Final Report

On-Board Emission Data Analysis and Collection for the New Generation Model
PR-CI-01-12239

Prepared for
US EPA
Specialized Service Center
4411 Montgomery Rd., Suite 300
Norwood, OH 45212

Prepared by
ENVIRON International Corporation
101 Rowland Way, Suite 220
Novato, CA 94945
415.899.0700
DUNS #11-030-3021

22 February 2002

INTRODUCTION

In connection with development of a new generation mobile source emissions model, EPA has sponsored the collection of in-use vehicle operation and emissions data using on-board portable emissions monitors (PEM). PEM data provide an opportunity to incorporate better estimates of "real world" emission factors corresponding to different conditions into EPA's new emissions model. In order to capitalize on this opportunity, it is necessary to develop procedures for using PEM databases to develop emission factors that can be applied to various sources that are to be modeled.

In this report, we describe the development and test application of an approach to modeling emissions using PEM data. We also provide recommendations for use of laboratory data to supplement those generated with PEMs systems for development of emission factors to be used in the new generation emissions model.

Our general approach to modeling emissions was to divide the second-by-second time series of vehicle operation recorded by the PEM into a series of microtrips. This follows from the logic of historic test cycle development but instead using a series of relatively short microtrips to describe different aspects of typical vehicle behavior. The microtrips were intended to be sufficient short to describe driving events for microscale analysis, while providing a means to scale driving activity over vehicle trips. The use of microtrips afforded an opportunity to avoid or minimize errors associated with mismatched timing of recorded emissions and vehicle behavior. In addition, microtrips can be viewed as a data filtering or smoothing method. In both cases, the microtrips were expected to reduce errors associated with single point estimates associated with the second-by-second PEM records.

CONCEPTUAL ANALYTIC METHODOLOGY

Data Preparation

Quality Assurance

Prior to beginning the contract, EPA and other contractors, UNC and CE-CERT, performed a detailed review and provided corrected light-duty data. Additional light-duty data quality issues were not found.

