more homogenous than the light-duty vehicle sample. Detailed vehicle information is shown in Tables 1 and 2.

Off-Road Vehicles Three nonroad pieces of equipment were used for the shootout: a bulldozer, compactor, and roller/scraper. These vehicles were recruited from a rental company's fleet of nonroad equipment in the area around Columbus, Indiana, and were used for a test program to assess the feasibility of EPA's prototype on-board emission measurement system. See Table 3.

Light-Duty Vehicle Test Procedure. All light-duty vehicles were first brought into EPA's National Vehicle and Fuels Emission Laboratory for a standard FTP prep, including draining the vehicle's fuel and refueling with standard certification fuel. The vehicles were then tested over the FTP and US06 cycles while collecting both bag and modal data, with the on-board measurement device (SEMTECH-G) installed to allow for correlation testing. The vehicle was then refilled with standard certification fuel and returned to the owner. The SEMTECH-G remained on the vehicle for a period of 1-3 days, in order to gather a minimum of 3 hours' worth of total operating time. During this period the owner was given no special instructions on how to operate the vehicle to ensure representative driving and operation patterns. The owners were given trip logs to record the number of passengers and estimated payload for each trip.

Heavy-Duty Vehicle Test Procedure. Instrumentation of heavy-duty vehicles occurred at the AATA's main garage. To circumvent the possibility of passenger concern, the buses were operated under normal routes and driving conditions, but without passengers (simulated stops were still made). The centralized fleet fuel was sampled to gain information on fuel parameters. The targeted sample period was four hours.

Nonroad Equipment Test Procedure. All vehicles were reviewed by the technician to confirm that the vehicle was in good working order before installing EPA's device. Installation usually took approximately one hour to install and was done before and after working hours at the working site. The on-board measurement device used for nonroad testing was a prototype of EPA's Simple Portable On-Board Test (SPOT) device. This device was being designed to handle the harsh environment in which nonroad equipment operate in and has the capability to operate non-attended, gathering both activity and emission data for up to a week.

Light-Duty Vehicle and Bus Instrumentation. Sensors Inc. provided the on-board emission measurement and data collection services for this effort under contract to EPA. Two prototype SEMTECH-G analyzers were used for gasoline powered passenger vehicles and one prototype SEMTECH-D analyzer for the diesel powered buses. A thorough discussion of the detectors and calibration procedures and equipment can be found in a separate report prepared by Sensors[10].

Except for the HC and brake-specific mass measurements the SEMTECH-G and SEMTECH-D analyzers are essentially the same. They both measure raw vehicle exhaust, collect vehicle engine command module (ECM) data, (e.g., real-time engine information for the on-road vehicles, including engine speed, throttle position, coolant temperature and air conditioning status for light-duty vehicles), and store the data on an internal data logger that is automated by key-on/key-off events. A post-processing utility computes real-time fuel-specific and distance specific mass emissions based on engine airflow computed from the ECM data. The SEMTECH-

D has an additional post processing utility which computes brake-specific mass emissions and uses a heated flame ionization detector (HFID) to measure total hydrocarbon emissions (The HFID system is operated at 195 $^{\circ}$C.) In contrast, the SEMTECH-G determines total hydrocarbons via direct measurement of hexane with a non-dispersive infrared detector (NDIR) which does not require a heated sample gas line.

The CO and CO_2 analyzers measure on a dry basis with non-dispersive infra-red sensors (NDIR). The CO analyzer in the SEMTECH-D prototype unit in this study was designed for gasoline exhaust and has not yet been optimized for the low concentrations found in diesel exhaust. The analyzer is calibrated between 0.5%, or 5000 ppm and 8%. The levels found in the buses in this study were below the lower portion of this range. Correlation testing showed a measurement uncertainty of 50 ppm.

The NDIR for CO_2 and CO are both single range devices, 0 - 16% and 0 - 8%, respectively. A manufacturer supplied multi-point calibration curve is hard-coded into each analyzer. To account for short term drift and linearity changes a single point and dual point user-calibrations are available to adjust the entire calibration curve to match the calibration gases.

Both oxides of nitrogen, NO and NO_2, were measured simultaneously through unique adsorption bands of NO and NO_2 in the UV range with a non-dispersive ultra-violet (NDUV) analyzer. The NDUV detectors are also single range devices. The NO range is 0 - 3000 ppm, and the NO_2 range is 0 - 500 ppm. The calibration procedure is exactly the same as for the NDIR analyzers.

A global positioning system (GPS) was used to keep track of the route taken by the vehicle with resolution of one meter and an absolute accuracy of 15 meters for latitude, longitude and altitude. Road grade was computed with the GPS data and some instantaneous results had significant uncertainty, especially at low speeds. Finally, a probe placed remotely from the SEMTECH analyzer was used to measure ambient pressure, temperature, and humidity each second.

Correlation results were compiled by Sensors, Inc. in this report. Overall the bag results from the SEMTECH-G system used for the on-road testing were within 5 percent of the laboratory bag analysis system for CO2, CO and NO. HC results were within 5 percent with the SEMTECH-G system was fitted with a FID; NDIR technology, which does not detect all HC species, underpredicted the FID-based bag analysis system by approximately 35 percent. The NDIR technology was used for the on-board testing; this did not pose an issue for the shootout analysis, since both the “modeling” dataset and “validation” datasets were based on the NDIR. Limited correlation testing was also performed with the SEMTECH-D system on 2 heavy-duty vehicles, with similar correlation to the FID-equipped SEMTECH-G demonstrated.

Nonroad equipment. The SPOT device allows for real-time measurements and presently consists of: a data logger for storing the data, a wide-lambda O2 and NOx sensor, a venturi mass air flow sensor, batteries and communication system. Data is gathered on a second-by-second basis, with date and time stamps. The O2 and NOx are measured directly within the vehicle’s exhaust stream with CO_2 being calculated from the O_2 readings.

Data provided to shootout participants. The shootout participants were provided with a "modeling" dataset of all trips on 12 light-duty vehicles and 12 buses, and 3 hours of operation on the nonroad equipment pieces, upon which to develop their shootout models. All data fields collected were provided to the participants, including (for light-duty) second-by-second fuel consumption and emissions, ambient parameters (temperature, humidity), engine parameters (e.g. engine speed, coolant temperature, throttle position, mass air flow), GPS coordinates (latitude, longitude, altitude), road grade (calculated from GPS altitude), and (for most light-duty vehicles) air conditioning compressor status. These data, which came from several instruments, had been time-aligned by Sensors prior to delivery to EPA. Sensors' data preprocessing also derived calculated fields prior to delivery to EPA. Nonroad data provided to the participants was limited to second-by-second emissions (NO_x and CO_2, the latter derived from O_2), exhaust flow (provided as a surrogate for engine load), engine RPM, ambient temperature, barometric pressure, and relative humidity.

ANALYSIS METHODS

Modal Binning

NCSU pursued a modal "binning" approach, in which they defined operational bins based on changes in speed and power, and refined the estimates within each modal binning using regression analysis. This proposed methodology falls under the second "Emission Rate Estimator" approach identified in EPA's April 2001 issue paper, to process instantaneous emissions measurements produced in the laboratory or in the field.

NCSU looked at the data in many ways before settling on their approach. After extensive quality control checks and data preparation, they looked at individual trips and the variability of those trips within the same vehicle and between vehicles. The next step in their visualization of the data was to look at the importance different variables had on the emissions of this dataset, which would also be included in the prediction dataset, or could be estimated from the available parameters. Scatter matrices were prepared for all pollutants to look for relationships among the explanatory variables, including speed, acceleration, ambient temperature, humidity, altitude, grade, air conditioning (on/off), and power demand. This analysis showed that there is a substantial amount of variability in the emissions data and that there is not any single variable which directly explains a large portion of the variability.

A spatial analysis utilizing the GPS information from the on-board data was also performed. They were able to get roadway functional class information and determine the effects of different roadway types on emissions. Based on this dataset there were no clear distinctions in emissions by roadway types for any of the pollutants. Effects on emissions due to intersections were also looked at in this effort. There were some effects found which were not consistent over functional classes. It was concluded that further study would be needed to understand the issues involved which was beyond the scope of this project.

Cold Start Identification. A non-linear regression was fit for each trip for each pollutant by using time as the predictor variable, see Figure 1. The assumption was made that there was decreasing emissions until the cold start period ended, then the emissions would stabilize at t_c. The upper limit of the confidence intervals for each pollutant of the duration of the cold start, t_c, were compared. In the decision for a duration for each trip, all three values of t_c were taken into account. If large discrepancies occurred, the soak time was also considered for that trip and previous trips. It was found that 34 of the trips had cold starts ranging from 70 to 391 seconds. The identification of cold starts was used for categorizing the data so that hot-stabilized driving could be separated.

Methods used for Modeling. Time series analysis revealed that the data in this study have autocorrelation, or history effects, and therefore need to be treated carefully. Some thought must be given to choosing proper statistical methods since the autocorrelation may invalidate the assumptions. After exploring some time series approaches, NCSU found them to be impractical for a model such as MOVES, which will require input data from a large number of vehicles and trips. Alternative approaches must destroy or at least reduce the autocorrelation in the data. Although there may be some loss of explanatory power associated with ignoring or destroying autocorrelation, they found it would be possible to use other modeling approaches that are more practical for taking advantage of the variety of available data sources.

NCSU found that binning the data was a feasible approach for the MOVES model which would reduce the influence of autocorrelation. They ended up employing a combination of techniques based upon modal analysis, regression and time series methods.

Hierarchical Tree-Based Regression (HTBR) and Ordinary Least Squares Regression (OLS). HTBR determines which variable in the model should be selected to produce the maximum reduction in variability of the response. HTBR lacks some desirable properties of OLS procedures, such as available statistical tests which might be used to test the differences in HTBR model formulations. In this study HTBR and OLS regression methods were combined to use the strengths of both methods. The data were stratified into smaller data sets by using HTBR and then OLS regression was done to capture relationships within the data strata.

Modal Emissions Binning. The second-by-second emissions data were divided into four modal categories after taking out the cold start defined earlier: idle, acceleration, deceleration and cruise. Idle is defined as zero speed and zero acceleration, acceleration is defined as a minimum acceleration of 2 mph/sec or 1 mph/sec sustained for 3 seconds or more, deceleration is similar to acceleration with negative rates, and cruise is all other events not defined in the other categories. Average emission rates for each mode were calculated for each trip, then an average of these estimates were calculated for all trips. Figure 2 shows these averages for all four pollutants with the 95 percent confidence intervals. Pairwise t-tests indicate that three out of twenty four pairwise combinations are not statistically different from each other. Two occurred for comparison of average emission rate between idle and deceleration mode for both CO and NO emissions, and the other between acceleration and cruise for HC emissions. This suggests that the modal definitions used are reasonable.

The HTBR technique was used to improve the driving modes. Trip data for each vehicle were combined together for analysis. Regression trees were formed for each mode for each pollutant (except CO_2) using explanatory variables related to vehicle operation and vehicle characteristics such as speed, acceleration, power demand, grade and engine size. For CO_2 emissions, the original modes were considered to be adequate for their explanatory power.

Power demand was found to be the most useful variable to improve the explanatory power within most of the driving modes. A single cutoff point was determined for all the pollutants for each mode. For the continuation of the analysis, the following cutoff points were used for each mode: 100 mi^2/h^2.sec for acceleration mode, -100 mi^2/h^2.sec for deceleration mode, 60 mi^2/h^2.sec for the cruise mode, and no cutoff for the idle mode since the vehicle is not moving. Average modal emission rates for the new modes were estimated, see Figure 3 for CO emissions.

With this approach, NCSU found that cold start and acceleration modes account for approximately half of the total emissions. More than 30 percent of emissions are emitted during acceleration mode for Nox, CO and CO_2 (and 25 percent for HC). 40 percent or more emissions for all emissions come from the cruise mode. See Figure 4.

After the development of modal definitions, OLS regressions were fit for each mode using the explanatory variables: speed, acceleration, power, engine size, ambient temperature, humidity, altitude and road grade. Second and third powers of speed and acceleration were also included in the regression analysis. Many terms zeroed out or proved insignificant for different modes.

Cold Start Model. Since the cold start data is in consecutive seconds, this data was autocorrelated and a time series model approach was used. It was assumed that all cold starts are from the same process and the data were combined. A regression model with time series was fit to the data using the explanatory variables, adding coolant temperature to the list for its known effect on cold start emissions. Since coolant temperature was not a part of the prediction dataset, the relationship between coolant temperature and soak time was investigated. A strong relationship was found between soak time and cold start duration. The fitted model is as follows:

$$CO = 0.175 - 0.00083 \text{ x coolant} + 0.0013 \text{ x speed} + 0.0002 \text{ x power} - 1.197 \text{ x } \varepsilon_{t-2}$$

where:

coolant = coolant temperature, degrees F
speed = vehicle speed, mph
Power = power demand, mi^2/h^2.sec
ε_k = error term

The R^2 for the relationship between the predicted cold start CO emissions and observed ones is 0.33, for NO is 0.53, and for HC is 0.09. The R^2 for the relationship between the soak time and cold start duration was 0.43. For the prediction dataset the cold start duration can be determined using the regression:

$$y = 52.249Ln(x) - 74.771$$

where:

y = cold start duration, seconds
x = soak time, minutes

With the cold start duration, the coolant temperature can be assumed for use in the above CO emissions prediction model using similar trip data, including ambient temperature and soak time.

Uncertainty Analysis. Residuals from each regression equation fitted for the observed and predicted data were obtained. Coefficient of variation of residuals were then determined by dividing standard deviation of residuals with the average observed values of emissions. Uncertainty in the observed data was also determined by estimating average and variation of individual modes for each trip. Trip averages and variations were then estimated using weighted averages. Weights were based on the time spent in each mode. Coefficient of variation was then estimated by dividing standard deviation with the average value.

Heavy Duty. NCSU took similar steps as for the light duty, for QA/QC, preliminary analysis and visualization of the bus data. Since there is no cold start for the bus data, there were only four modes to separate: idle, acceleration, deceleration, and cruise. The modal emissions analysis results suggest, as in the light duty, that the modal definitions assumed were reasonable. HC shows little variability among the four modes. After analyzing the results from the HTBR analysis it was determined that acceleration equal to 2 mph/sec should be used as a cutoff point for the acceleration mode for CO emissions. No reasonable cutoff was found for the other pollutants. The acceleration mode was found to contribute the most emissions for the buses as well as for light duty, see Figures 5-7.

Nonroad. The five possible explanatory variables for the nonroad equipment were exhaust flow, engine RPM, ambient temperature, barometric pressure, and relative humidity. Exhaust flow is a surrogate for engine load and was found to be highly correlated with both pollutants, NO and $CO_{2,}$ for all three pieces of equipment based on the data visualization techniques used.

A regressions with time series model and a modal binning approach were both explored for the nonroad data. In the modal approach the data was binned based on the exhaust flow rate. OLS and multiple OLS regression models were also investigated, even though the data was known to be autocorrelated. In the end the modal approach seemed to have the largest degree of explanatory power, also having the advantage of being the simplest and reducing the influence of autocorrelation in the data by dividing it into segments.

Database Lookup of Individual Vehicle and Trip Results

UCR College of Engineering-Center for Environmental Research and Technology (CE-CERT), pursued a database approach, deriving separate emissions for macroscale, mesoscale and microscale based on a database lookup of individual vehicle and trip results. This methodology is a modification of the third suggested approach identified in EPA’s April 2001 issue paper.

CE-CERT explored three conceptual approaches for this project: multivariate statistical equation-based, driving summary statistic, and a hybrid database modeling methodology. In the multivariate statistical equation approach emissions are estimated using statistical relationships between the measured variables such as speed and measured emissions. This 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. In the 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, such as average speed. This 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. In the hybrid GIS/database approach emissions are estimated directly from data in a database. Pre-processing, or hybridization, of the data is necessary to facilitate matching of the driving segments to be predicted with the best available driving segment in the database. This approach 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.

The challenge for the database approach is the near infinite number of combinations of conditions that must be matched for accurate emissions prediction if an exact match is required. CE-CERT's solution to this problem was 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. 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.

This methodology depends on the matching of the existing emissions measurements to the operating conditions in the prediction dataset. CE-CERT preprocessed the data then used the GPS-based location data to identify roadway type and to obtain accurate grade information. They then identified the factors about a driving segment which affect emissions, and then matched these factors to the driving segments in the prediction dataset.

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 would vary by vehicle technology type.

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 links. At the *macroscale* level, the driving traces were used in a trip-based manner, see Figure 8. 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. For the macro-scale level, regression on principal components analysis is used to identify groupings of variables that are correlated with emissions to simplify the search process.

In this hybrid approach, data from the on-board emission measurement 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.

Microscale. The first step is dividing the trip to be predicted into seperate modal events, see Figure 9. For this project they were visually divided, but if this methodology will be developed for MOVES it would have to be automated. Initially the modes were divided at their end points, however in the case for acceleration events the matching driving trace frequently did not end at the correct speed, see Figure 10. Differences in emissions were found between accelerations peaking and similar accelerations that did not peak at the end of the segment. As a result, acceleration modes included the peak inflection point to ensure that the matching trace was the closest event that ended at the same speed.

Each modal segment is matched for speed, acceleration, and power. CE-CERT's methodology matches each modal segment to all possible length segments within the prediction dataset. A moving window of the same number of seconds from the prediction data set is compared with the driving trace to be matched. Match scores are 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. A weighting of 80, 10, and 10 for speed, acceleration and grade was used, which was determined empirically.

Trips were divided into cold and hot operation sections. Matching was done accordingly using a soaktime regression, with the prediction data set. Once segments were matched, the grams/second emission rates were summed for the trip to calculate total grams/mile.

Mesoscale. The limitations of the small dataset were magnified with the aggregation from modal segments to roadway segments. There was much more variability introduced due to driving behavior and terrain covered. A multivariate classification for each event based on the physical characteristics of the roadway, such as length, average grade, maximum grade, posted speed, etc., was established.

With the GPS information provided with the On-board emission measurement data, CE-CERT was able to determine the location of road links. From this they were able to break down the trips into roadway links and determine the roadway characteristics for the analysis. A database of average speed, average grade and average total emissions in grams was created by direction for each link. It will not be possible to collect multiple sets of On-board emission measurement data for multiple vehicles on even a small portion of the roads in a particular area.

It should be sufficient to find a similar set of driving conditions in the On-board emission measurement database that does have sufficient emissions estimates for characterization.

Typically the emissions which are to be predicted are on a specific road link which does not exist within the database. This requires matching the road link characteristics, in addition to the appropriate driving behavior for those vehicles on the correct links. Figure 11 shows an example, with the gray line representing links with existing data and the red line 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.

Macroscale. A similar approach of sorting driving characteristics is used at this level. For this scale the whole trip is defined not just an individual roadway section. Because of the increased aggregation, it is even more critical for the summary statistics to have descriptive power. Trip summary statistics were calculated and used in a stepwise regression against all of the pollutants to determine which were the best descriptives. This excercise identified ten significant driving summary statistics, see Table 4. A principal components analysis was conducted on a subset of the driving statistics, based on these results. Soak time, cycle length and driving distance were added to the set of driving characteristics because of their effects on emissions.

This approach identified five significant factors within the data. The first factor accounts for 49% of variability between trips. It is primarily a factor weighted high for cumulative variables such as sum velocity > 0 and sum acceleration > 0, etc. The second factor, which accounts for 11%, is more heaviliy weighted on the higher power and acceleration variables. The third through fifth factors account for 6 or 7% each. The third is primarily a function of mean acceleration and mean grade; the fourth - loads heavily on the summaries of the higher power events; the fifth - a mixture of the deceleration summary, soak time and mean specific power. Further analysis narrowed this to factors one and four for CO2 and NO, and factors one and two for CO and HC, see Table 5. These were plotted on an XY plot of the corresponding principal components scores.

The emission rates for each of the test trips were then calculated using the average emisison rate of the three closest test trips on the appropriate plot. For this pilot study, 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.

Heavy Duty. The procedures for predicting the bus data set were similar to the light duty for all three scales.

Nonroad. Only micro-scale predictions were made for the off-road equipment due to the lack of road link and trip events. The modal events were matched using exhaust flow data instead of speed, which was less smooth than the speed data but proved to be sufficient.

Microtrips

ENVIRON's basic approach was to divide the second-by-second driving from the On-board emission measurement data into a series of microtrips. The microtrips were intended to be sufficiently short to describe driving events for micro-scale analysis, while providing a means to scale upwards to meso-scale and macro-scale modeling. Their approach attempts to avoid or minimize errors from timing offsets of recorded emissions and vehicle behavior. This approach can be looked at as a method for data filtering or smoothing. The microtrips were expected to reduce errors associated with single point estimates from the second-by-second On-board emission measurement data. This methodology falls outside of the three basic approaches defined by the April 2001 EPA Issue Paper.

Environ based their approach on a calculation of vehicle specific power (power per unit mass, or VSP, Jimenez-Palacios[11]), aggregating results over driving events defined by periods of stable operation. The first step in their process, they did include a mass term in the calculation of power:

$$Power_1 = (a + b * Speed_1 + c * Speed_1^2) * Speed_1 + 0.5 * Mass * (Speed_1^2 – Speed_0^2)$$
$$+ Mass * g * grade * Speed_1 + Auxiliary\ Power$$

The coefficients a, b, and c were supplied by EPA for the light-duty vehicles in this study and those for a transit bus were supplied by West Virginia University (WVU)[12]. See Tables 6, 7.

The concern about second-by-second emissions correlations was that emissions and vehicle behavior need to be exactly matched in time or errors could occur in determining average emission rates. Depending on the operation of the vehicle, offsets in load and recorded emissions could occur and be variable during driving operation. As shown in Figure 12, there may be a lag between the calculated load determined from the vehicle speed and grade, and the emission measurements. Even correcting for the lag may not entirely account for all conditions and lags in the detector response labeled "distributed response" in Figure 12.

Another reason for using a microtrip approach was to avoid data smoothing requirements of noise signals transmitted through various speed and grade signals of vehicle behavior and emissions results. With or without a mircrotrip approach, data smoothing of the load and emission signals should be considered when analyzing the data to avoid instances where noise or outliers could affect the results.

ENVIRON developed a microtrip search program to determine microtrips during hot running conditions. Start periods were selected out and evaluated separately. The microtrips themselves were defined with minimum length and an end point criteria. Emissions and explanatory variables were recorded and averaged over each microtrip.

Start Period. The start emissions were determined from the difference in the hot running emissions and those measured within the first 200 seconds. The criteria of 200 seconds for start emissions were determined from Singer[13]. After 200 seconds the vehicle operation was considered to be in a hot running mode. The emissions during the first 200 seconds of operation after a start were predicted with the hot running emission estimates, and start emissions were determined as the difference between the actual and predicted emissions. This difference was then compared to the soak time. ENVIRON recommended that the start period end point be defined with a direct measurement such as engine, exhaust, or catalyst temperature.

Microtrip Criteria. The criteria for choosing a microtrip is schematically shown in Figure 13 where the beginning and end points were determined using the criteria of constant load (steady-state condition) so that small time differences and detector response between emissions and load would not be carried into the emissions correlations. The load was specified to remain constant to within, for example, +/- 5 – 15 hp over the course of 3 or 5 seconds. (The speed time stamp was corrected by 3 seconds for this bus (Bus #10) in order to capture, for instance, the large CO increases during the initial part of the acceleration event demonstrated in Figure 13).

Explanatory Variables. Average load over the microtrip was the primary variable used to distinguish the microtrips and emissions, however other variables were tested to explain the data variance. Averages of the following were compiled over the microtrips: 1) load increases over the microtrip - to distinguish between highly transient driving and steady-state driving trips of similar average load; 2) previous trip load - to determine “memory effects” associated with the operating temperature of the engine and emission control system; 3) agressive load events causing enrichment - did not occur in this data set therefore did not use; 4) malfunction indicator light - only occurred on one vehicle which did not exhibit unusual emission behavior, therefore not used; 5) ambient temperature and humidity - only a limited range for this dataset therefore did not indicate importance and did not use; 6) load vehicle weight relationship - was not useful for such a small dataset, but could be important when looking at a whole fleet of vehicles.

For light duty, buses, and nonroad equipment the hot running emissions were predicted and compared with the start emissions to predict the start emissions. The hot running emissions predictions were determined through stepwise regression using load as the primary variable and adding additional variables as they improve the fit. For all cases the emissions were transformed to make the variance evenly distributed across mean load.

Light Duty Vehicles. Two separate modes were defined, idle or no load conditions, and the microtrips with positive mean loads. Load was found to be a reasonable predictive variable for CO, NO and CO_2. HC results indicated more scatter, possibly due to noise associated with the lower detection limits. In order to put all vehicles in the same terms, specific load, or “spload” - the wheel load divided by vehicle weight - was used to develop equations describing the emissions during microtrips. There were no enrichment conditions found in the dataset which would cause the emissions to spike, possibly due to limited driving or vehicles tested.

Below are the equations used to describe the emissions during the microtrips, with the regression coefficients in Table 8. A weight term should have been used to describe CO2 emission predictions, but since the weights did not differ significantly in this dataset, the error was ignored.

*Sqrt(mean.hc) = intercept + A * sqrt(mean.spload) + B * spload.changes +*
*C * sqrt(prev.mean.spload)+ D * mean.humid + E * mean.temp*

*Log(sqrt(mean.co)) =intercept + A * sqrt(mean.spload) + B * spload.changes +*
*D * mean.humid*

*Sqrt(mean.no) = intercept + A * mean.spload*

*Log(mean.co2) =intercept + A * log(mean.spload)*

The relationship between start emissions and soak time was established, and used to predict start emissions of the unknown validation vehicles.

Heavy Duty. Similar regressions were made with the bus data, as for light duty vehicles, using load as the primary descriptive variable. Starts were not modeled separately since very few buses had any data on start emissions.

Nonroad. The microtrips were defined according to the exhaust flow instead of load since the equipment load and engine speed were included in the dataset to be predicted.

VSP Binning

EPA pursued an approach based on the binning of vehicle specific power on a second-by-second basis using pre-defined equations developed for characterizing Vehicle Specific Power, or VSP. The conceptual differences between the NC State method and the VSP binning method relate only to how operating modes are defined; the conceptual difference between the Environ approach and the second-by-second binning method are fundamentally the amount of time emission results and VSP are aggregated over.

VSP is generally defined as power per unit mass of the vehicle. The calculation of absolute power generally centers on the forces a vehicle must overcome when operating on the road, including: acceleration, the force of gravity due to positive road grade, tire rolling resistance, and aerodynamic drag. Normalizing this power by mass to calculate VSP allows for this metric to be estimated based only on the instantaneous speed of the vehicle and road grade, if assumptions for the coefficients of rolling resistance and drag are made and no wind speed is assumed. Jimenez-Palacios developed the following equation for calculating VSP for light duty vehicles using this approach:[11]

VSP (kW/Metric Ton) = $v[1.1a + 9.81 (\mathrm{atan}(\sin(\mathrm{grade})))+0.132] + 0.000302v^3$

where v in m/s
a in m/s^2
1.1 = coefficient of equivalent mass for rotating components
9.81 = acceleration of gravity (m/s^2)

0.132 = rolling resistance coefficient
0.000302 = drag term coefficient

The basic concept of Vehicle Specific Power has been applied in numerous studies in different forms, and has been shown to be a useful metric for characterizing vehicle emissions. As discussed by Jimenez-Palacios, similar metrics have included “Positive Kinetic Energy” (PKE) proposed by Watson et al.[14], and “Specific Power” employed in studies including EPA’s FTP Revision Study[15] and the development of MOBILE6 driving cycles[16], which were based on the product of speed and acceleration without consideration for road load effects. Both Environ and North Carolina State University employed different forms of the specific power concept as part of their shootout analysis.

For the bus analysis, the general concept of Vehicle Specific Power was used but was based on work performed by West Virginia University (WVU) for heavy-duty vehicles.[17] The WVU work presented an equation for absolute power which took the same basic components of acceleration, the force of gravity due to positive road grade, tire rolling resistance, and aerodynamic drag. Coefficients for the road load components were presented specifically for transit buses. To generate VSP from this absolute power equation, we divided through by the curb weight of the buses (12.02 metric tons) to develop the following equation:

$$\text{VSP (kW/Metric Ton)} = v[a + 9.81 (\sin(\text{grade}))+0.0094] + 0.42v^3$$

where
v in m/s
a in m/s^2
9.81 = acceleration of gravity (m/s^2)
0.0094 = rolling resistance coefficient
0.42 = drag term coefficient

The approaches for analyzing the light-duty and heavy-duty vehicles were essentially similar, with a few minor differences. VSP was calculated using the equations above for every second on data for the 12 vehicles in the modeling dataset using the second-by-second inputs of speed, acceleration and road grade. For NOx, only 11 light-duty vehicles were used. Vehicle 12 was not included because the data was indentified by Sensors as erroneous. The raw VSP results were then assigned to VSP bins in increments of 1 kW/ton from -15 kW/Ton to +30 kW/Ton for light-duty, and -30 kW/Ton to +30 kW/Ton for heavy-duty. All VSP values outside of these boundaries were assigned to the “boundary” bin. The boundary bin levels were chosen as they were so that a large set of data seconds (nominally at least 100 seconds) were contained in the highest and lowest bins, in order to reduce the noise of a low number of data points beyond these boundaries.

Light Duty Analysis. For the light-duty analysis, because there was variability in vehicle parameters and operating conditions, additional variables were evaluated in order to improve the explanatory power of the model. In keeping with the MOVES design concept of fleet and activity bins, these additional variables were characterized as “bins”; bins were developed for mileage (less than 50,000 miles or greater than 50,000 miles), soak time (less than 1 hour, 1 to 4 hours, greater than 4 hours), number of cylinders (4, 6), transmission type (manual/automatic), air conditioner compressor status (engaged or not engaged). An additional segregation was made in the light-duty dataset between start and running mode; the first 505 seconds of each trip was defined as a start, a number chosen for consistency with Bag 1 of the FTP.

A General Linear Model (Univariate) was run in the SPSS software package with gram per second emission rates (CO_2, HC, CO and NOx) as the dependant variables and the following independent variables (specified as covariate): VSP bin, mileage bin (less than or above 50,000 miles), start or running mode, number of cylinders, transmission type (automatic or manual), A/C compressor status (on or off). Because of the large sample size, all variables were determined to be significant; therefore, partial R^2 and parameter estimates were used as the primary screening criteria for determining additional "binning" variables. Partial R^2, calculated from Type I sum of squares, is an indication of how much each variable contributes to the total explained variability. The parameter "range" expresses how much the dependent variable varies from the mininum to the maximum value of the independent variable; it therefore provides another means of comparison the relative importance of each variable. The results are shown in Table 9. Using these metrics, VSP was determined to be the most important explanatory variable of those analyzed for CO_2, CO and NOx; it was less effective for describing HC, but was included in the analysis to provide continuity in the modeling approach. Other binning parameters chosen for inclusion were number of cylinders for air conditioning status (whether the compressor was engaged or not) for $CO_{2,}$ and number of cylinders, mileage, and start/running mode for CO, NOx and HC. For start modes, an additional bin parameter was added based on soak time (less than one hour, between 1 and 4 hours, and greater than 4 hours).

Once the important binning variables were defined for each pollutant, emission rates in grams per second were developed for each bin combination. For CO_2, unique emission rates were calculated in bins defined by VSP, cylinder and air conditioning status by calculating the average value over all seconds of operation falling in a given bin, across each of the 12 modeling dataset vehicles. For HC, CO and NOx separate emission rates were calculated for running and start. Running emission rates were generated by the VSP, cylinder, mileage and soak time bins. Start emission rates were generated by the VSP, cylinder, mileage and soak time bins, and are expressed as the difference in emissions between start and running (i.e. start "increment") by VSP bin. The resulting emission rates are shown in Figures 14 through 23, with the start increments shown in Figures 24 through 33..

A Microsoft Excel spreadsheet was developed to enable the prediction of total trip emissions for each of the light-duty validation trips, for each of the pollutants. This spreadsheet required the necessary vehicle and operating information to choose the correct emission rates according to bin. The vehicle information required as input are the number of cylinders and mileage bin. Trip information also required include VSP bin distributions. The VSP information needs to be as a total and for the first 505 seconds to compute start emissions. Other information on trips required are the soak times, A/C on/off status, and the total trip time.

Heavy Duty Analysis. VSP was the only variable considered for the heavy-duty analysis. This was considered appropriate because most of the vehicle trips were after very short soak periods, hence start emissions were not significant; all of the buses were the same in terms of engine parameters and technology; and all buses were of similar mileage level (generally between 200,000 and 300,000 miles).

Using vehicle speeds and the vehicle position, the distance traveled per second could be determined along with the grade. Data consistency and physicality checks could be made between and on the measured variables. Once the data checks were made the power was determined using the equation given above for each individual bus. Figures 34-41 display the results for bus 2 and 10.

The power per unit mass relationships with each of the four pollutants were then averaged together to produce final emissions per second functions for CO, CO_2, NOx, and HC. They are displayed in Figures 42-45. A key difference between the bus analysis and light-duty analysis was that the bus emission factors were based on the average gram per second results across each *vehicle* in a given bin; the light-duty results were based on the average gram per second results across each *second* in the bin. The bus methodology did not account for how much time a given bus spent in the bin; all vehicles were weighted equally.

Nonroad Analysis. Nonroad emission rates were developed simply by taking a straight average of the three-hours worth of operation for each equipment piece, leaving out negative emission values. This method does not account for any variability in activity during the time period, and hence represents a grosser level of aggregation than the current NONROAD model, which accounts for activity through the application of load factors and transient adjustment factors. The resulting emission rates are shown in Table10.

RESULTS AND CONCLUSIONS

Trip-by-trip results were compiled for the methods presented in the contractor reports and those developed by EPA as presented in this paper. For the on-road analyses, these methods are characterized as follows: the EPA approach is termed “VSP Bin”, the NCSU approach is termed “Modal Bins/OLS”, the Environ approach is termed “Microtrips”, the UC Riverside approaches are termed “Microscale Database”, “Mesoscale Database”, and “Macroscale Database”.

The complete trip-by-trip results for each source (light-duty, heavy-duty, off-road), method, and pollutant are presented in Appendix A, Table 1, along with the results averaged across the six trips by light-duty/heavy-duty and pollutant. The focus of MOVES will be to predict emissions at a more aggregate level than individual trips; even emission produced at the finest level, microscale, is defined for MOVES as 15 minutes at a specific location. Under this approach, all emission predictions within MOVES would be based on multiple vehicles operating at a given place for a given period of time. As a result, the analysis of results based on trip averages is most pertinent, and our conclusions regarding model performance are based on the more aggregate results.

On-Road Results

Overall model performance was first judged by looking at all pollutants and all sources simultaneously; a promising method for estimating emissions must be robust across pollutant and vehicle type. The absolute percent difference in trip-average emissions was computed and averaged across the four pollutants for light-duty and heavy-duty, with results shown in Figure 46. The green dots on the chart represent results averaged across light-duty and heavy-duty; the bars are ranked from lowest to highest based on this average.

Individual pollutant results are shown in Figures 47 through 55. In the first chart for each pollutant, the trip mean results for each method compared with the actual trip mean results, with a 95 percent confidence interval determined based only on the individual trip results. This confidence interval only accounts for the variability between trips, not the error in the prediction methodologies used to estimate the individual trip results. The spread of these bands is therefore smaller than if within-trip variability were also characterized. For the second chart for each pollutant, the percent difference from the trip mean is shown.

The primary conclusions drawn from the results presented in these figures are the following:

1) Uncertainty intervals for the trip mean predictions overlapped with the uncertainty bands of the actual trip mean predictions for nearly all methods, pollutants and (on-road) sources. Because these uncertainty bands were conservative in that they only accounted for trip-to-trip variability but not within-trip variability, this suggests that all of the methods would likely be successful in predicting the observed trip averages within the uncertainty bounds.

2) The VSP Binning and Microtrip approaches, which both employed vehicle specific power (VSP) as the fundamental explanatory variable, performed the best based on the percent difference from the trip average across all pollutants, and across each pollutant individually. In particular the VSP binning approach had the most consistent performance when judged in terms of the individual pollutants, predicting HC, CO and CO2 for both light-duty vehicles and buses to within 10 percent or less. From the performance of these approaches we conclude that VSP is an excellent metric for characterizing vehicle emissions.

3) The Modal Bins/OLS approach predicted within 20 percent of the trip means across all pollutants, on average. From the performance of this approach and the VSP Bin approach, we conclude that modal binning approaches are promising.

4) UC Riverside’s database approach performed well for buses, in which there was little variability in vehicle parameters; but for light-duty vehicles, performance suffered for lack of data to provide adequate coverage across vehicle parameters such as mileage and engine size. The one exception was light-duty NOx, as discussed in conclusion (5).

5) Light-duty NOx performance was generally not as good as the other pollutants, with the exception of the database approaches. UC Riverside and NCSU determined in the course of their analyses that the validation trips had trip characteristics on outer edge of trips contained in the modeling dataset, and/or ambient conditions different from the modeling dataset. It is therefore

hypothesized that the database approaches were able to more closely match anomolies in the validation dataset using individual vehicles compared to the VSP Binning, Microtrip and Modal Bins/OLS approaches, which rely on predictions of average emission rate. It is likely that model performance for the non-database approaches would improve if the models were applied to independent observations generated under conditions within the bounds of the modeling dataset.

Off-Road Results

The off-road methodologies were termed as follows: EPA, "Straight Average"; NCSU, "Modal Bins"; Environ, "Microtrips"; UC Riverside, "Microscale Database". Similar to the on-road results, the off-road models were judged based on the ability to predict total emissions for the three hours of operation for the validation dataset, across the three equipment pieces for off-road. Figure 56 shows the summary results, averaged across CO_2 and NOx. CO_2 and NOx results are shown separately in Figures 57 and 58.

The primary conclusions drawn from these results are the following:

1) All approaches performed relatively well; within 10 percent for the average of CO2 and NOx, and within 15 percent for each pollutant. This was likely because the validation dataset was comprised of the same pieces of equipment as the modeling dataset.

2) In particular it is important to note that the relatively simplistic aggregate approach performed well compared to the more sophisticated approaches. This suggests that for off-road there is less need or less value added for adopting finer-scale modeling approaches.

APPLICABILITY OF SHOOTOUT APPROACHES IN MOVES

The predictive results of the shootout indicate that all of the methods could likely be developed to produce accurate methods of modeling using on-board emission data. This is underscored by the fact that nearly all of the methods predicted to within the uncertainty bounds of the trip mean. With more data and additional refinement, it is likely that each of the methods could be furthered to produce reasonably accurate emission rates for MOVES. Given this, consideration of which method is "best" for MOVES centers on an evaluation of how well the methods fit within the MOVES design objectives, summed up by the following questions: Can the method be applied consistently across the analysis scales? Can it be easily updated as new data becomes available? Can it adapt data from a number of sources, including possibly laboratory second-by-second data, bag data, inspection/maintenance program data and remote sensing data? Would a software implementation of the approach be efficient? Each of these questions is considered in relation to the three basic approaches developed for the shootout (modal binning, database, and microtrips).

Can the method be applied consistently across the analysis scales?

A primary goal of MOVES is to allow the prediction of emissions at multiple scales, specifically the microscale (a specific location for a time interval as short as 15 minutes), mesoscale (link-level analysis for a specific region), and macroscale (county-level analysis for a large region, up to the national scale). A key challenge to estimating emissions at multiple scales is the desire for consistent emission rates across analysis scales. Without this consistency, we are concerned that analysis at the different scales will produce fundamentally different results of uneven quality.

Emission rates derived using the microtrip approach could be applied at either the macroscale or mesoscale, but microscale applications could be problematic if the operation in the area of study was shorter than the duration of a predetermined "microtrip" (stable period to stable period) definitions, which was defined as 20 seconds or longer in Environ's analysis. The maximum length of a microtrip could be very long if the vehicle did not achieve stable operation, to the point were the period of time a vehicle spent in an intersection was shorter than a single microtrip.

The database approach as pursued by UC Riverside generated separate emission rates for each analysis scale, which does not meet the objective of consistency across scales. It is concievable that the microscale database approach could be applied to all three scales, however this could impose a computational burden which comprised the goal of software efficiency.

We believe that the modal binning approaches provide the most flexibility for application across analysis scales. The characterization of activity as time spent in a given mode applies at all scales. Using this approach, MOVES could provide the same set of modal emission rates without needing to be "aware" which scale the model was operating on.

Can it be easily updated as new data becomes available?

A key recommendation of the NRC panel in "Modeling Mobile Source Emissions" was the need for more frequent updates, to allow more responsiveness to new data as it became available. Meeting this recommendation requires a method of producing emission rates which is simple and can be automated as much as possible. The ultimate evolution of this concept would take the form of a "data crank" which takes raw data and produces emission rates for MOVES automatically.

We think all of the methods presented in the shootout could meet this criteria. However, the purely "data-driven" approaches (database and modal binning) would likely enable this more than any approach requiring the development of a statistical regression model, which requires more subjectivity on the part of the model developer.

Can it adapt data from a number of sources, including possibly laboratory second-by-second data, bag data, inspection/maintenance program data and remote sensing data?

No one data source can provide an accurate picture of emissions over the range of vehicle operation, over the range of the in-use fleet. Typically, current emission models rely on a primary source of data (i.e. laboratory bag) and do not take full advantage of other types (e.g. second-by-second) or sources (e.g. I/M data) to improve the characterization of real-world emissions. A primary objective for MOVES is to take advantage of many types of data, from many sources, to get a more accurate picture of in-use emissions.

Analyses have been performed which suggest that a binning approach could be applied to any source of data; the shootout methods which employed modal binning demonstrated how on-board second-by-second data could be used to generate emission rates, and these methods could easily be extended to second-by-second data sources such as lab and IM240 data. NCSU's shootout report also contained a proof-of-concept analysis for deriving modal emission rates from bag data, and several remote sensing studies have used VSP binning to characterize remote sensing data. It is not clear that the database and microtrip approaches could be applied across this same range of data, and it is likely that emission rates based on these approaches would require a more limited data set.

Would a software implementation of the approach be efficient?

Given the scope of MOVES, it is likely that performance will be an issue aside from the calculation of emission rates. For example, the calculation of a county-level national inventory over several vehicle classes, vehicle ages, roadway types, and pollutants would require millions of calculations internal to the model. It is therefore desirable to minimize the processing of emission rates in order to keep the performance time of MOVES manageable. The method which causes the most concern for this is the database approach, which at the microscale level (as discussed, the only level which could provide consistent emission rates across all scales) would require extensive searches of second-by-second data in order to find the best "match". The modal binning and microtrip approaches would considerably reduce the amount of data necessary for emission rate processing compared with the database approach.

Feasibility Assessment and Next Steps

When model performance and feasibility are considered, we judge that the modal binning approach best meets the MOVES design criteria and provides promise for model accuracy and representativeness. It is simple, data-driven, can be extended to data from multiple sources, and is easy to update with new data. In particular, vehicle-specific power, which combines speed, acceleration, road grade and road load parameters, appears to be an excellent metric for characterizing vehicle exhaust emissions. We therefore plan to pursue additional proof-of-concept work looking specifically at the modal binning approach on a wide variety of data sources, including laboratory second-by-second data, bag data, inspection/maintenance program data and remote sensing data, using vehicle specific power as a means of defining modal bins. This "phase 2" work will focus on concepts presented in three of the approaches: use of VSP, which was applied by EPA and Environ; use of binning, applied by EPA and NCSU; and evaluation of different "averaging" times, which would take into account the basis of Environ's work on Microtrips.

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TABLE 1 Passenger Vehicles in On-Board Emissions Study

Vehicle Number	Vehicle Company	Model Year	Displacement (liters)	Number of Cylinders	Gross Vehicle Weight (gvwr)	Rated Power	Odometer
1*	GM	1998	3.1	6	4473	160	44362
2	FORD	1997	3	6	4687	145	79984
3*	FORD	1996	3	6	4707	200	96099
5	GM	1998	1.9	4	3327	124	37278
4**	CHRYSLER	1997	2.5	6	4122	160	54733
6	GM	1999	3.1	6	4013	150	26288
7	GM	1999	1.9	4	3237	100	43242
8*	FORD	1999	2	4	3485	104	39429
11	FORD	1998	3	6	4721	145	78187
10**	NUMMI	1999	1.8	4	3485	120	57000
12	FORD	1997	2	4	3485	110	71446
13	FORD	1998	3	6	4721	145	47439
15	GM	1996	2.2	4	3670	120	86999
16	GM	1998	2.2	4	0	120	56803
17	FORD	1998	2	4	4078	125	29233
14	FORD	1998	3	6	5166	200	41319
18	FORD	1996	3	6	4707	145	94321
9**	FORD	2000	2	4	3485	110	25486

*Vehicles in validation set
**Vehicles were not used for quality issues.

TABLE 2 Buses in On-Board Emissions Study

Contractor Test ID	Enginie Company	Vehicle Model Year	Engine Model Year	Displacement (liters)	Rated Power	Odometer
BUS380	DETROIT	1996	1996	8.5	275	223471
BUS381	DETROIT	1996	1996	8.5	275	200459
BUS382	DETROIT	1996	1996	8.5	275	216502
BUS383	DETROIT	1996	1996	8.5	275	199188
BUS384	DETROIT	1996	1996	8.5	275	222245
BUS385*	DETROIT	1996	1996	8.5	275	209470
BUS386	DETROIT	1996	1996	8.5	275	228770
BUS379	DETROIT	1996	1996	8.5	275	260594
BUS377	DETROIT	1996	1996	8.5	275	252253
BUS363	DETROIT	1995	1996	8.5	275	283708
BUS361	DETROIT	1995	1996	8.5	275	280484
BUS375*	DETROIT	1996	1996	8.5	275	211438
BUS360*	DETROIT	1995	1996	8.5	275	270476
BUS372	DETROIT	1995	1996	8.5	275	216278
BUS364	DETROIT	1995	1996	8.5	275	247379
BUS352**	DETROIT	1992	1992	0	253	0
BUS404**	NAVISTAR	2000	2000	0	0	0

*Vehicles in validation set
**Vehicles were not used for quality issues.

TABLE 3 Nonroad Equipment in On-Board Study

Equipment Type	Vehicle Number	Engine Company	Model Year	Number of Cylinders	Ignition Type	Engine Series	Rated Power
Scraper	BET00611	CATERPILLAR	2001	6	CI	3406	515
Compacter	COMPACT20947	CATERPILLAR	1980	6	CI	3306	170
Track Dozer	D8LANDFILL	CATERPILLAR	1990	6	CI	3406	305

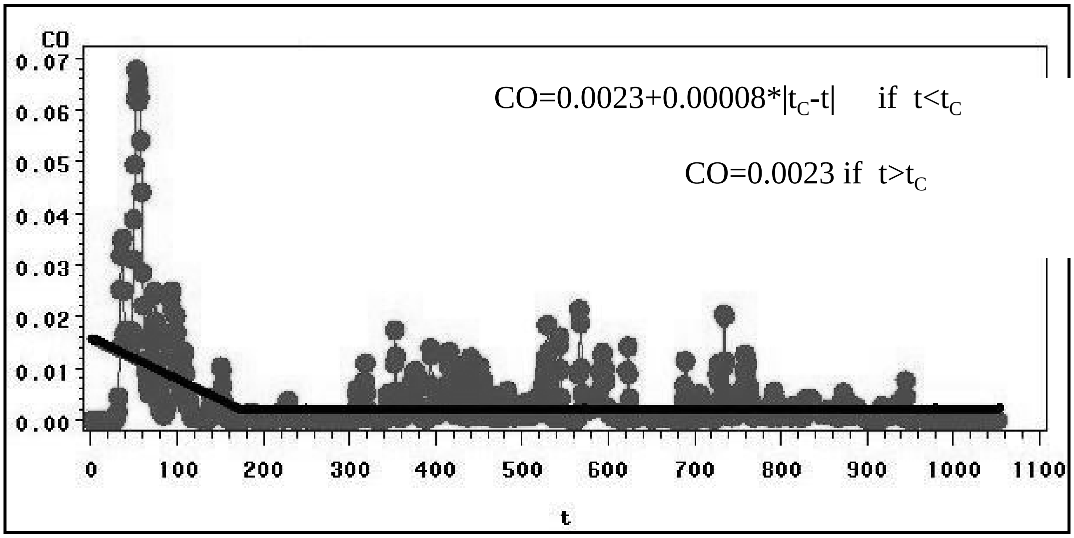

Figure 1. Determination of Presence and Duration of Cold-Start using Non-Linear Regression

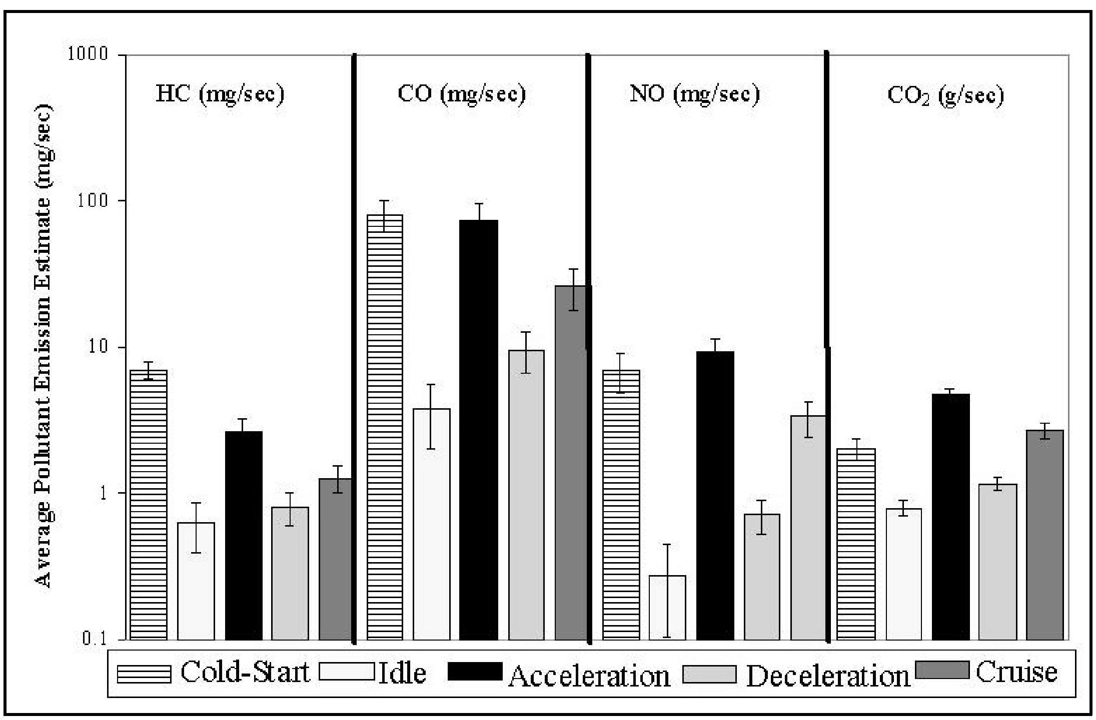

Figure 2. Average Modal Emission Rates for All Trips

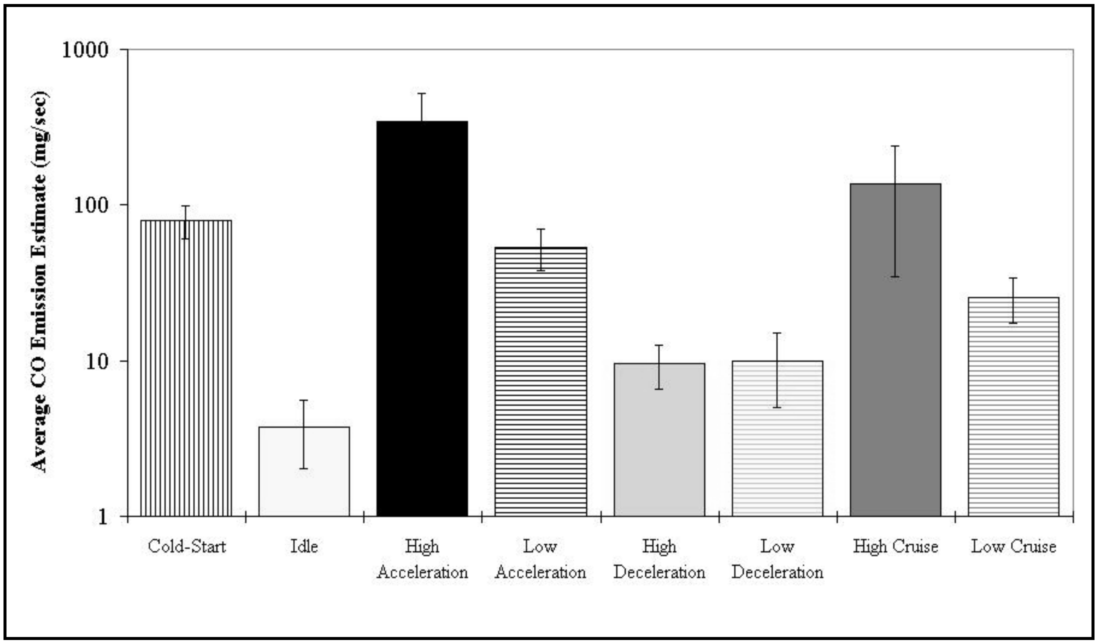

Figure 3. Improved Average Modal Emission Rates for All Trips for CO

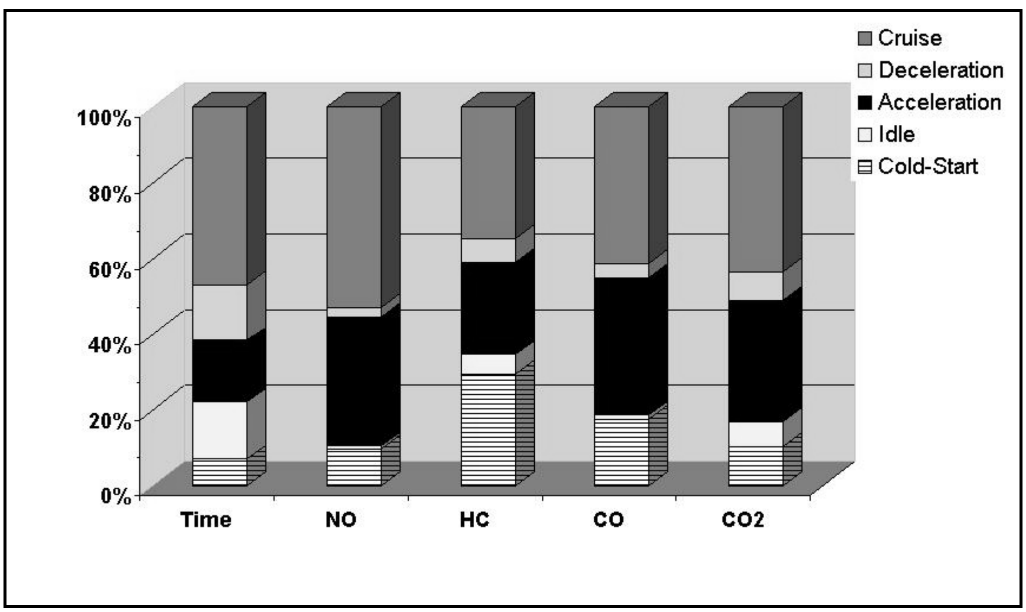

Figure 4 Average Distribution of Time and Emissions with respect to Modes

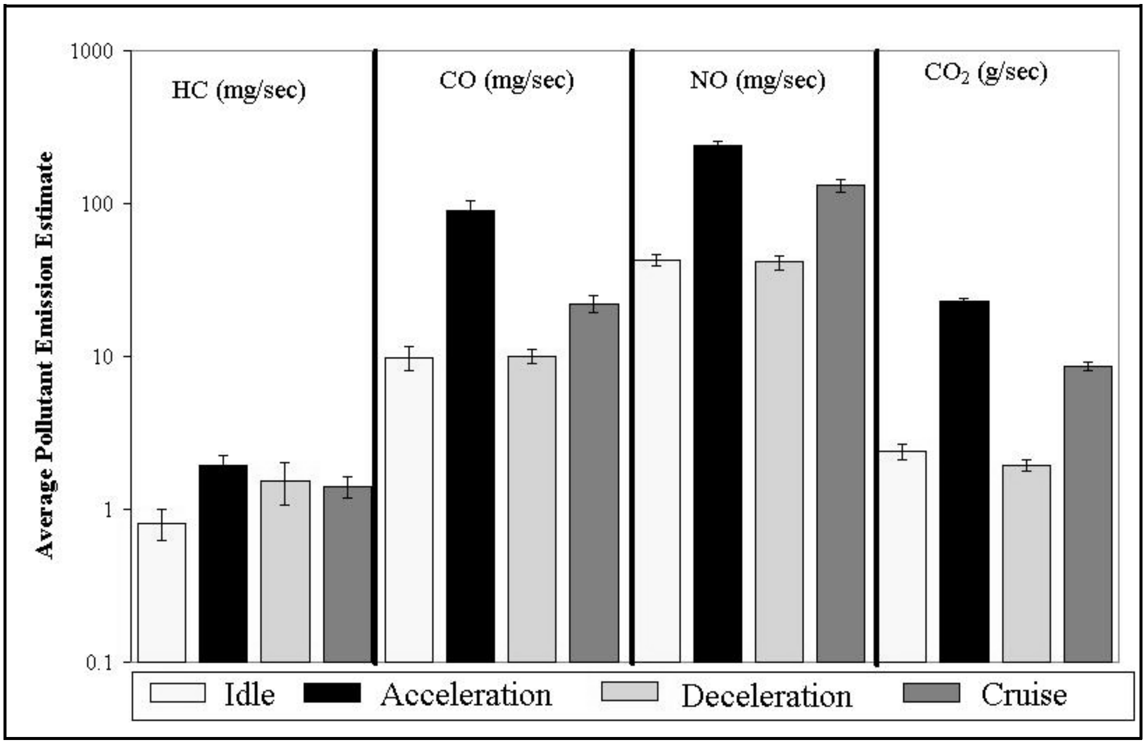

Figure 5. Average Modal Emission Rates for All Trips for HDDV

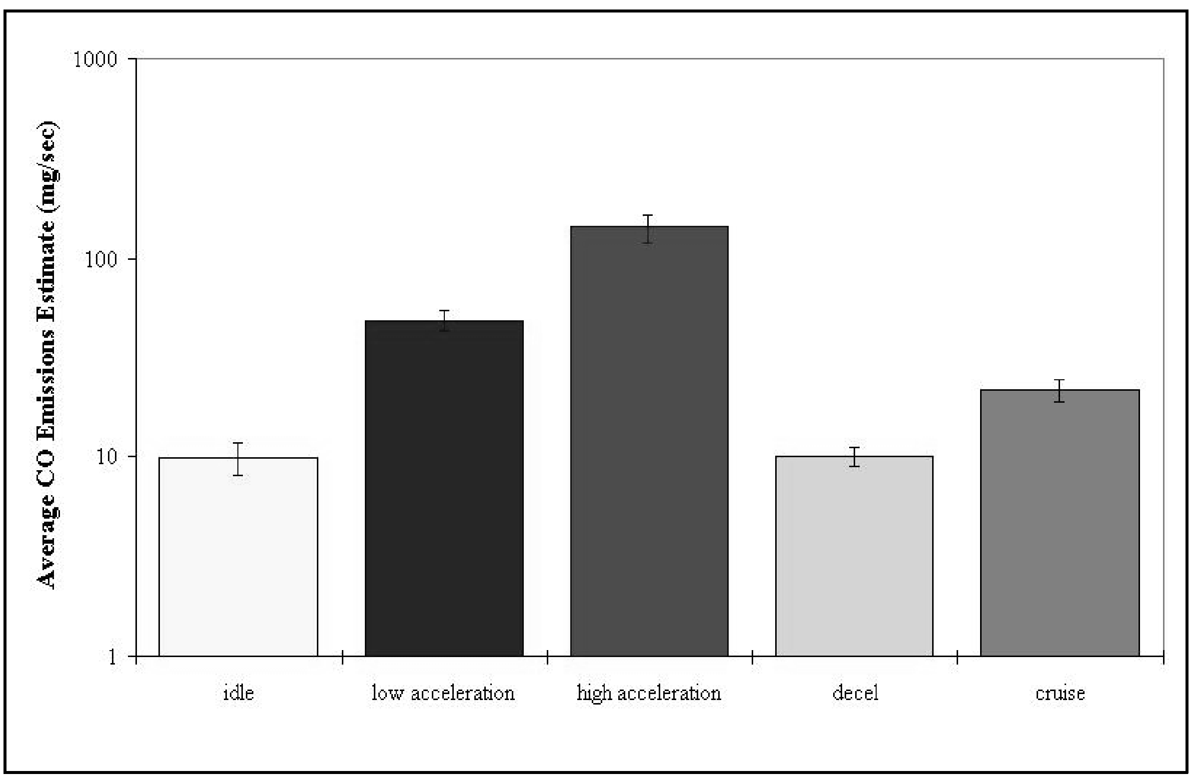

Figure 6. Improved Modal Emission Rate for All HDDV Trips for CO

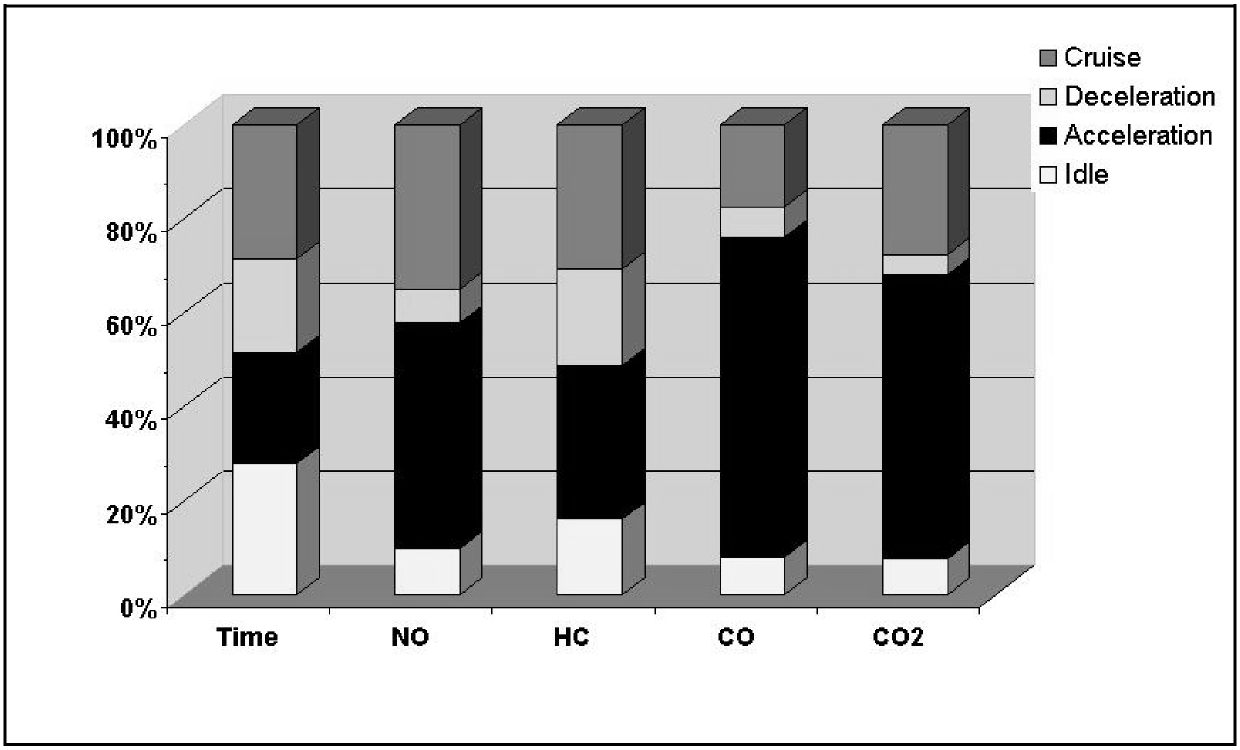

Figure 7. Average Distribution of Time and Emissions with respect to Modes for HDDV

Trip based	Facility specific link based	Mode based

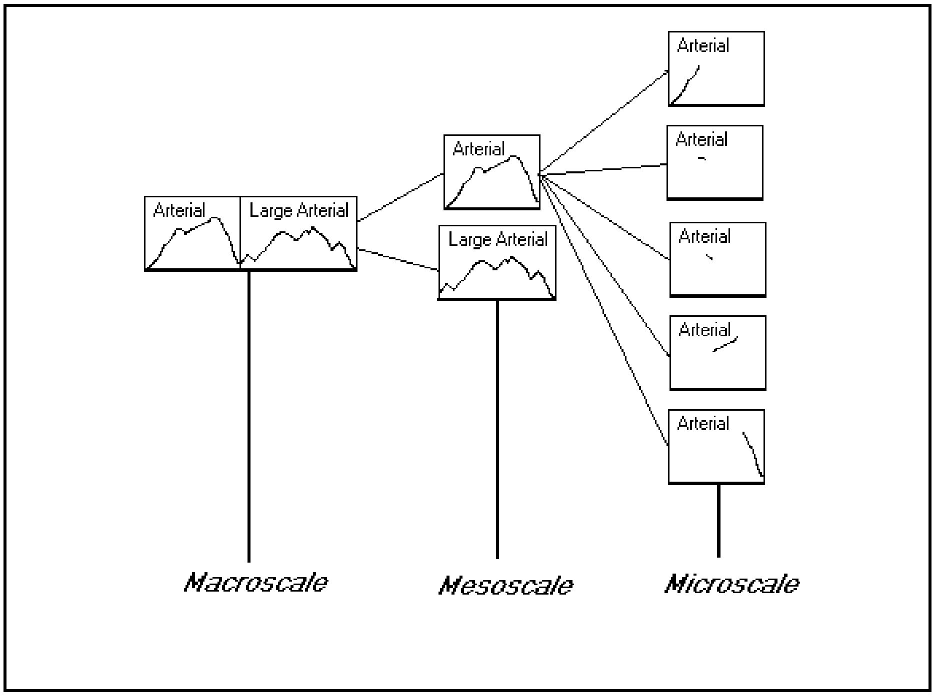

Figure 8. Disaggregation of PEMS driving data for hybrid emissions database/GIS approaches.

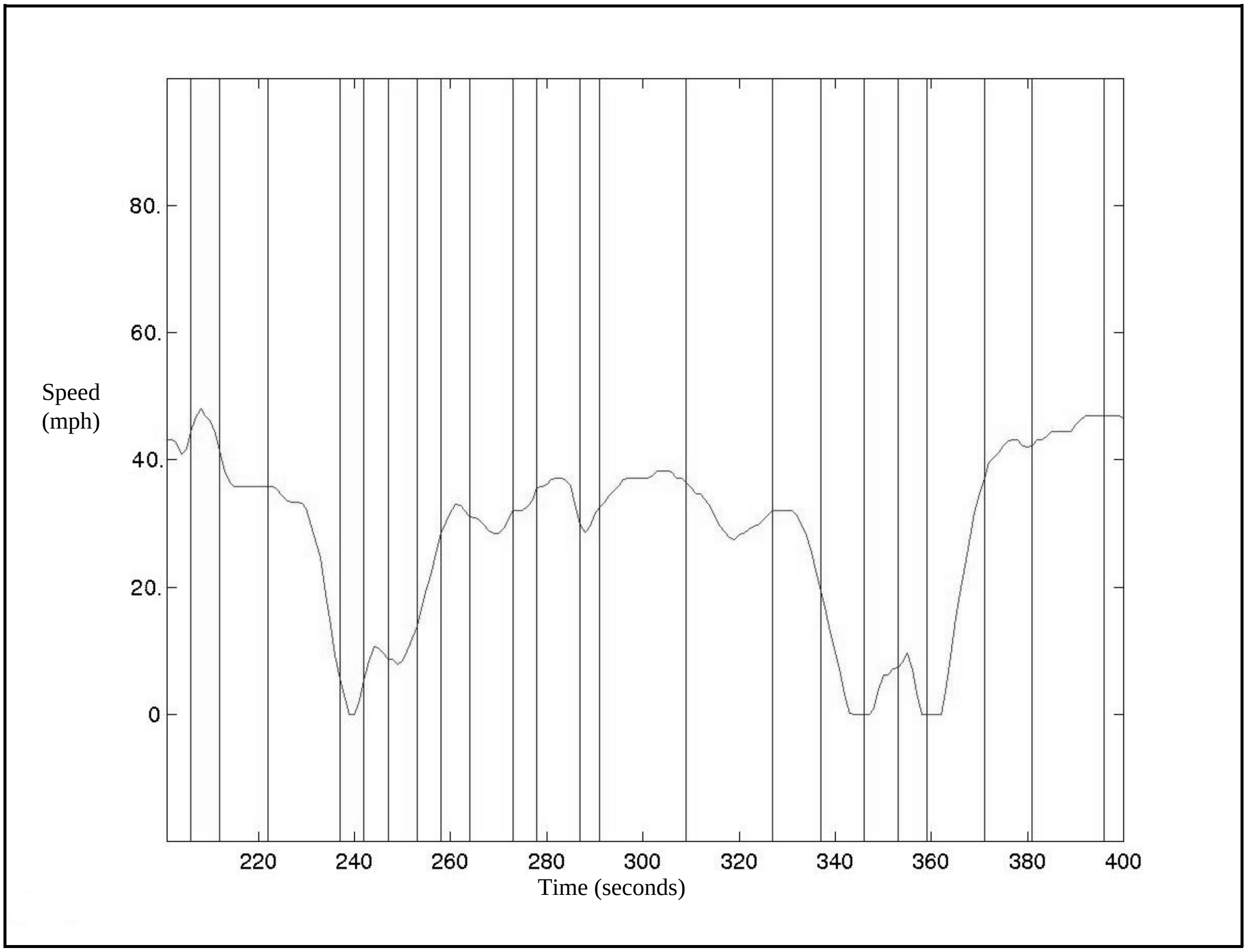

Figure 9. Example speed trace divided into modal segments.

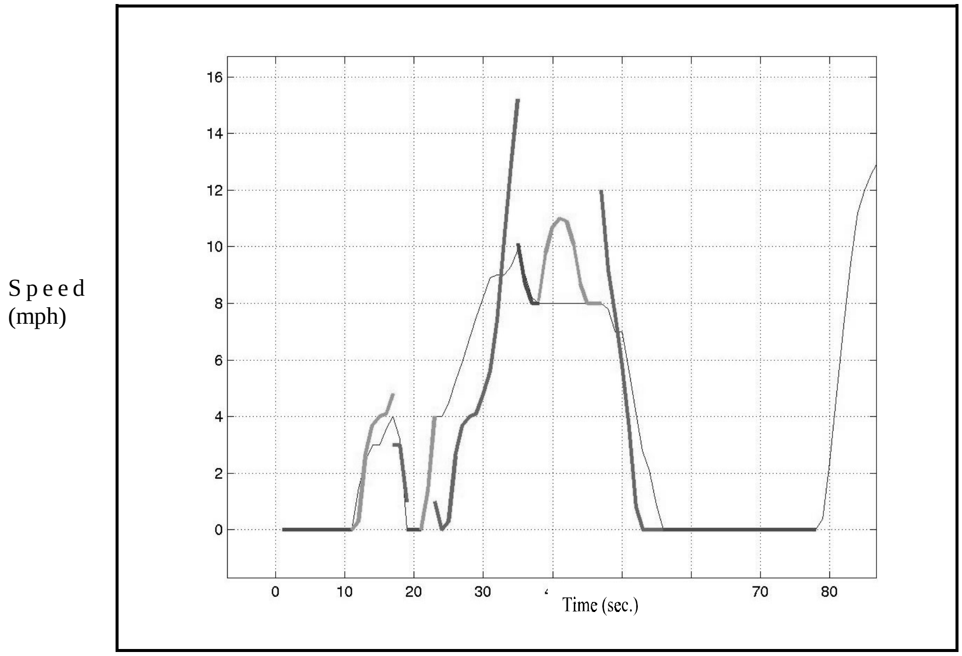

Figure 10. Example speed trace modally divided at the peak with matched speed segments appearing in alternating colors.

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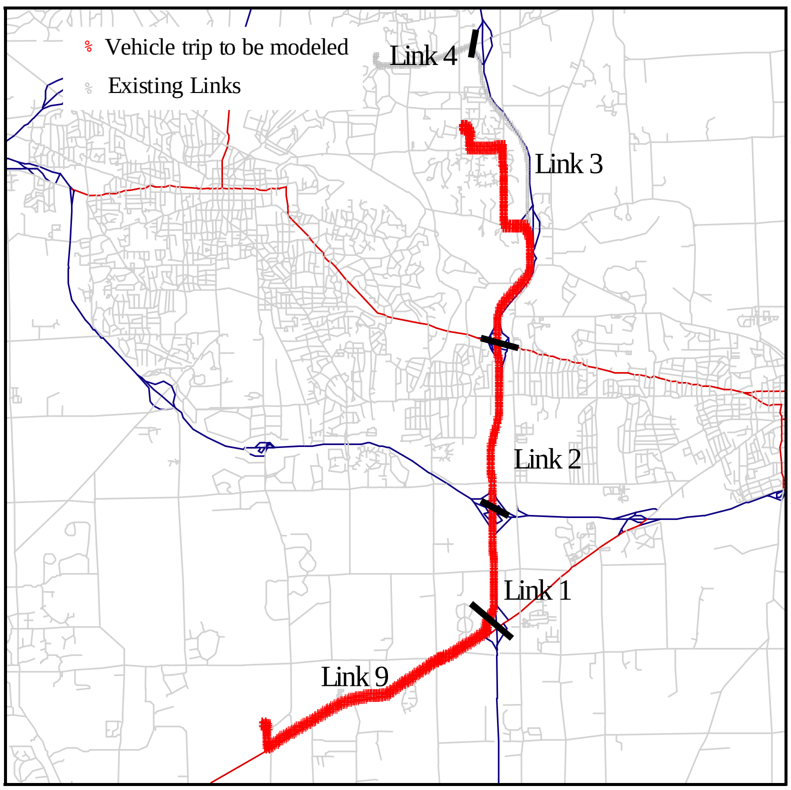


Figure 11. Example of link based mesoscale methodology, see text for details.

Table 4 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

Table 5 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

. **Table 6.** Road load coefficients for light-duty vehicles.

Vehicle Number	a (lbf)	b (lbf/mph)	c (lbf/mph2)
1*	8.85	-0.05	0.02
2	4.09	0.09	0.02
3*	5.57	0.01	0.02
4**	38.85	-0.05	0.02
5	23.7	0	0.02
6	34.1	0	0.02
7	23.7	0	0.02
8*	4.36	0.01	0.02
9**	4.36	0.01	0.02
10	34.39	0	0.02
11	11.74	-0.14	0.02
12	4.36	0.01	0.02
13**	4.09	0.09	0.02
14	11.74	-0.14	0.02
15	32.9	0	0.02
16	32.9	0	0.02
17	4.13	0.03	0.02
18	11.74	-0.14	0.02

* Validation vehicles

** No data

*** Faulty instrumentation

Table 7. Road load coefficients for a bus (WVU) and a truck (EPA).

Source	A (Hp/lbm/(ft/sec))	b	c (Hp/(ft/sec)^3)
WVU (2000)	1.68985E-05	0	0.000130600
EPA (1995)	1.84520E-05	0	0.000124035

Table 8. Regression coefficients for light-duty microtrips above zero load and zero load rates

Pollutant	**Intercept**	**A**	**B**	**C**	**D**	**E**	**Zero Load (g/s)**
HC	0.0474	0.2784	1.1403	-0.0486	-0.0003	-0.0005	0.000377
CO	-2.1729	11.1279	0.0615	---	-0.0203	---	0.000000
NO	0.0153	12.2165	---	---	---	---	---
CO_2	3.9911	0.4864	---	---	---	---	0.828444

Table 9. General Linear Model, VSP Binning Approach

Variable	CO2		HC		CO		NO	
	Partial R2	Parameter Range	Partial R2	Parameter Range	Partial R2	Parameter Range	Partial R2	Parameter Range
VSP Bin	0.6531	10.24	0.0835	0.0043	0.0854	0.2411	0.3301	0.0260
Cylinder	0.2051	0.78	0.0663	0.0013	0.0060	0.0154	0.0252	0.0011
Start / Running Mode	0.0000	0.04	0.0762	-0.0035	0.0177	-0.0688	0.0097	-0.0027
A/C	0.0004	0.19	0.0000	0.0002	0.0001	0.0063	0.0001	-0.0001
Auto/Manual Transmission	0.0001	0.00	0.0004	0.0003	0.0001	0.0037	0.0000	0.0009
Mileage Bin	0.0001	0.07	0.0026	0.0005	0.0046	0.0215	0.0070	0.0020
Temperature Bin	0.0004	-0.20	0.0016	0.0007	0.0029	0.0395	0.0000	-0.0003
Humidity Bin	0.0003	-0.23	0.0001	0.0002	0.0008	-0.0185	0.0000	0.0001

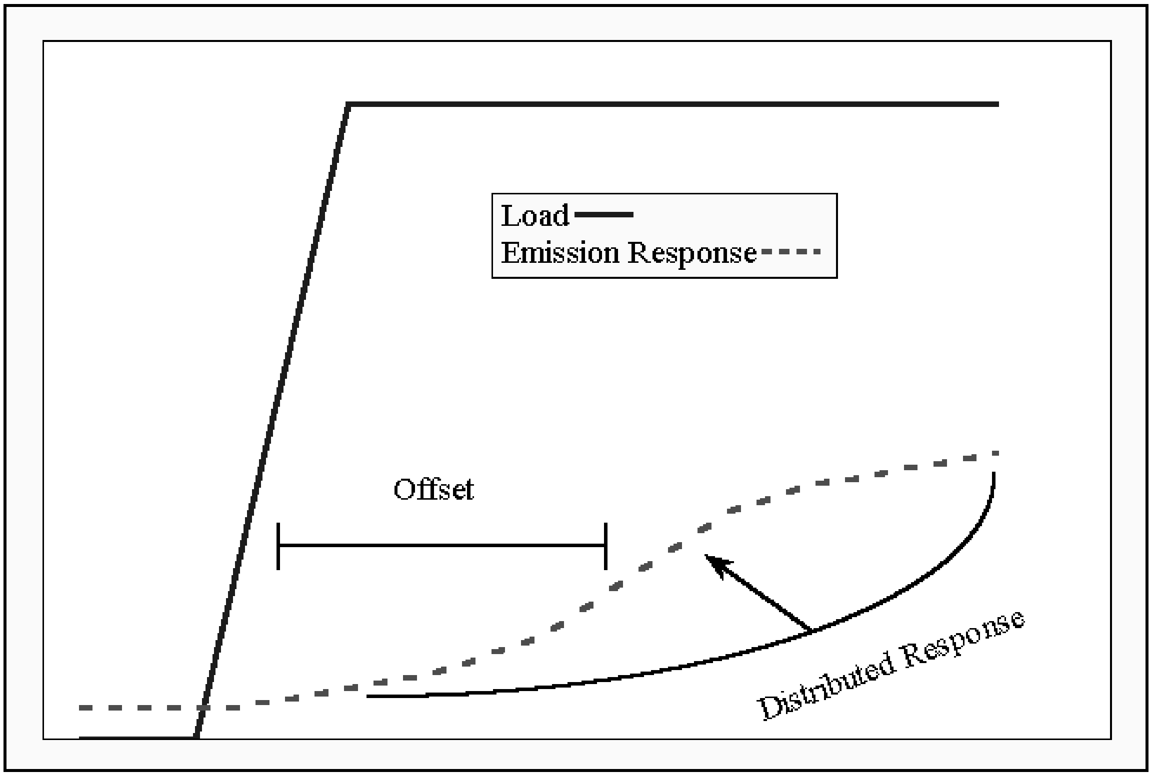


Figure 12. Load and Emission Response Offset Diagram

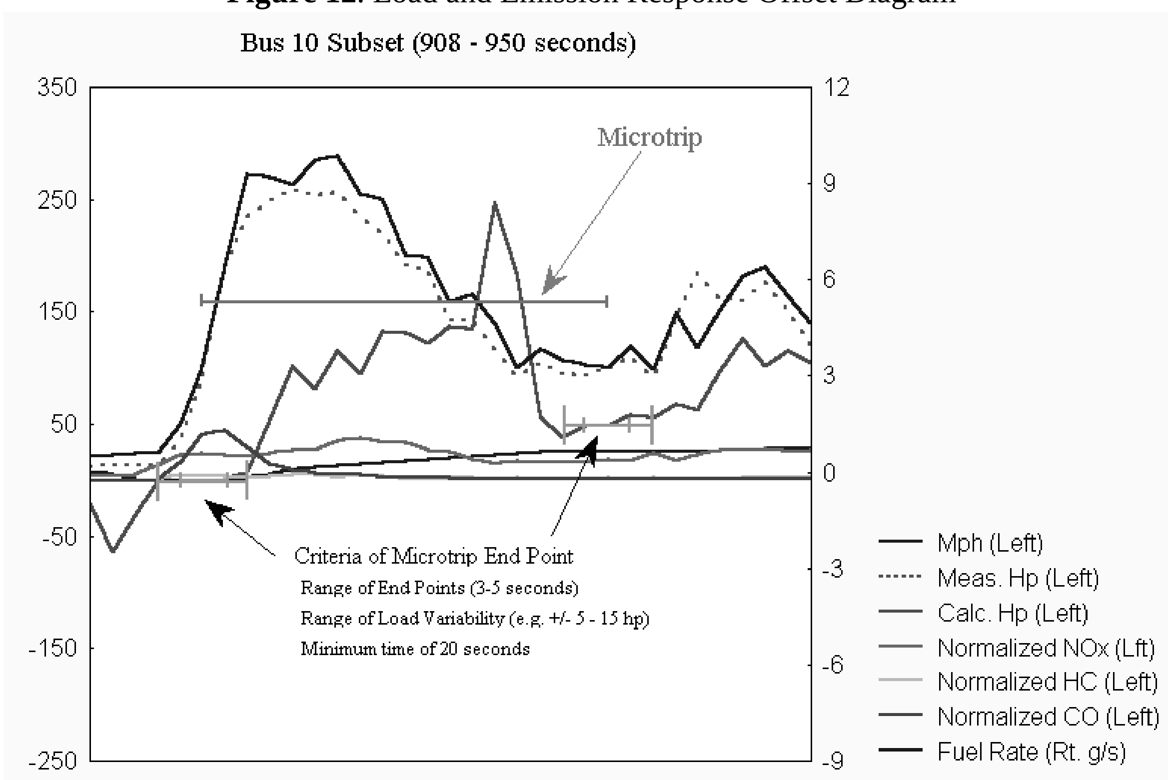


Figure 13. Example Microtrip Determination

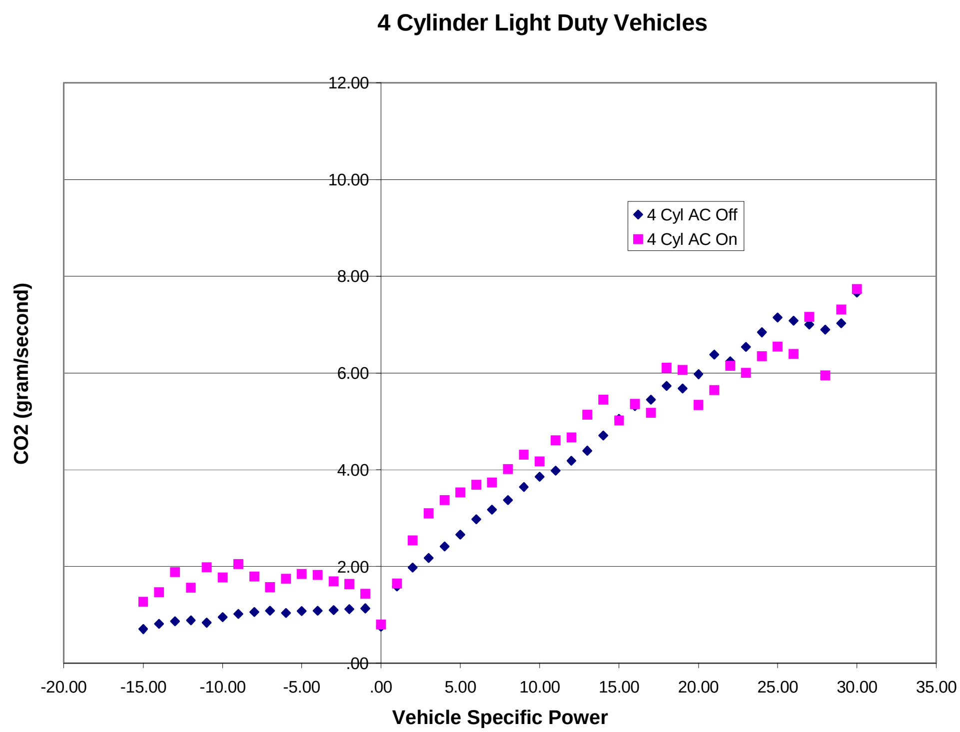
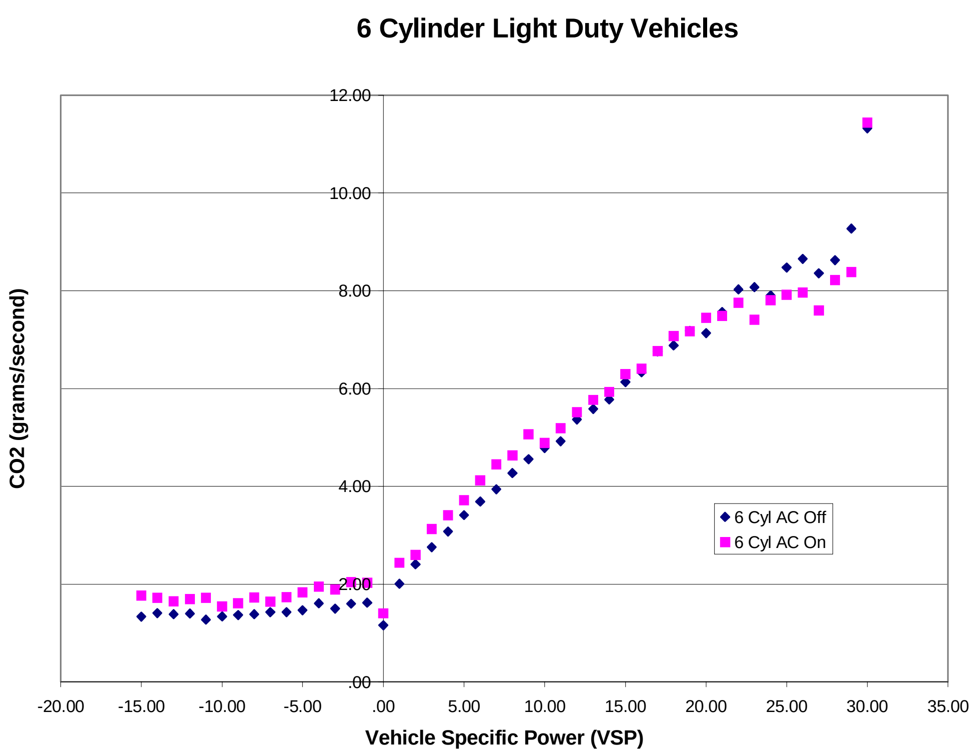


Figure 14



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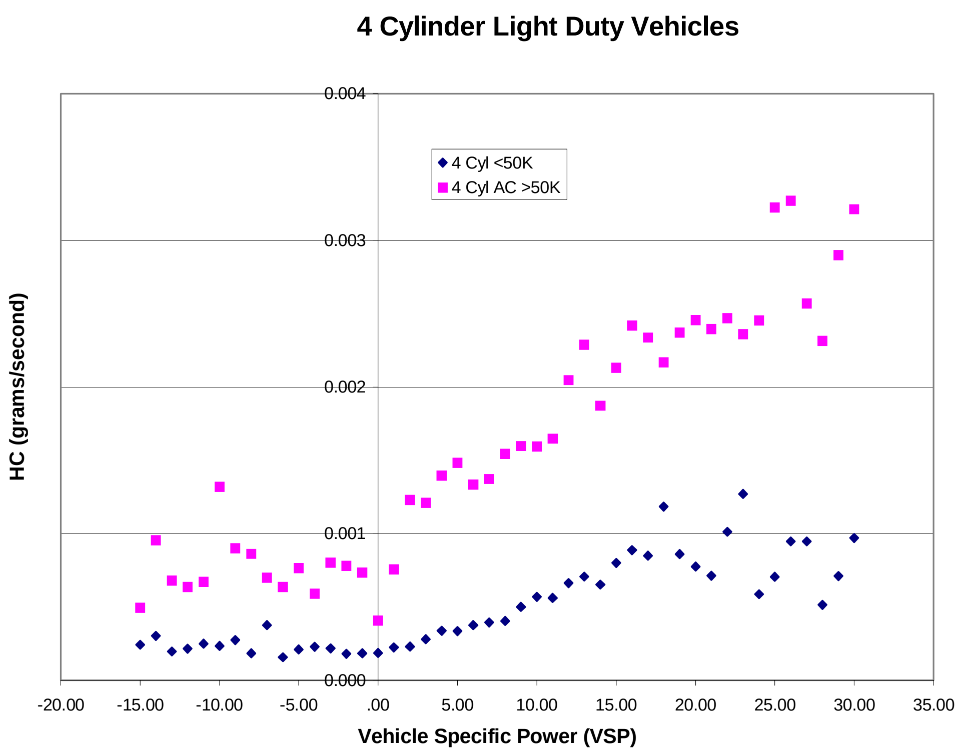
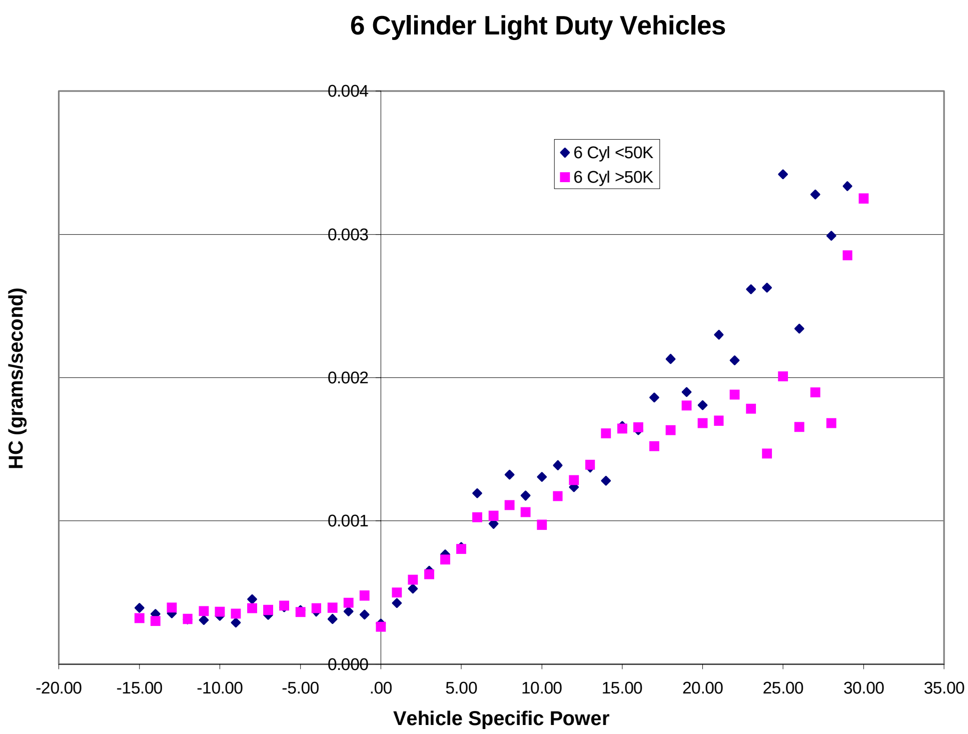


Figure 16



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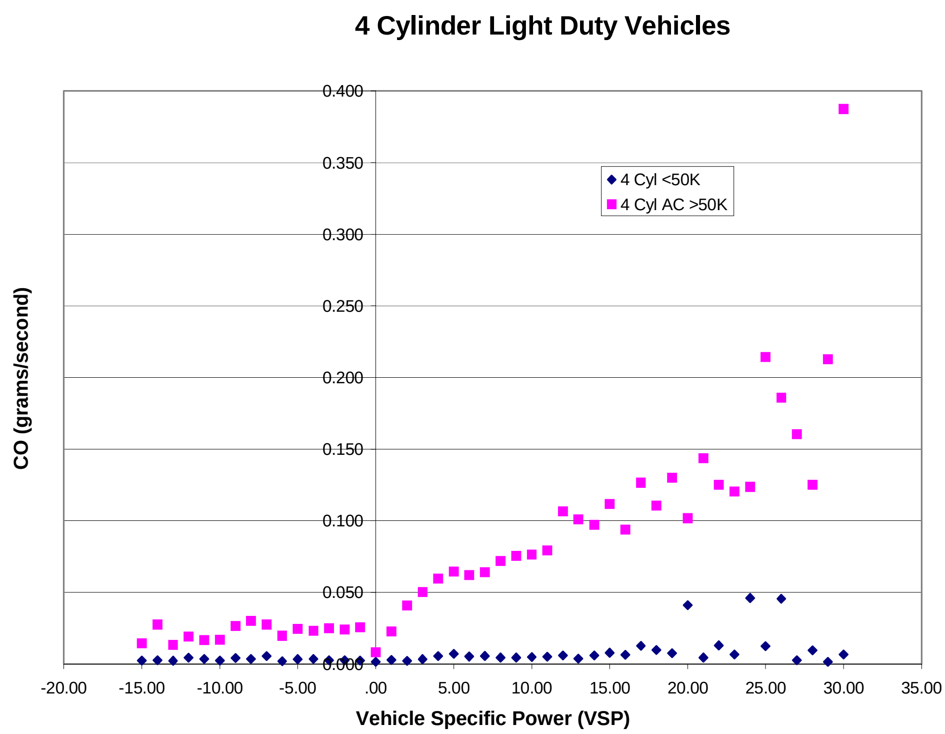

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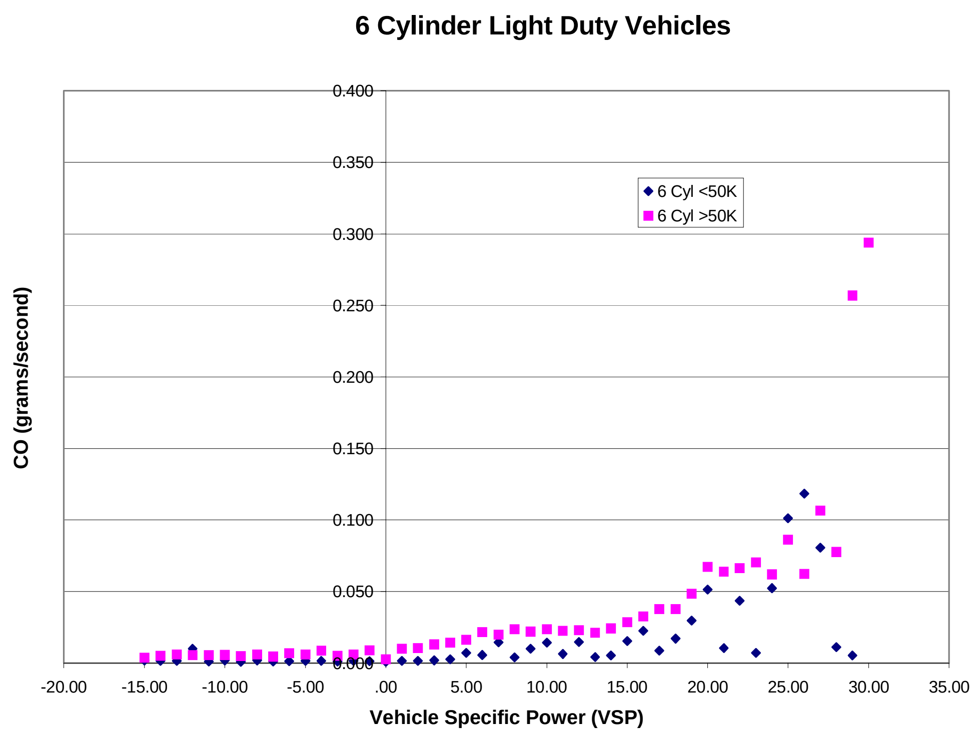

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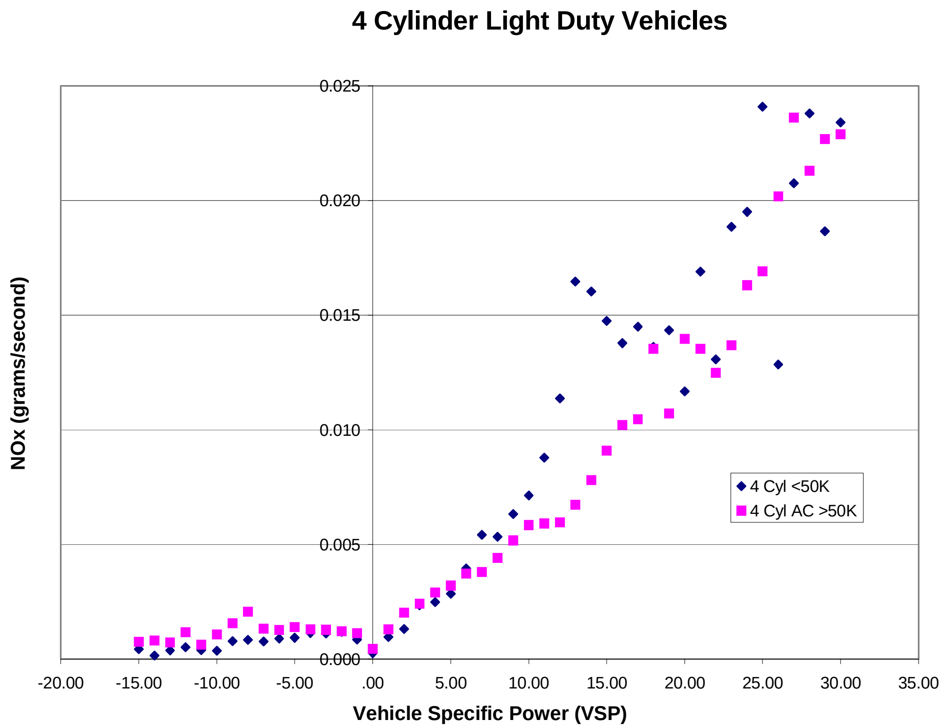

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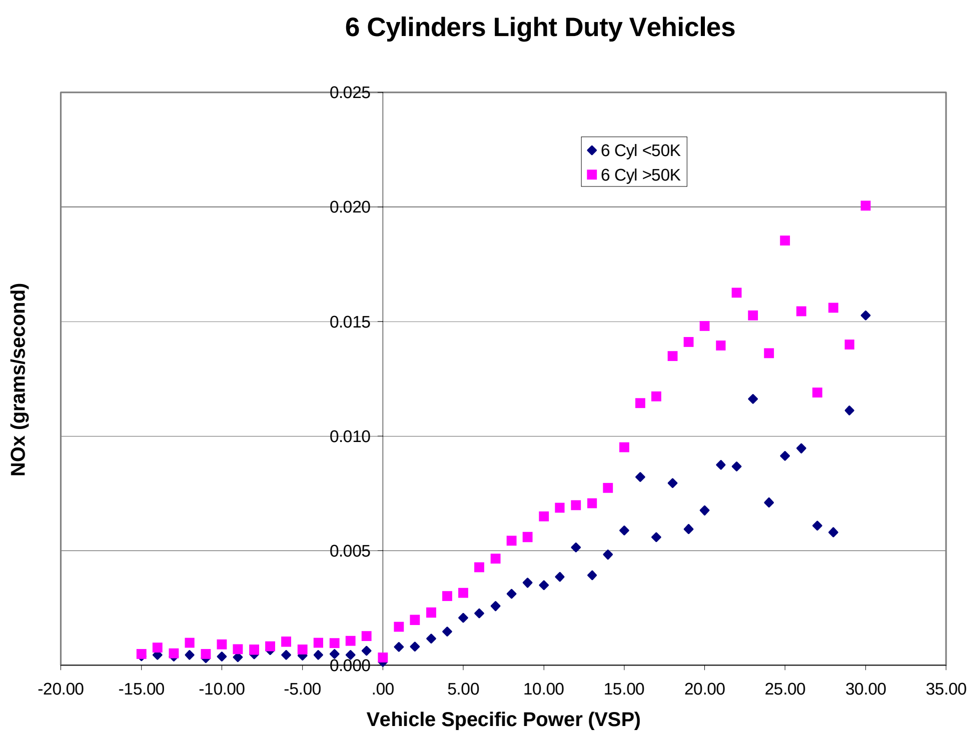


Figure 21

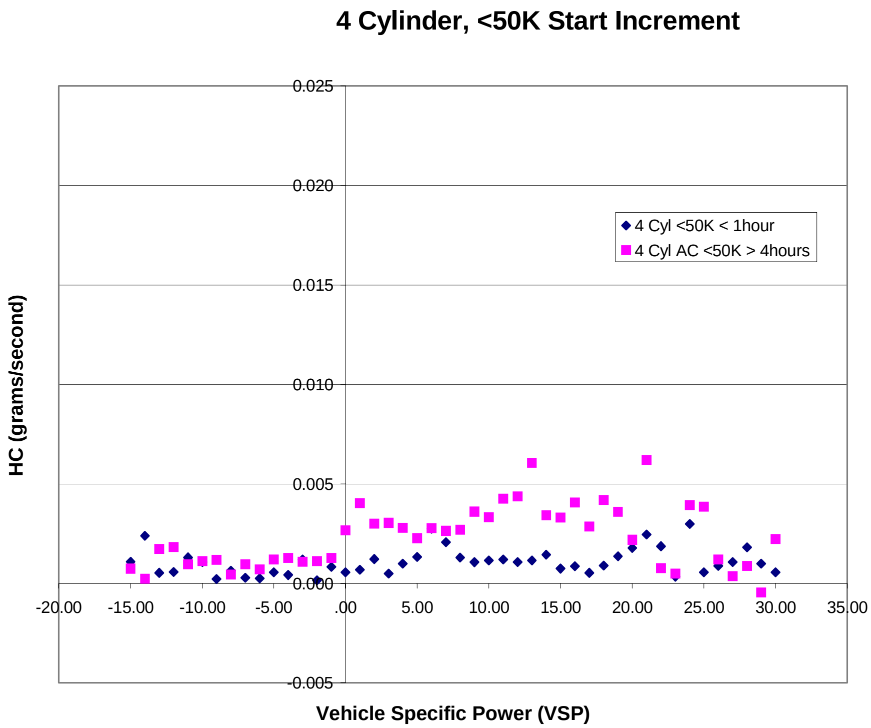


Figure 22

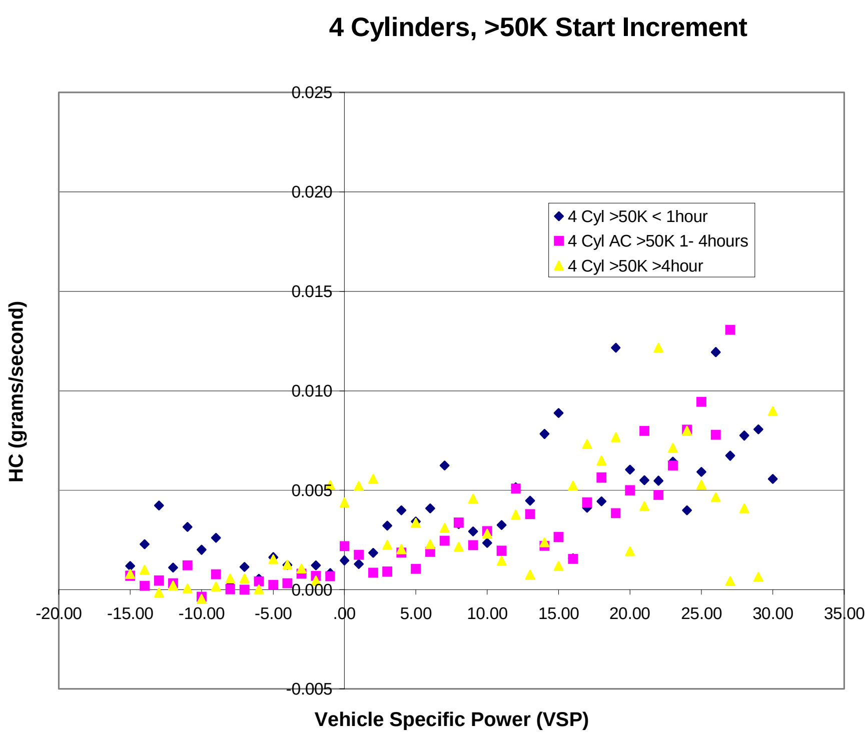
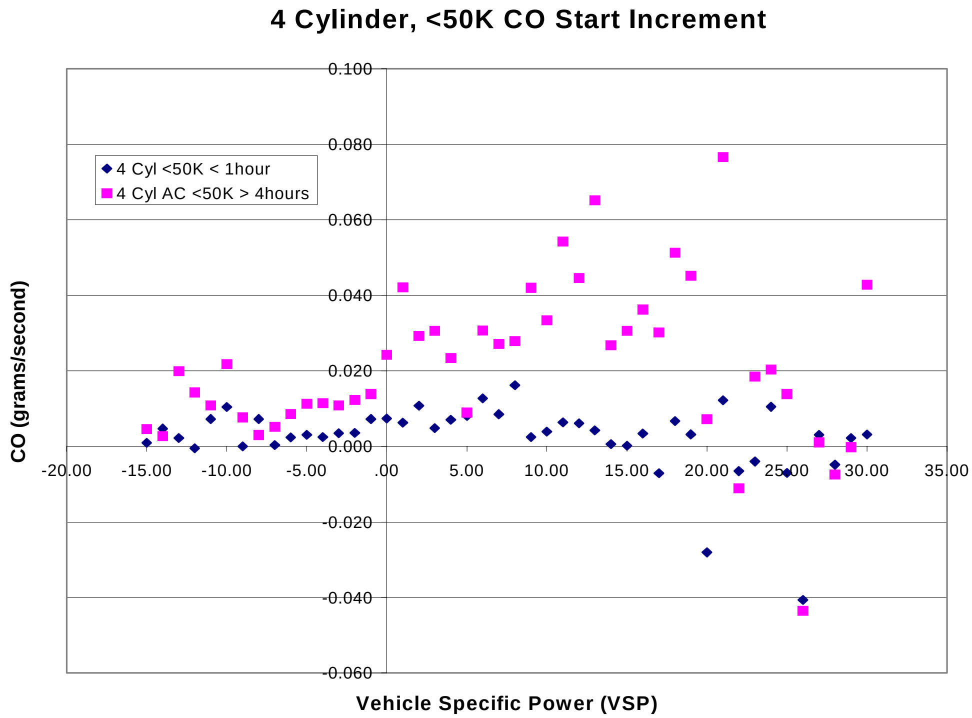


Figure 23



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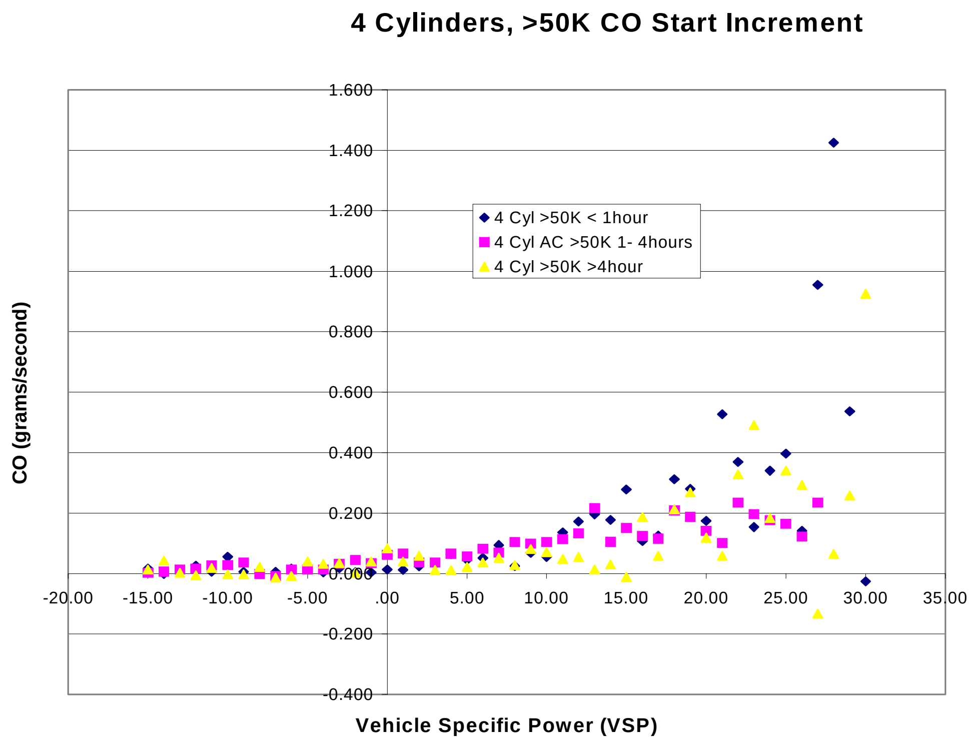

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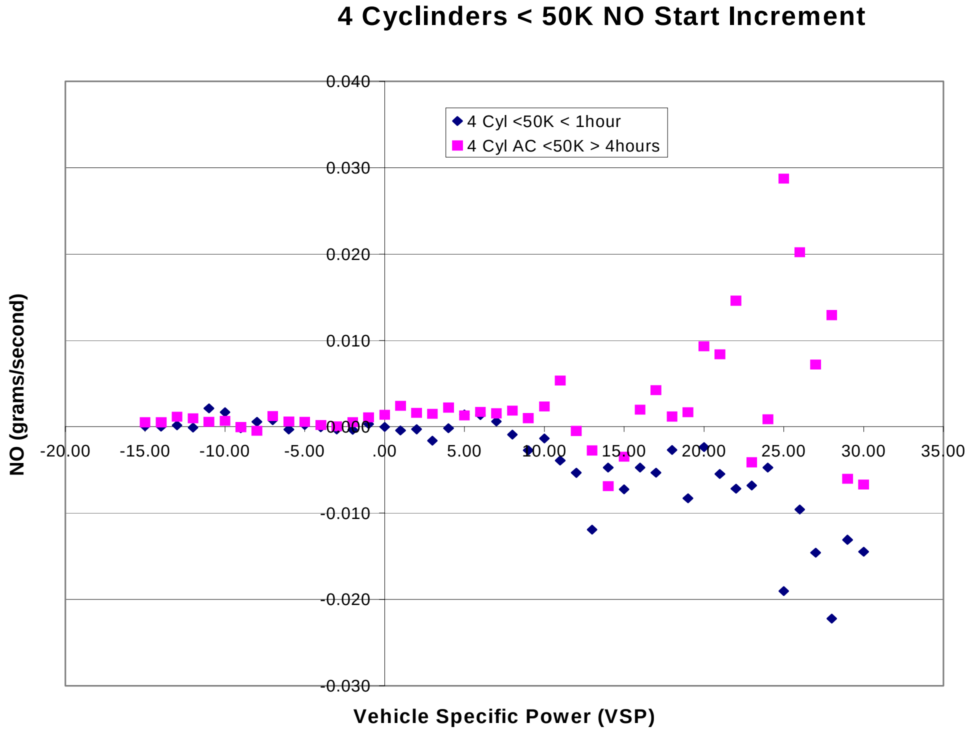


Figure 26

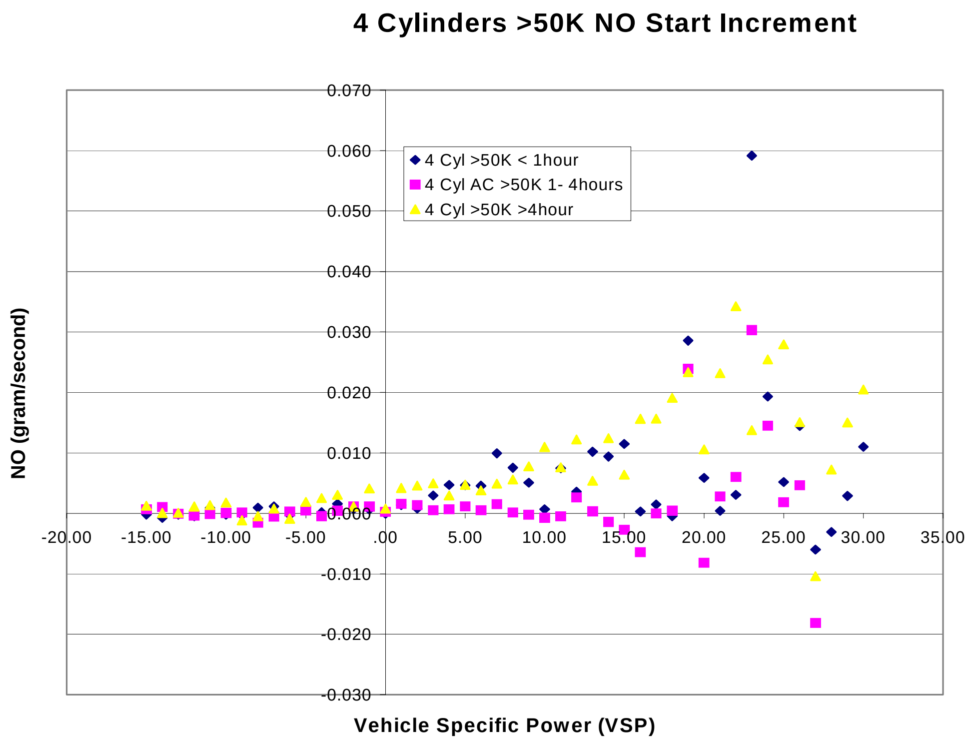


Figure 27

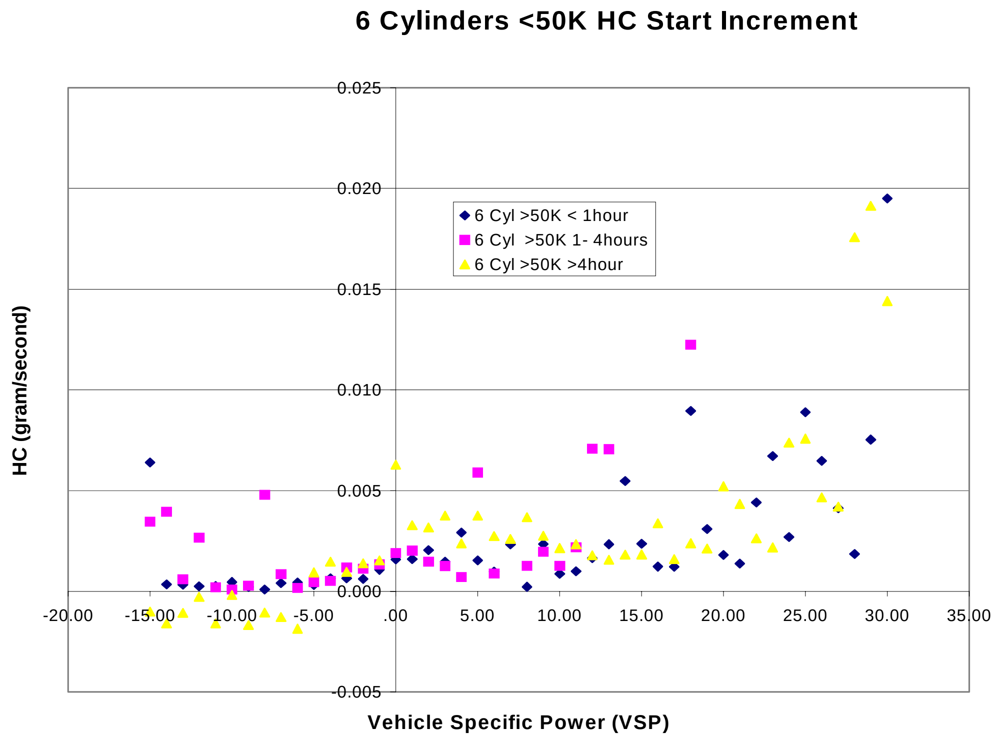


Figure 28

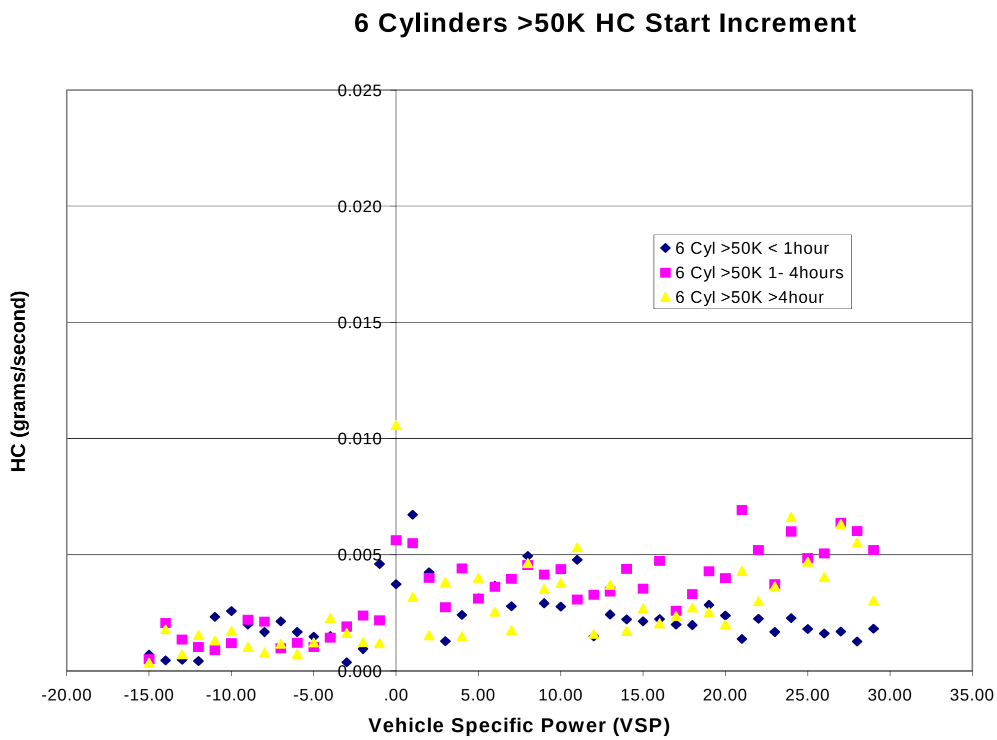


Figure 29

6 Cylinders < 50K CO Start Increment

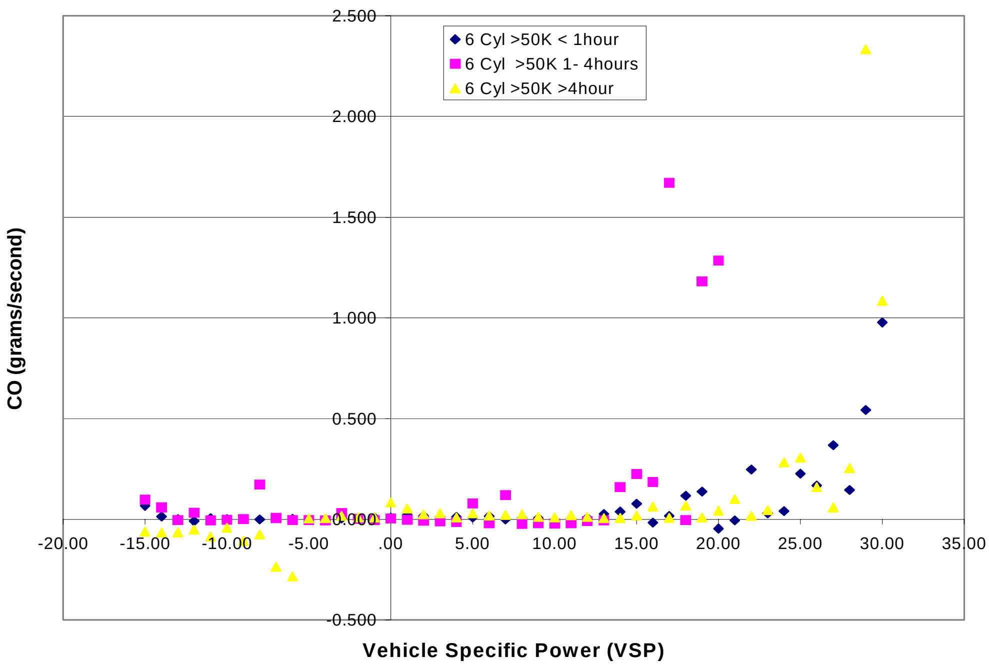


Figure 30

6 Cylinders >50K CO Start Increment

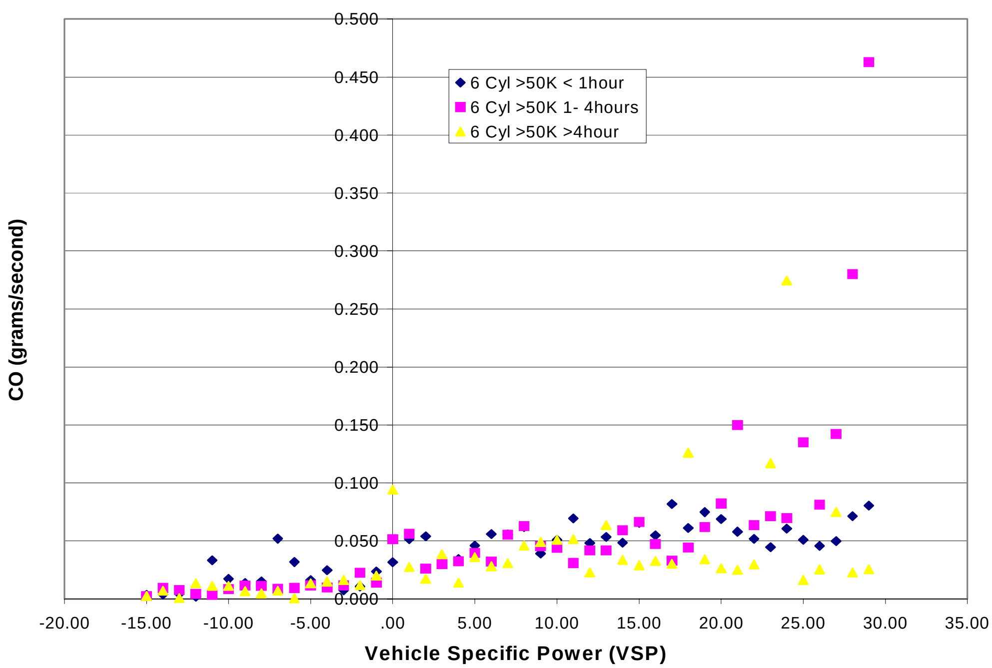


Figure 31

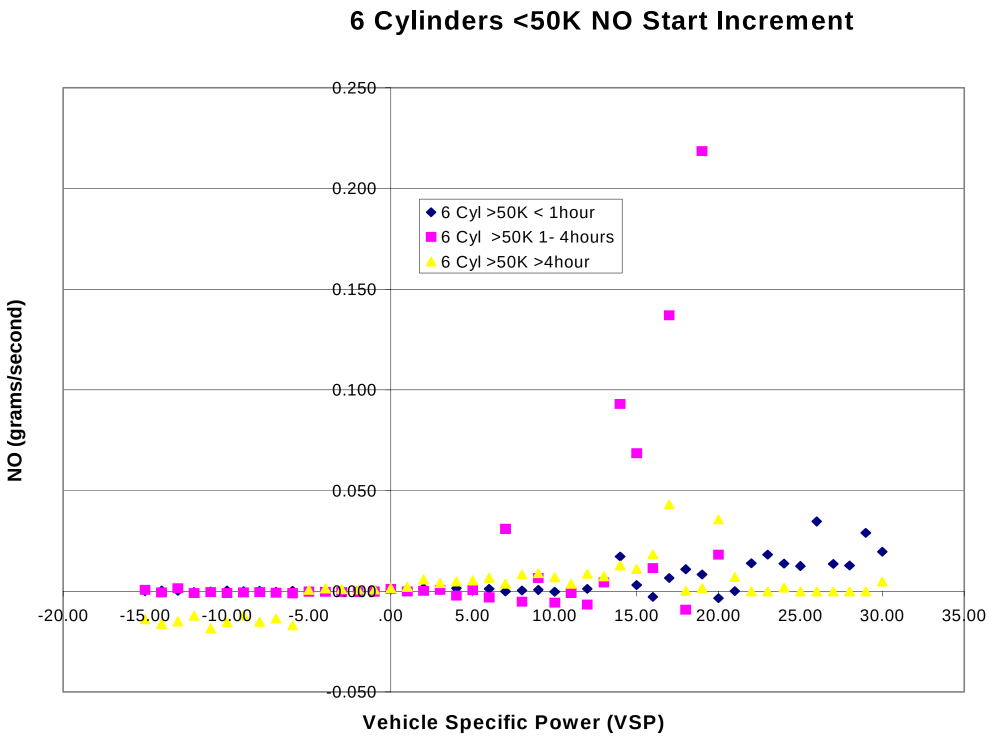


Figure 32

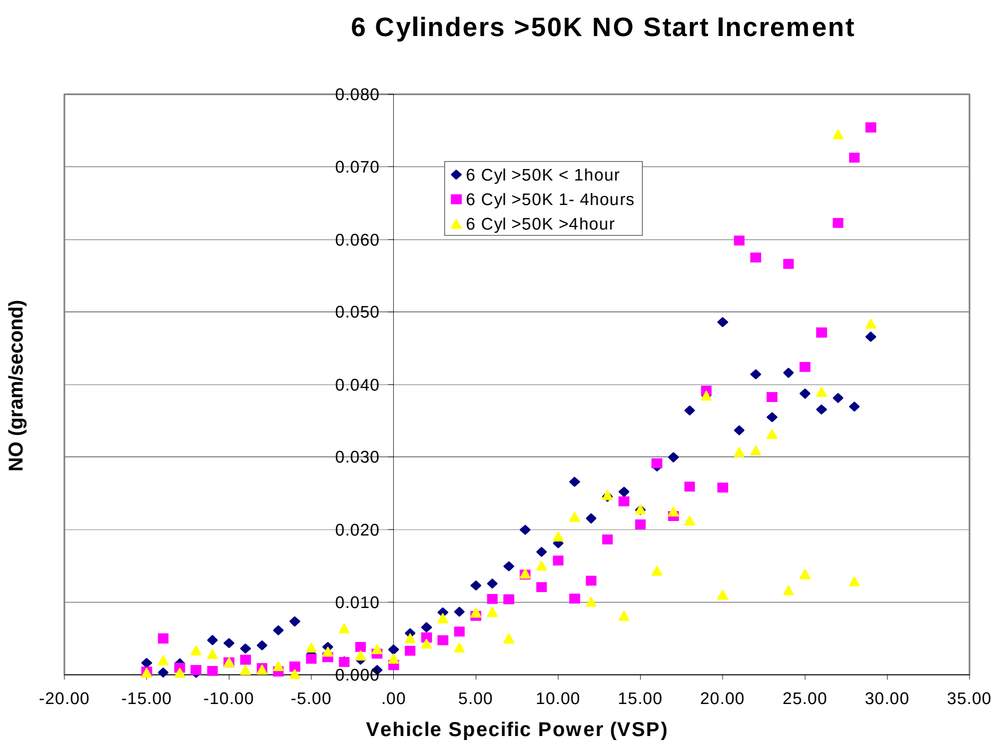


Figure 33

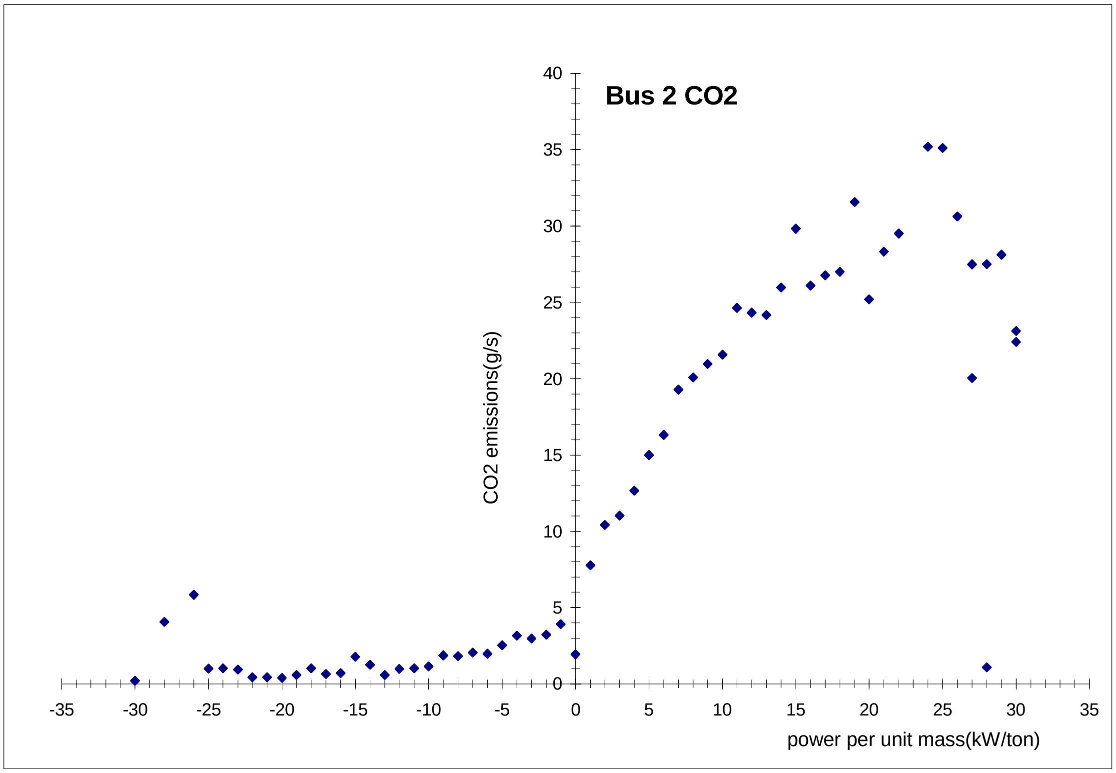


Figure 34. CO_2 results for bus #2

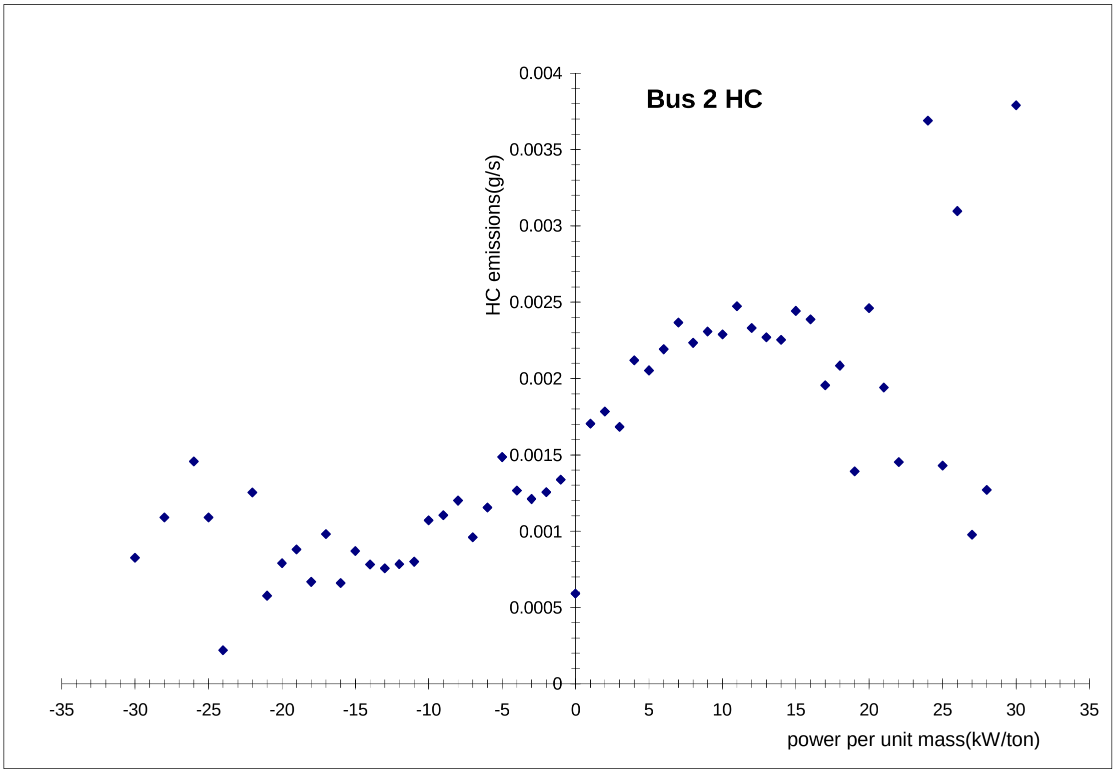


Figure 35. HC results for bus #2

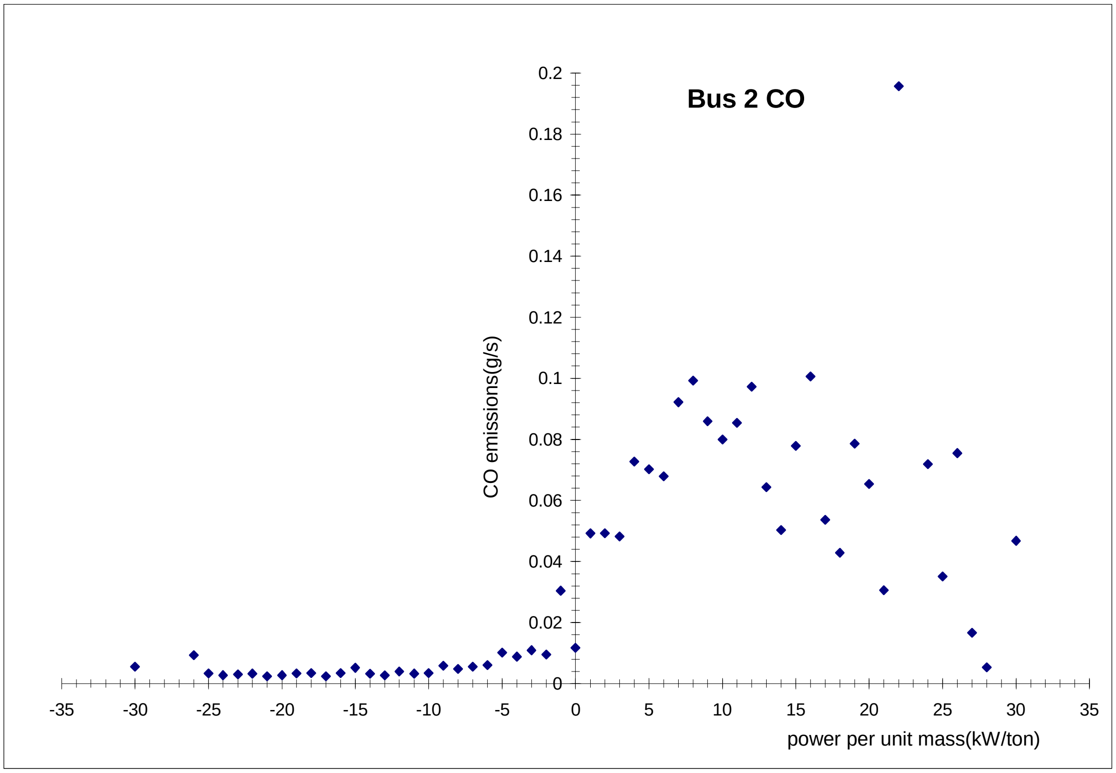


Figure 36. CO results for bus #2

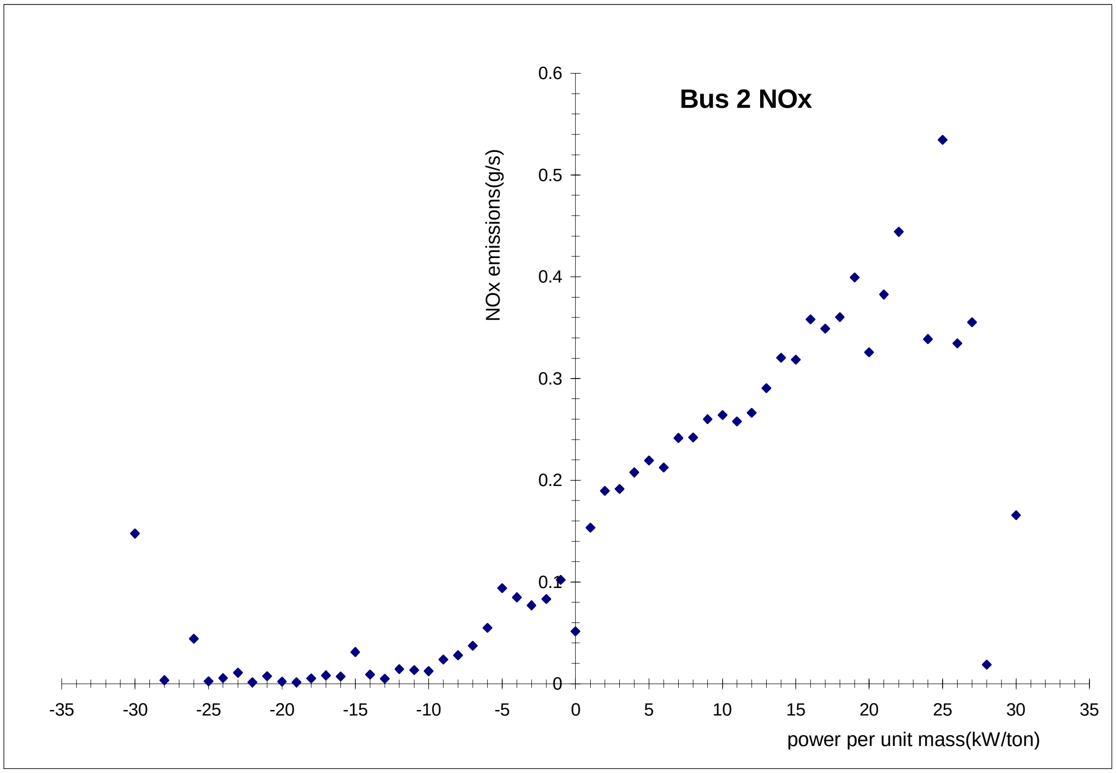


Figure 37. NOx results for bus #2

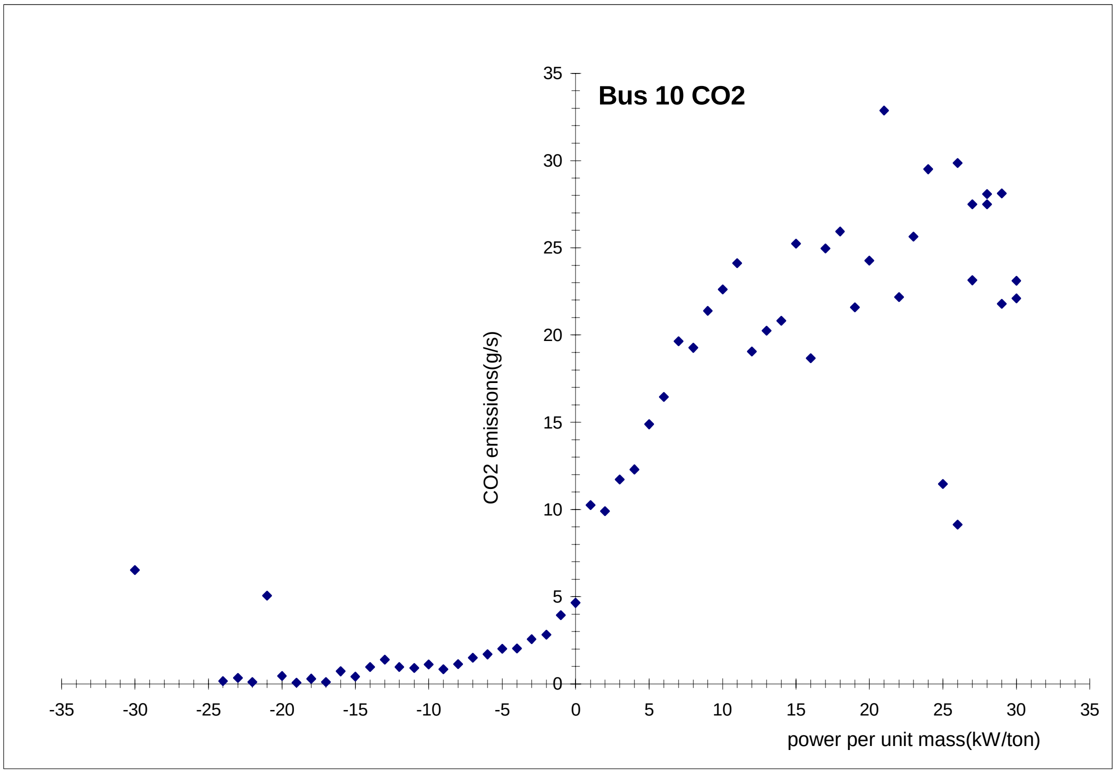


Figure 38. CO_2 results for bus #10

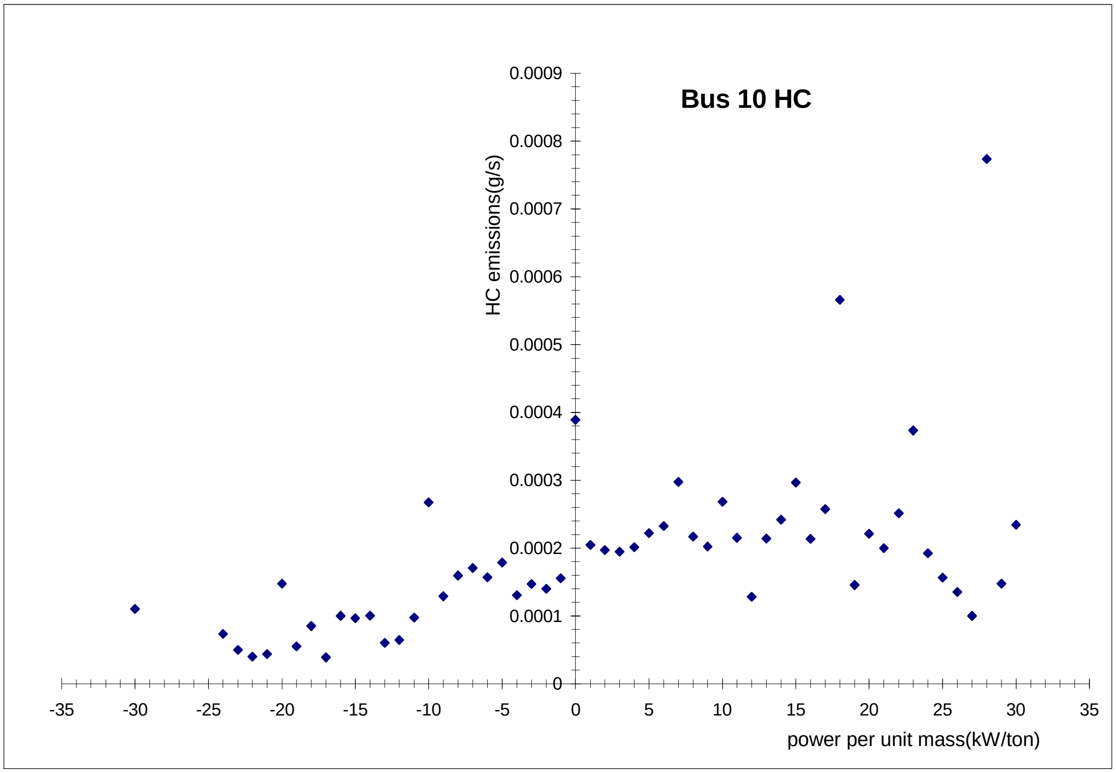


Figure 39. HC results for bus #10

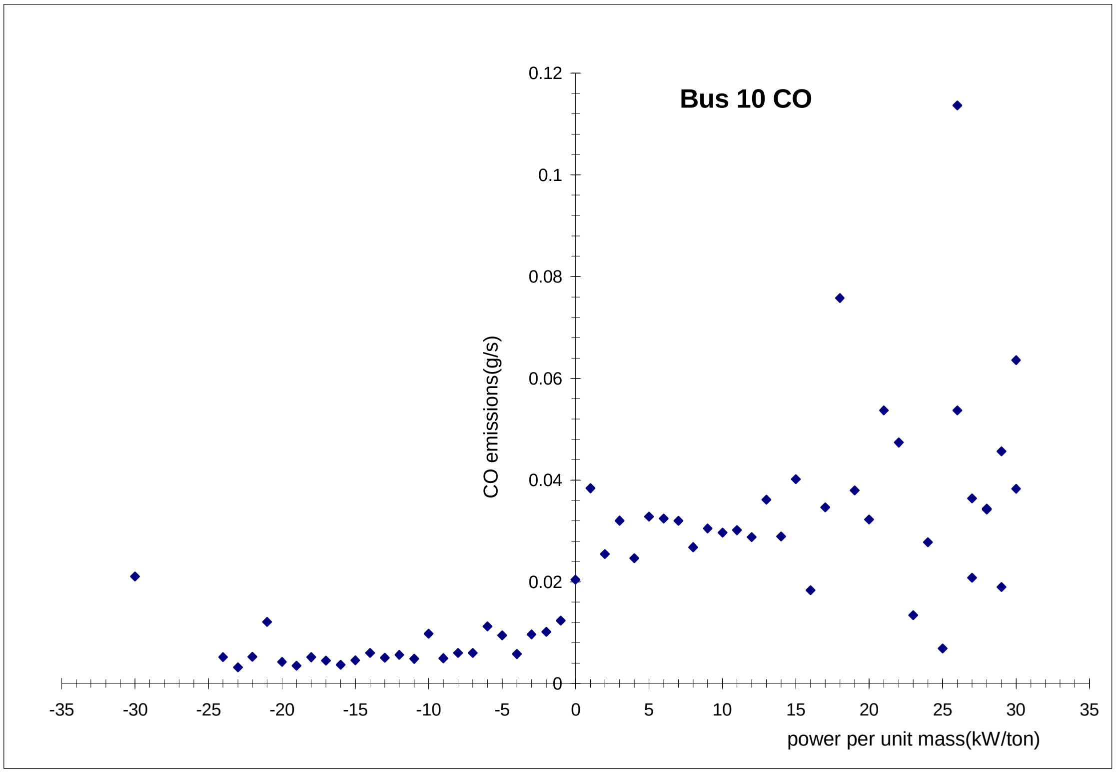


Figure 40. CO results for bus #10

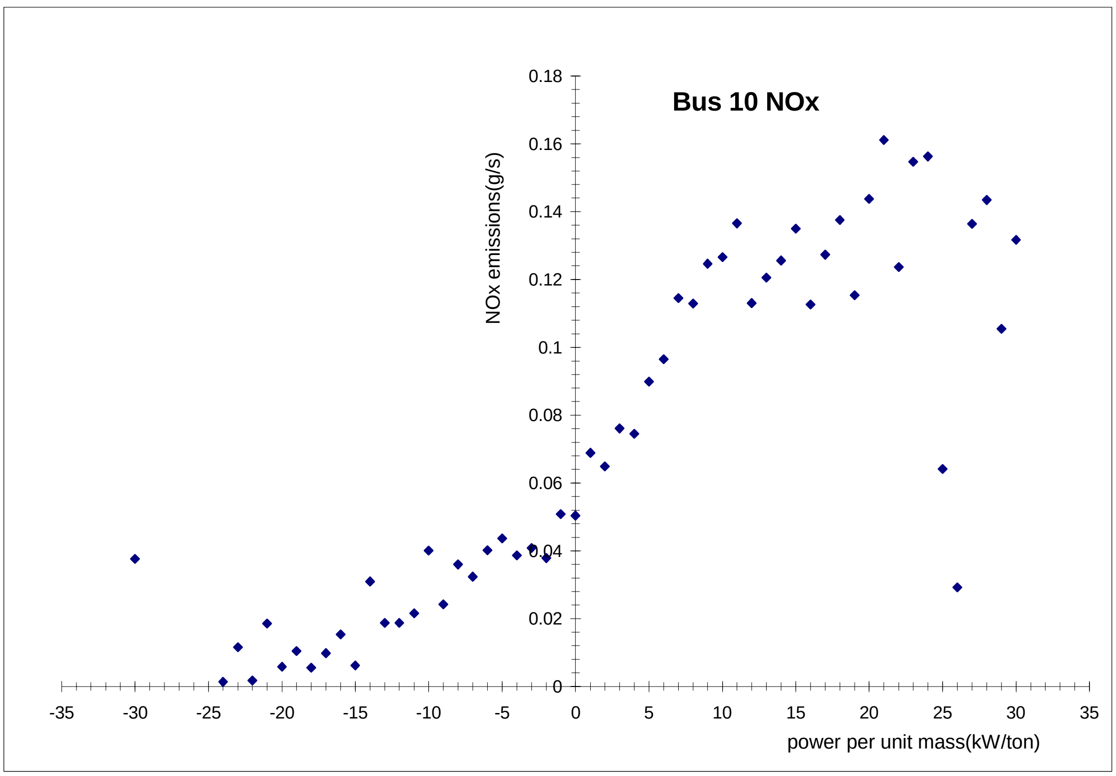


Figure 41. NOx results for bus #10

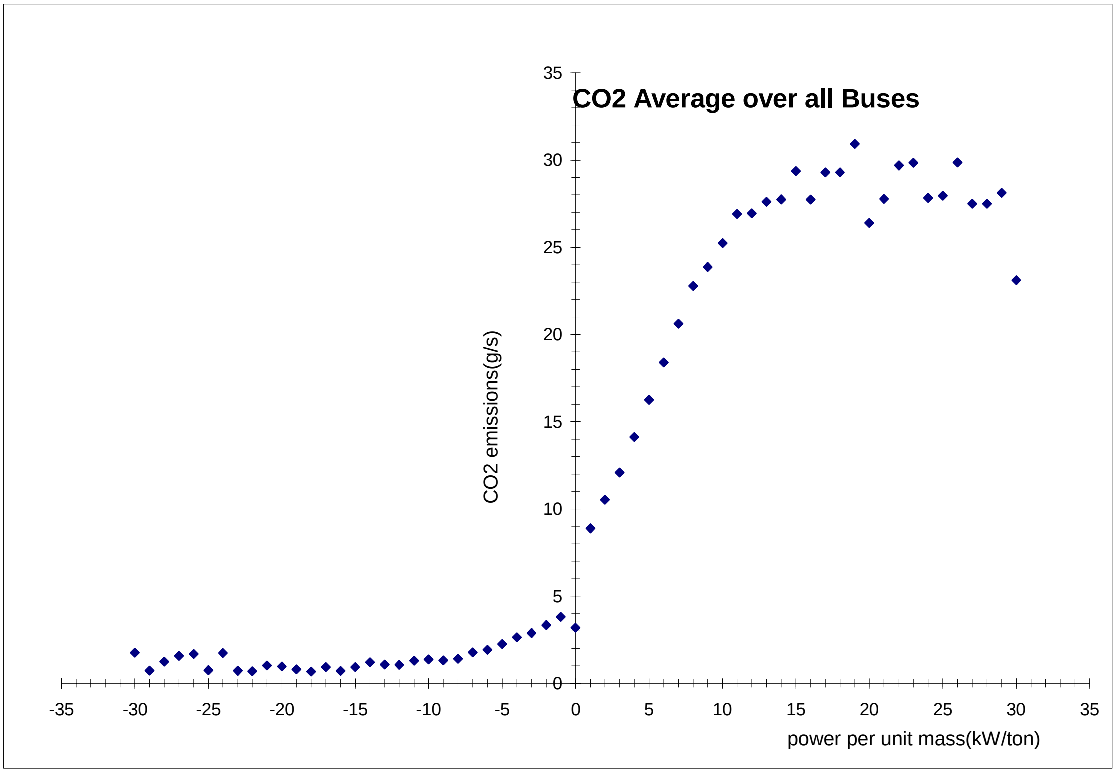


Figure 42. CO_2 results for buses #'s 1,2, 4,5,6,7,8,9,10,11,14, and 15.

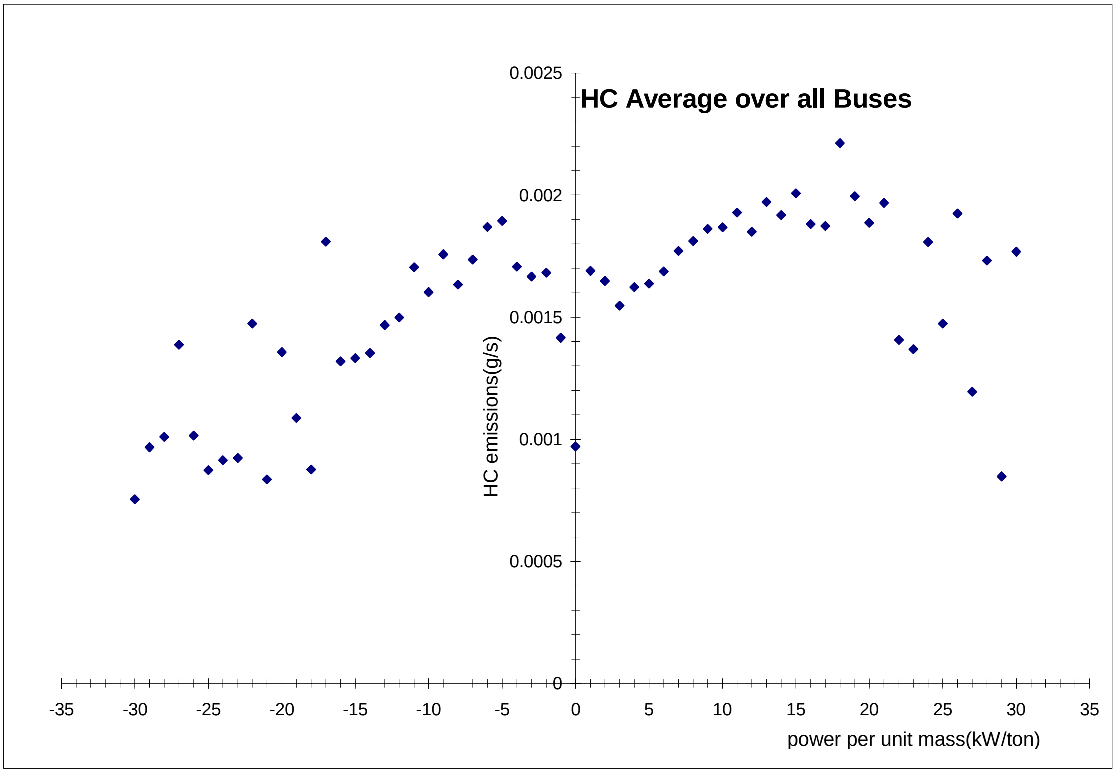


Figure 43. HC results for buses #'s 1,2, 4,5,6,7,8,9,10,11,14, and 15.

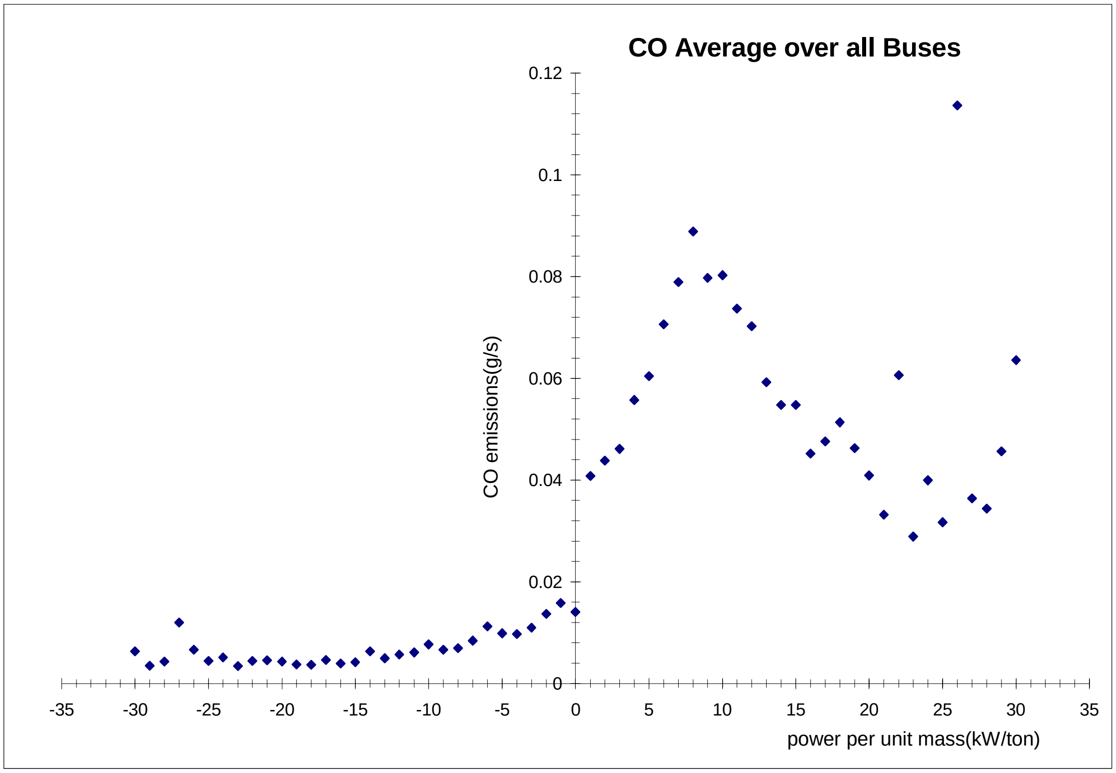


Figure 44. CO results for buses #'s 1,2, 4,5,6,7,8,9,10,11,14, and 15.

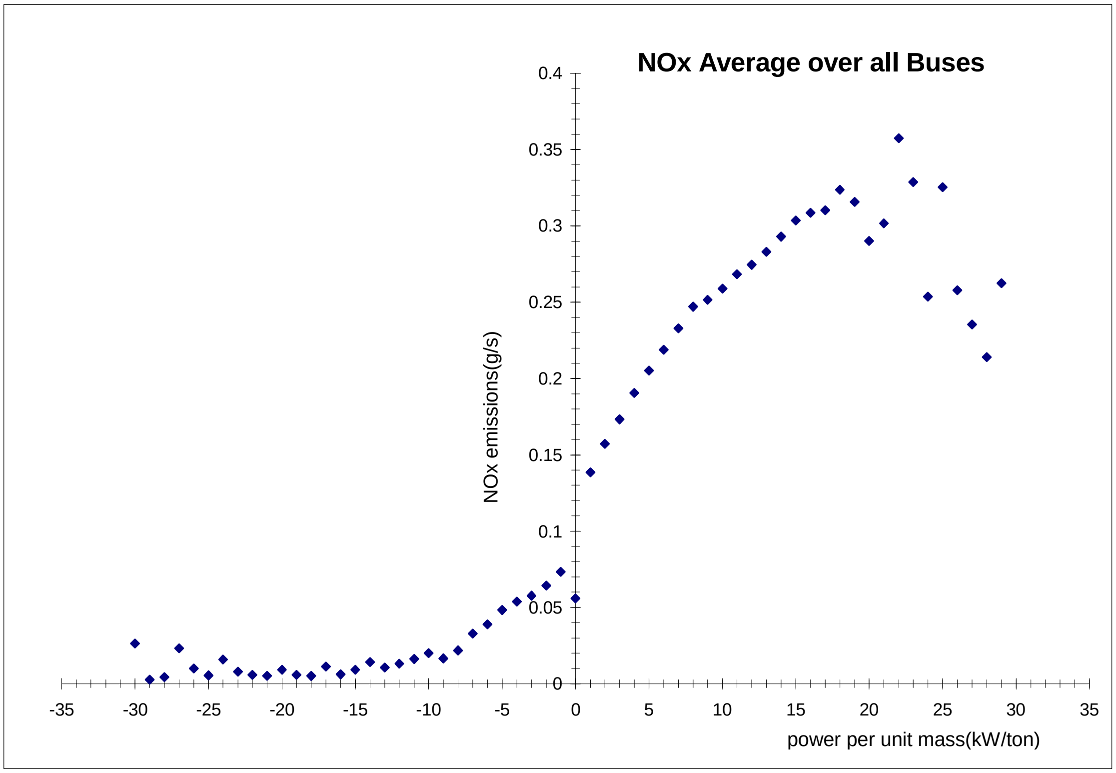


Figure 45. NOx results for buses #'s 1,2, 4,5,6,7,8,9,10,11,14, and 15.

TABLE 10 Nonroad Emission Factors

Machine	Mean	Standard Deviation	N	Comments
Scraper	673	390.5	10,695	Removed records where NOx rate <=0
Compacter	349	194.6	10,542	Removed records where NOx rate <=0
Track Dozer	1894	1001	10,800	

Figure 46: On-Road Summary Results - Absolute Percent Difference From Trip Mean, Averaged Across All Pollutants

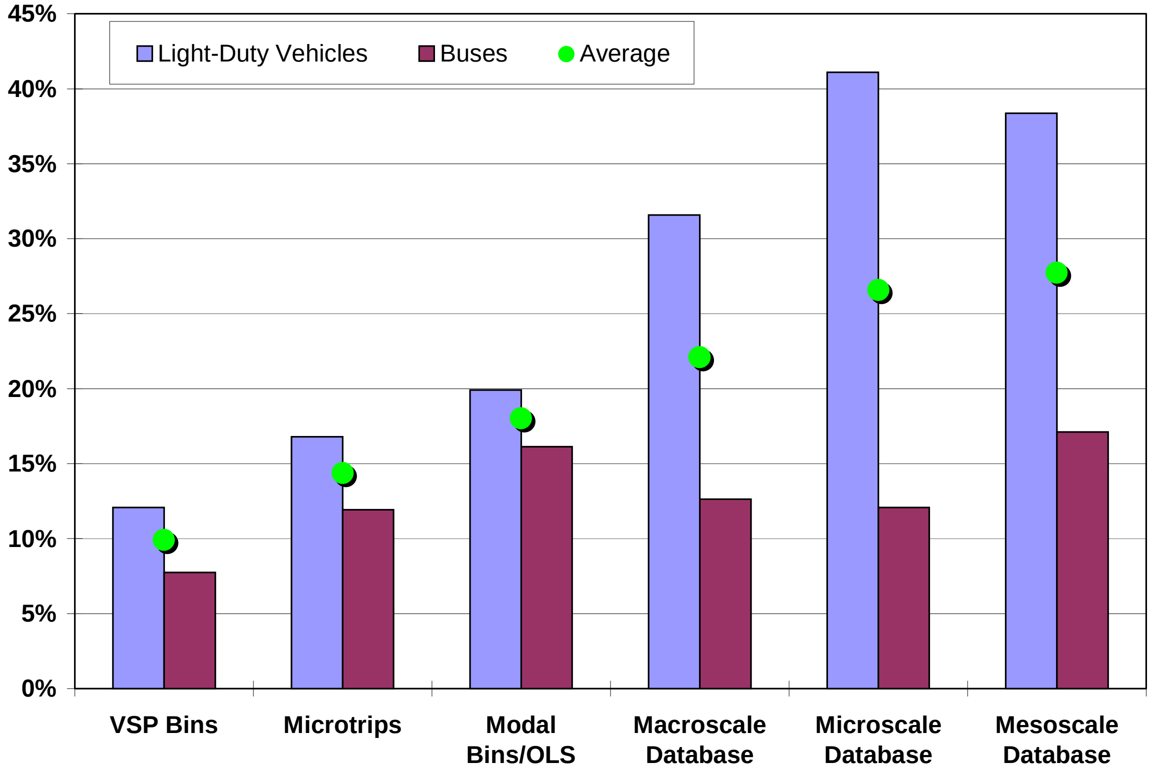


Figure 47 - On-Road HC Results: Trip Average Results w/ Confidence Intervals (Grams)

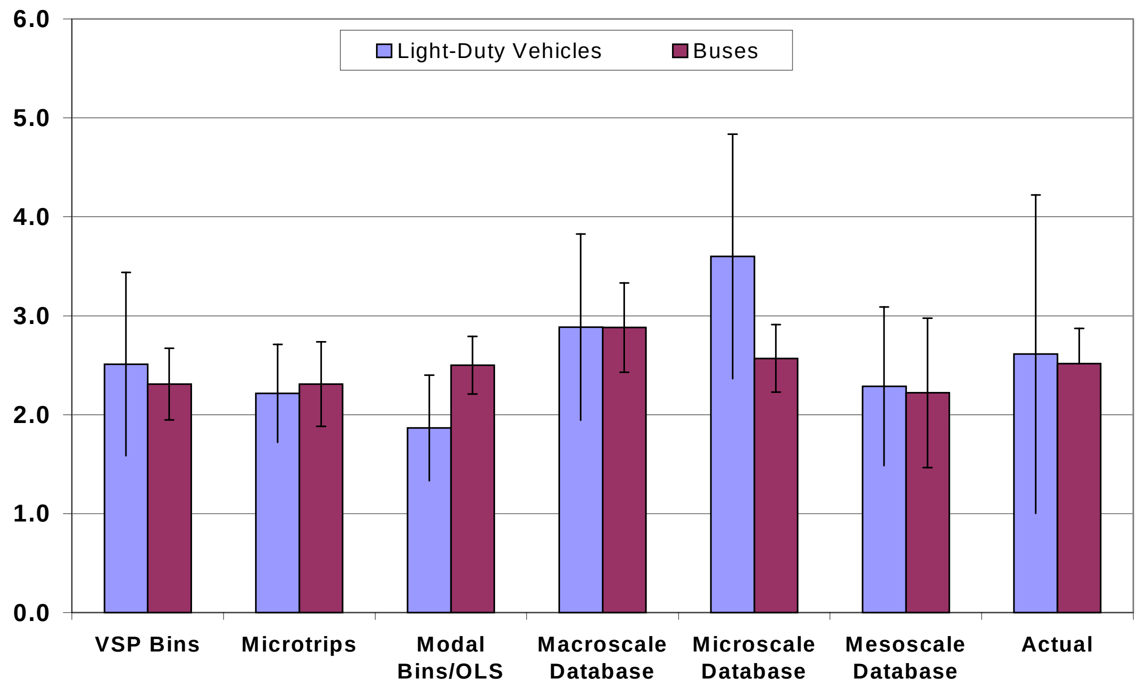


Figure 48 - On-Road HC Results: Percent Difference From Trip Mean

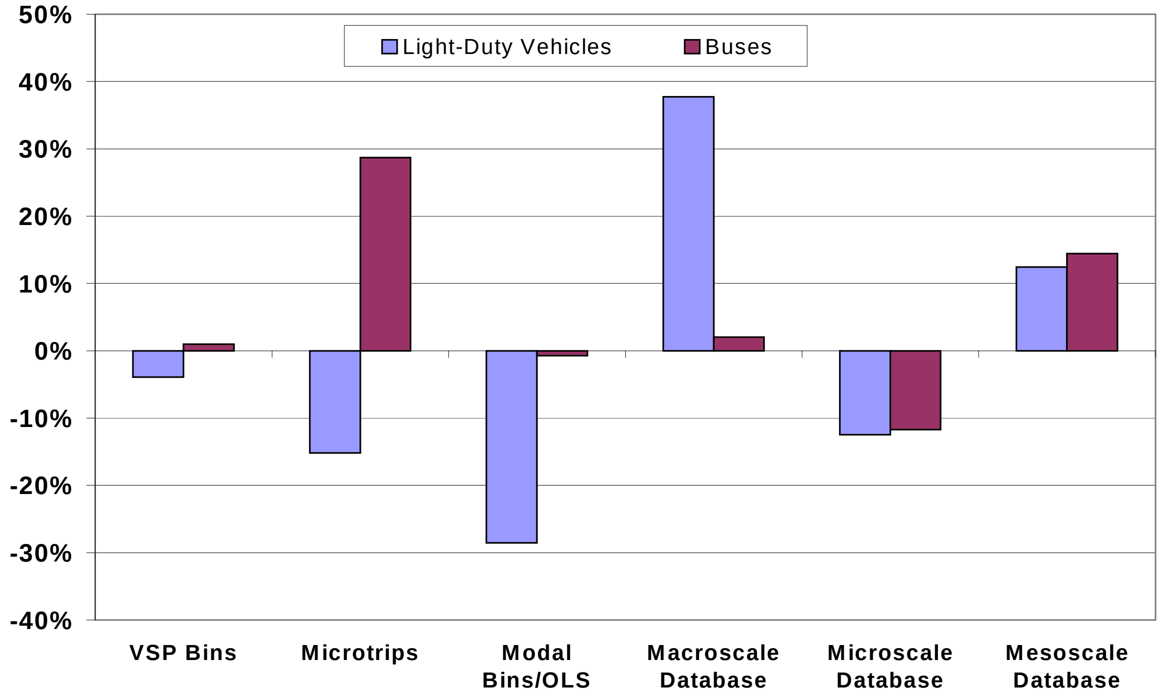


Figure 49 - On-Road CO Results: Trip Average Results w/ Confidence Intervals (Grams)

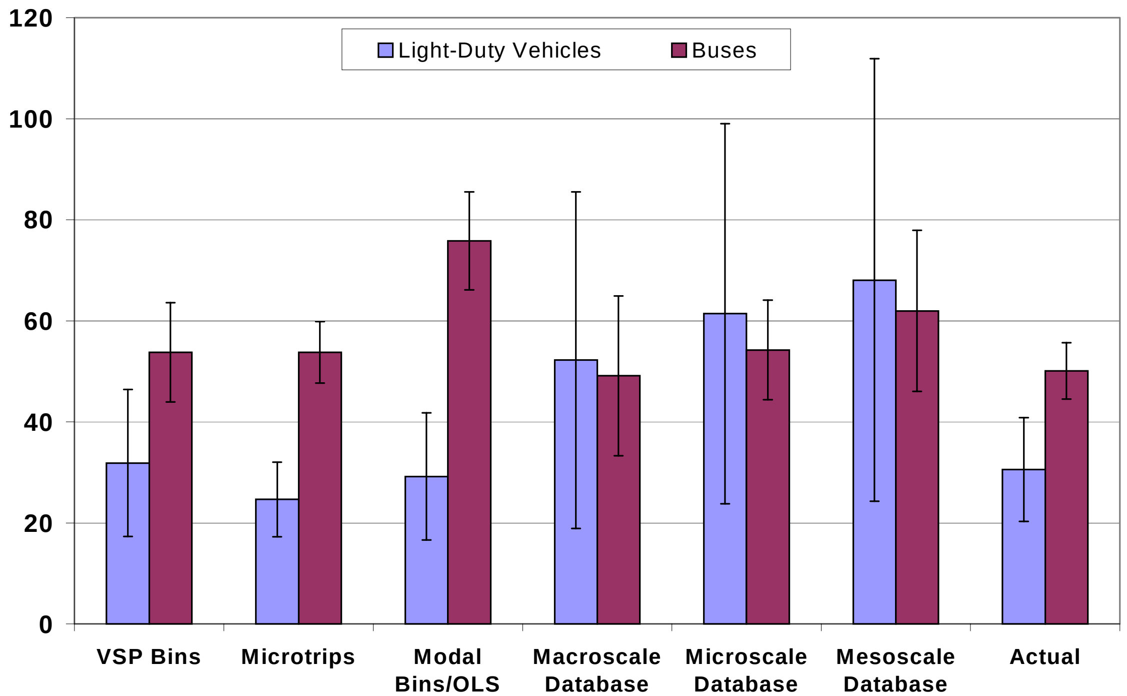


Figure 50 - On-Road CO Results: Absolute Percent Difference From Trip Mean

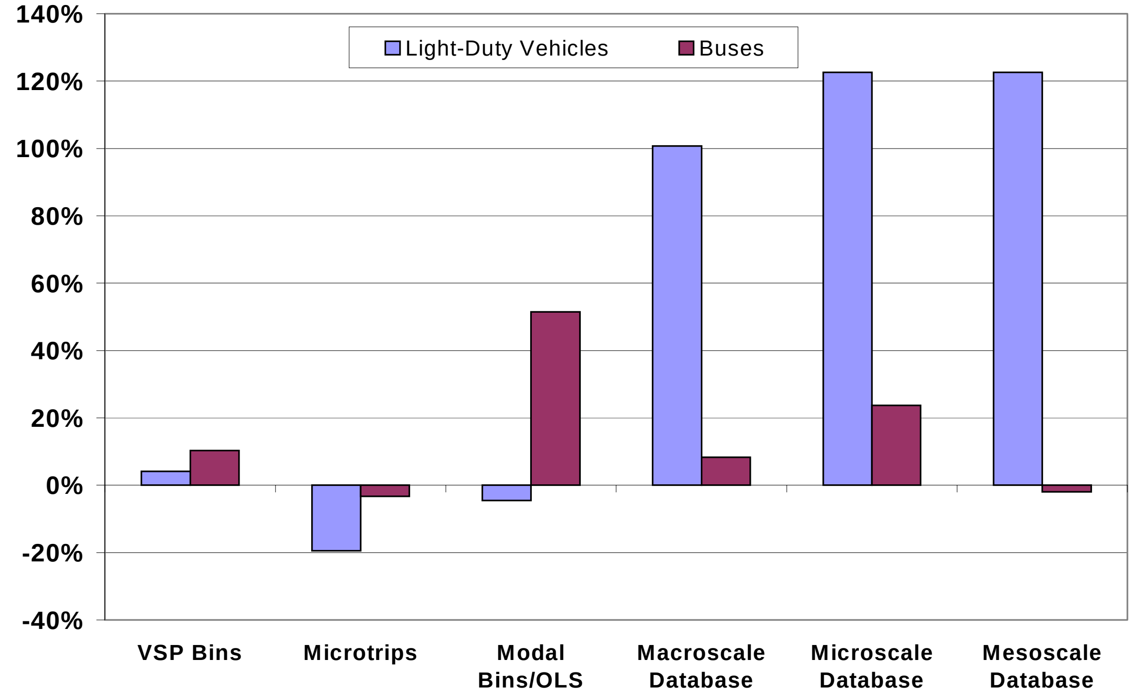


Figure 51 - LDV NOx Results: Trip Average Results w/ Confidence Intervals (Grams)

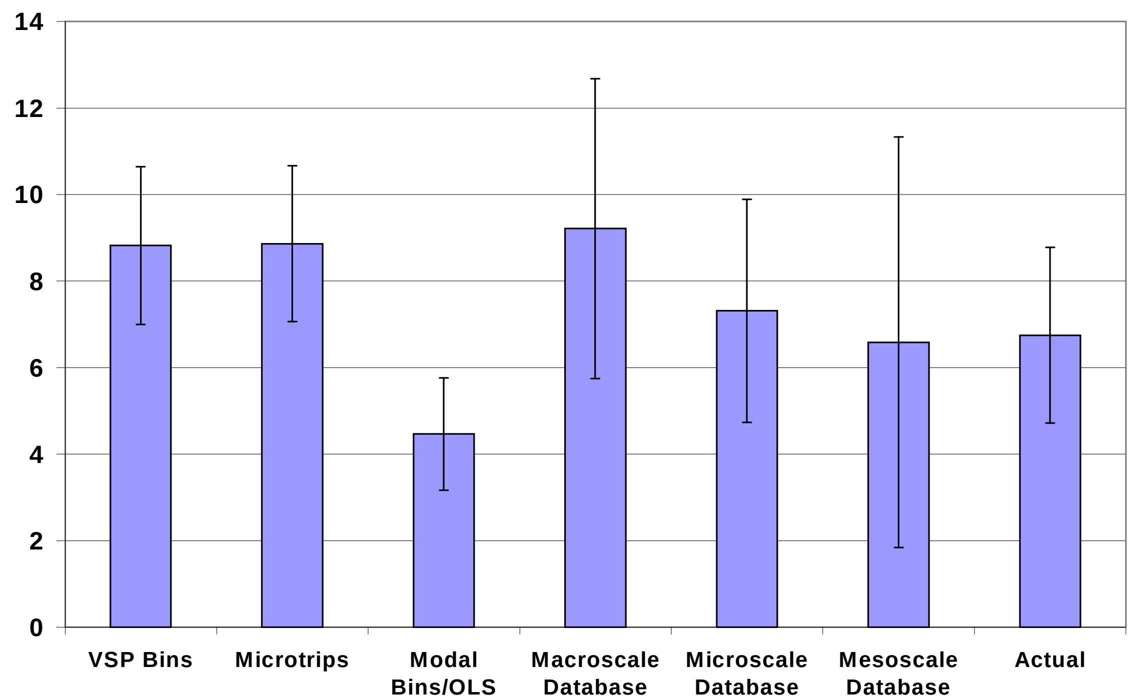


Figure 52 - Bus NOx Results: Trip Average Results w/ Confidence Intervals (Grams)

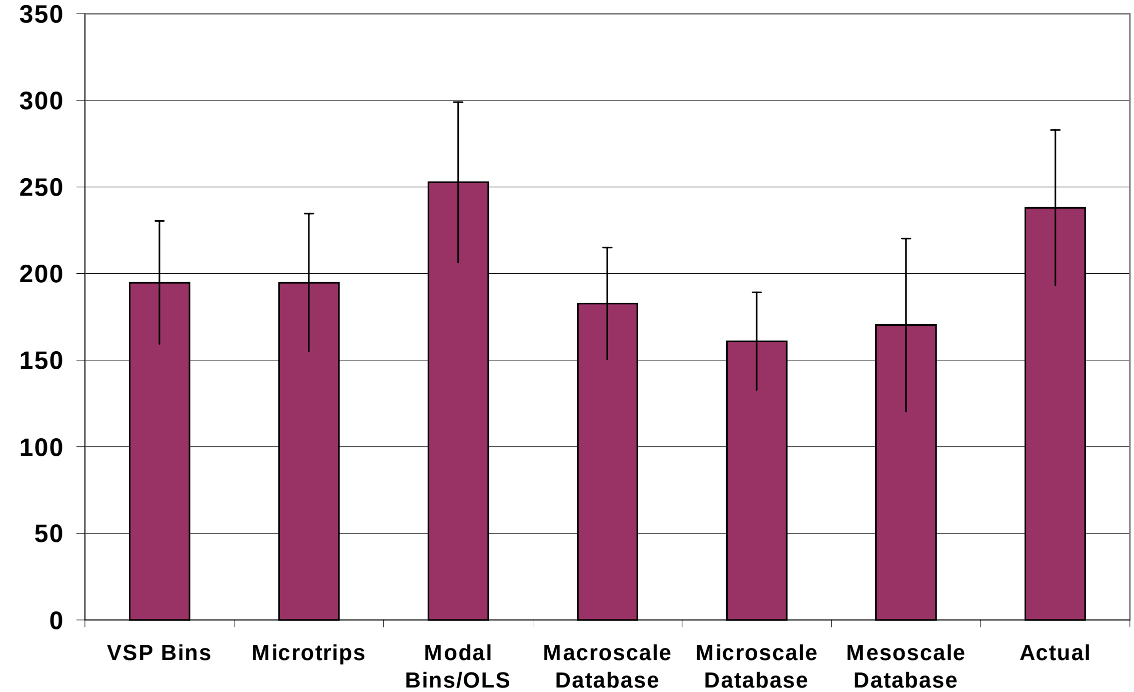


Figure 53 - On-Road NOx Results: Percent Difference From Trip Mean

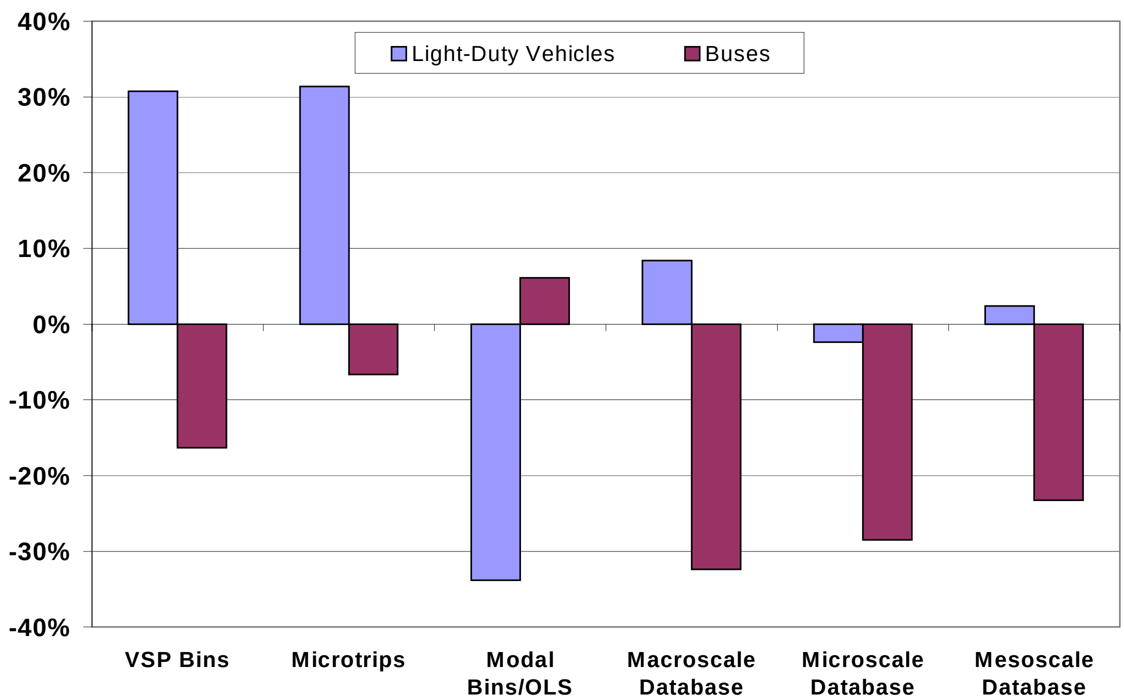


Figure 54 - On-Road CO2 Results: Trip Average Results w/ Confidence Intervals (Grams)

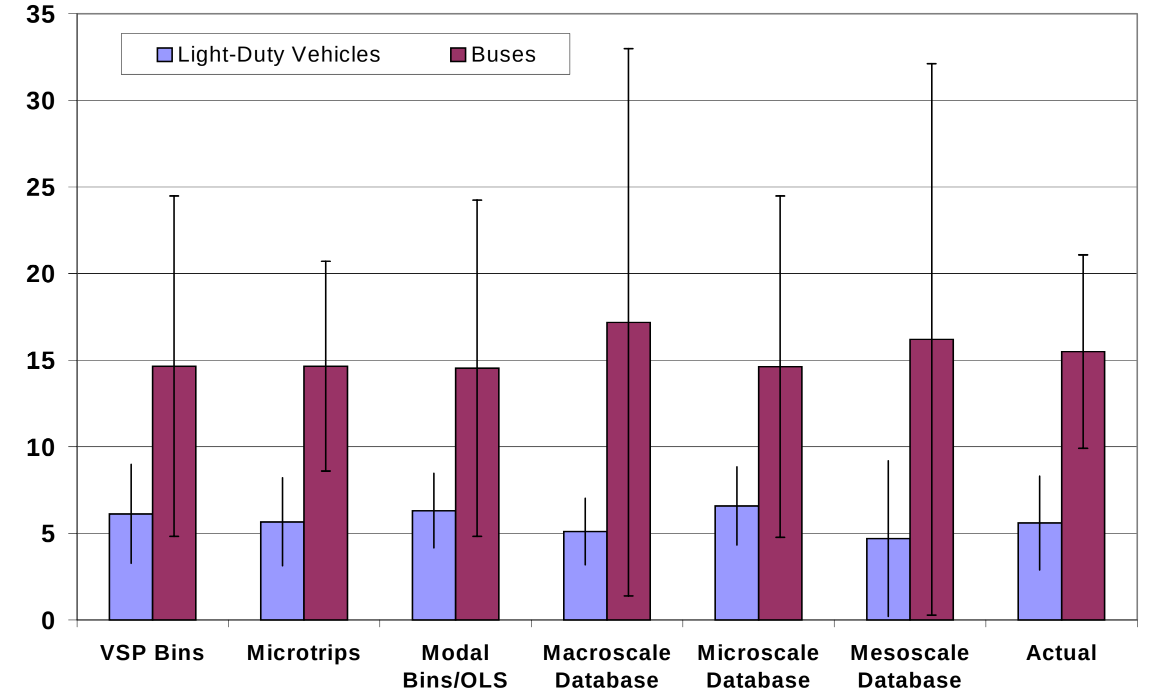


Figure 55 - On-Road CO2 Results: Percent Difference From Trip Mean

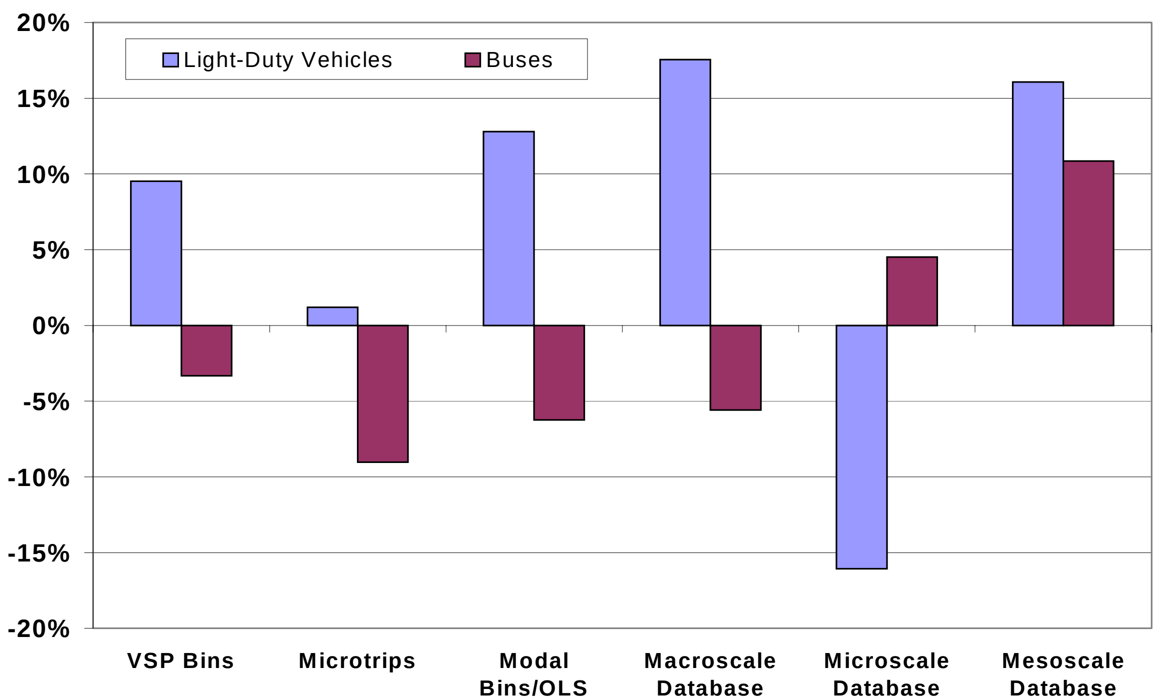


Figure 56: Off-Road Summary Results: Absolute Percent Difference From “Trip” Mean, Averaged Across CO_2 and NOx

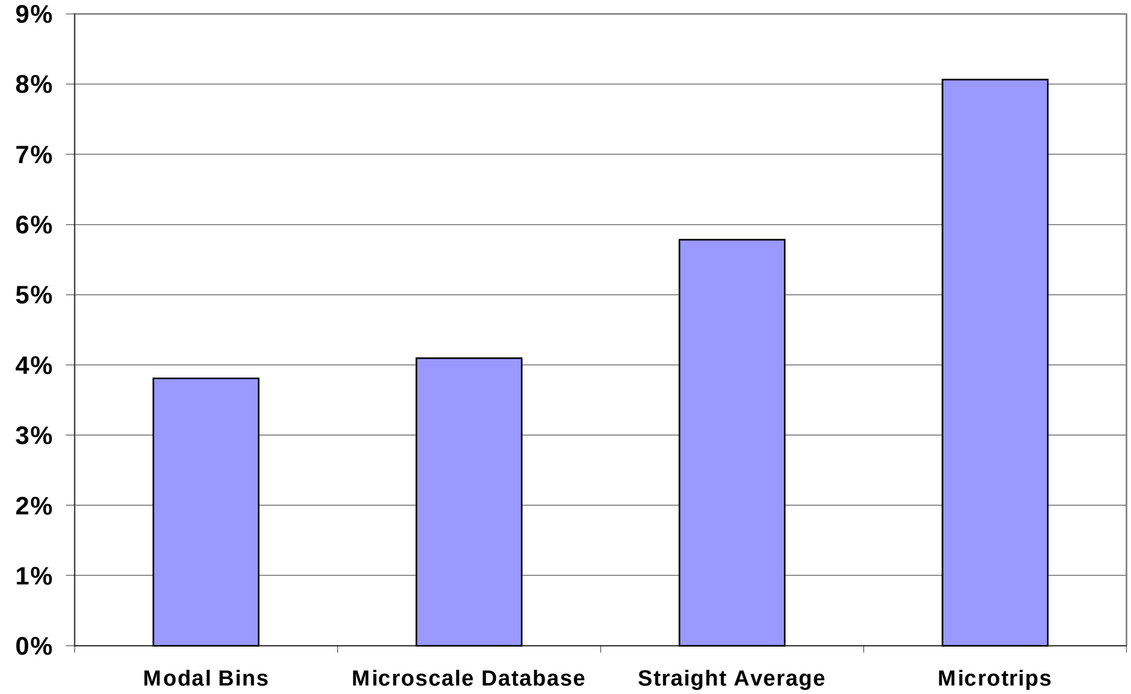


Figure 57: Off-Road CO2 Results: Percent Difference From “Trip” Mean

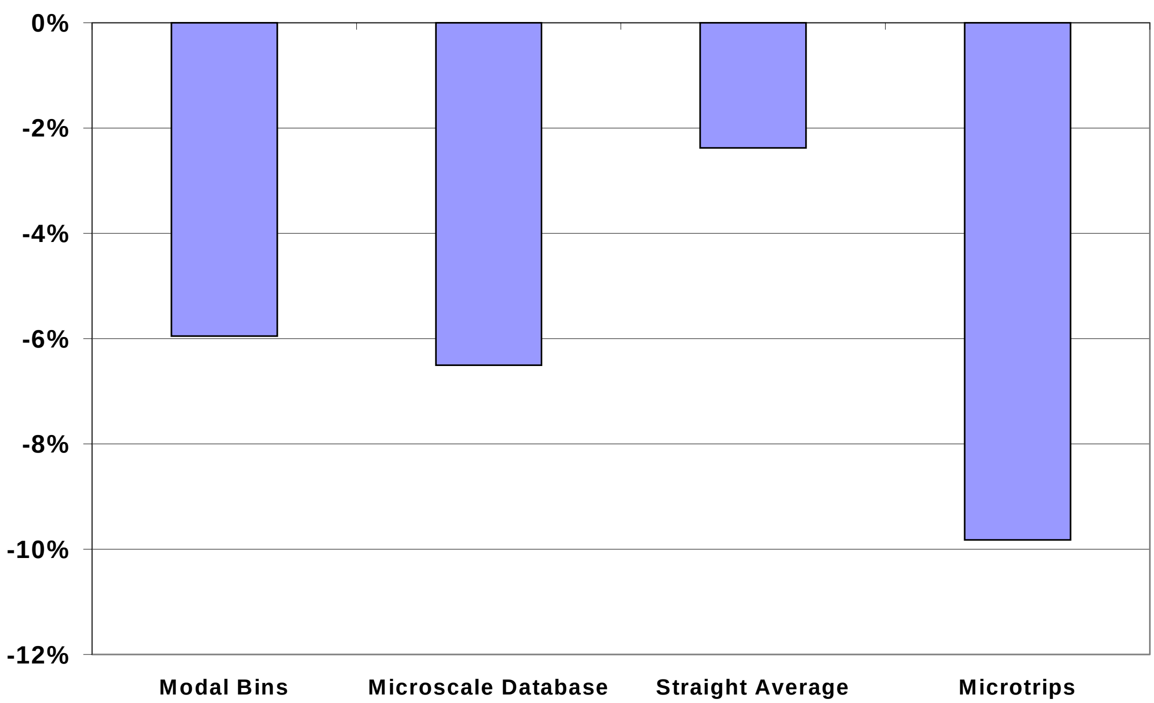
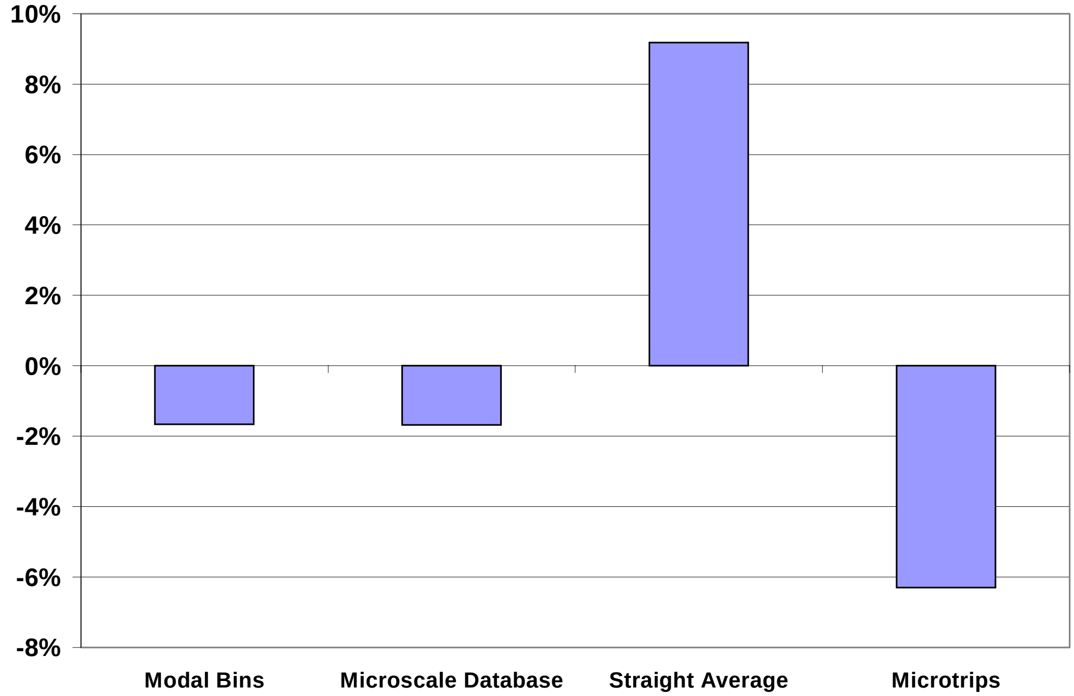


Figure 58: Off-Road NOx Results: Percent Difference From “Trip” Mean



Appendix A:

Individual Validation Trip Results

Draft July 11, 2002

Trip ID	Observed Emissions (grams)				"VSP Bin" Predictions				"Modal Bins/OLS" Predictions			
	HC	CO	CO2 (kg)	NOx	HC	CO	CO2	NOx	HC	CO	CO2	NOx
SRM089TR_2	2.93	36.82	10.5	5.09	4.14	43.79	12.7	8.98	2.62	35.2	12.9	6.1
3DAU86TR_3	3.02	35.08	5.2	7.40	2.93	45.28	5.5	8.75	1.55	20.2	5.5	3.4
3DAU86TR_5	6.24	45.10	8.1	8.29	3.36	54.4	8.5	13.1	1.99	22	8.2	3
RAK416TR_2	1.56	36.25	2.9	10.77	1.76	18.5	2.9	7.2	2.65	58.4	3.4	6.7
RAK416TR_4	1.296	19.789	3.5	4.411	1.82	19.27	3.4	8.24	1.34	24.2	4.0	4.6
RAK416TR_5	0.630	10.438	3.4	4.513	1.06	9.83	3.8	6.66	1.06	15.2	3.9	3
Trip Average	2.61	30.58	5.60	6.75	2.51	31.85	6.13	8.82	1.87	29.20	6.32	4.47
+/-	1.61	10.27	2.45	2.03	0.93	14.55	3.05	1.82	0.53	12.61	2.93	1.30
BUS385TR_3	3.264	51.91	17.1	252.26	2.82	67.11	19	246	2.9	87	17.1	257
BUS385TR_4	2.52	40.81	10.10	143.20	1.78	37.44	9.8	137	2.3	62	11.4	164
BUS375TR_2	2.52	58.49	16.7	253.43	2.51	59.25	16	214	2.5	80	15.8	282
BUS375TR_3	2.66	52.57	18.90	290.09	2.52	61.44	16.5	220	2.6	84	16.8	328
BUS360TR_2	2.12	54.29	17.6	286.05	2.52	57.83	15.8	209	2.8	83	15.1	275
BUS360TR_3	2.03	42.41	12.6	203.29	1.71	39.52	10.8	143	1.9	59	11	210
Trip Average	2.52	50.08	15.50	238.05	2.31	53.77	14.65	194.83	2.50	75.83	14.53	252.67
+/-	0.35	5.58	2.71	44.77	0.36	9.82	2.86	35.52	0.29	9.70	2.15	46.29
Compactor			89.0	334.32			82	340			85	362
Bulldozer			90.0	1666.29			98	1890			84	1640
Scraper			73.0	655.58			66	670			68	610
Trip Average			84.0	885.4			82.0	966.7			79	870.7

Trip ID	Observed Emissions (grams)				"Microtrips" Predictions				"Database Micro" Predictions			
	HC	CO	CO2 (kg)	NOx	HC	CO	CO2	NOx	HC	CO	CO2	NOx
SRM089TR_2	2.93	36.82	10.5	5.09	3.16	36.64	10.5	12.46	1.91	12.98	11.5	7.77
3DAU86TR_3	3.02	35.08	5.2	7.40	2.22	26.24	4.7	7.07	2.75	45.56	6.6	3.94
3DAU86TR_5	6.24	45.10	8.1	8.29	1.77	16.27	6.8	7.12	4.97	40.75	9.1	3.8
RAK416TR_2	1.56	36.25	2.9	10.77	2.66	33.62	3.7	10.5	5.27	137.8	3.6	11.15
RAK416TR_4	1.296	19.789	3.5	4.411	2.05	21.3	4	9	4.68	98.41	4.3	10.82
RAK416TR_5	0.630	10.438	3.4	4.513	1.44	13.71	4.3	7.03	2.02	32.88	4.4	6.39
Trip Average	2.61	30.58	5.60	6.75	2.22	24.63	5.67	8.86	3.60	61.40	6.58	7.31
+/-	1.61	10.27	2.45	2.03	0.50	7.40	2.09	1.80	1.23	37.60	2.51	2.58
BUS385TR_3	3.264	51.91	17.1	252.26	3.8	57.1	18.5	274.7	2.78	69.82	18	211.04
BUS385TR_4	2.52	40.81	10.10	143.20	2.7	42.7	10.8	160.38	2.23	52.7	11	127.8
BUS375TR_2	2.52	58.49	16.7	253.43	3.25	46.1	13.9	227.5	2.74	46.66	14.6	152.7
BUS375TR_3	2.66	52.57	18.90	290.09	3.68	52.1	16.1	269.85	3.09	46.29	15.7	189.4
BUS360TR_2	2.12	54.29	17.6	286.05	3.52	54.94	15.1	236	2.67	68.96	16.9	165.4
BUS360TR_3	2.03	42.41	12.6	203.29	2.5	37.6	10.2	165	1.91	40.99	11.6	119.4
Trip Average	2.52	50.08	15.50	238.05	3.24	48.42	14.10	222.24	2.57	54.24	14.63	160.96
+/-	0.35	5.58	2.71	44.77	0.43	6.06	2.54	39.75	0.34	9.85	2.26	28.25
Compactor			89.0	334.32			83.8	344			83.9	371.99
Bulldozer			90.0	1666.29			78.1	1547.5			84.3	1618.24
Scraper			73.0	655.58			65.34	597.3			67.4	621.27
Trip Average			84.0	885.4			75.7	829.6			79	870.5

Trip ID	Observed Emissions (grams)				"Database Meso" Predictions				"Database Macro" Predictions			
	HC	CO	CO2 (kg)	NOx	HC	CO	CO2	NOx	HC	CO	CO2	NOx
SRM089TR_2	2.93	36.82	10.5	5.09	2.3	128.66	7	12.33	2.85	126.12	8.1	13.06
3DAU86TR_3	3.02	35.08	5.2	7.40	2.72	39.78	3.4	3	4.3	31.1	3.9	8.82
3DAU86TR_5	6.24	45.10	8.1	8.29	3.63	146.66	7.9	15.86	4.06	74.7	7	15.85
RAK416TR_2	1.56	36.25	2.9	10.77	2.83	38.76	3.8	2.83	1.42	17.5	3.2	5.09
RAK416TR_4	1.296	19.789	3.5	4.411	1.26	19.04	2.9	2.94	1.71	21.16	3.9	6.15
RAK416TR_5	0.630	10.438	3.4	4.513	0.99	35.45	3.2	2.55	2.98	42.7	4.6	6.3
Trip Average	2.61	30.58	5.60	6.75	2.29	68.06	4.70	6.59	2.89	52.21	5.12	9.21
+/-	1.61	10.27	2.45	2.03	0.80	43.79	1.74	4.74	0.94	33.33	1.57	3.47
BUS385TR_3	3.264	51.91	17.1	252.26	2.9	75.43	17.4	203.12	2.87	65.64	19.7	196.6
BUS385TR_4	2.52	40.81	10.10	143.20	1.63	46.34	11	118.66	3.12	25.81	16.7	222.9
BUS375TR_2	2.52	58.49	16.7	253.43	3.16	77.79	20.3	216.65	1.84	59.56	17	130.35
BUS375TR_3	2.66	52.57	18.90	290.09	3.13	85.79	24.8	254.31	2.83	59.02	17.7	176.8
BUS360TR_2	2.12	54.29	17.6	286.05	1.47	47.23	11.8	125.65	3.14	62.68	19.1	227
BUS360TR_3	2.03	42.41	12.6	203.29	1.05	39.2	11.9	102.88	3.49	21.89	12.9	142.4
Trip Average	2.52	50.08	15.50	238.05	2.22	61.96	16.20	170.21	2.88	49.10	17.18	182.68
+/-	0.35	5.58	2.71	44.77	0.76	15.92	4.49	49.96	0.45	15.80	1.92	32.35
Compactor			89.0	334.32								
Bulldozer			90.0	1666.29								
Scraper			73.0	655.58								
Trip Average			84.0	885.4								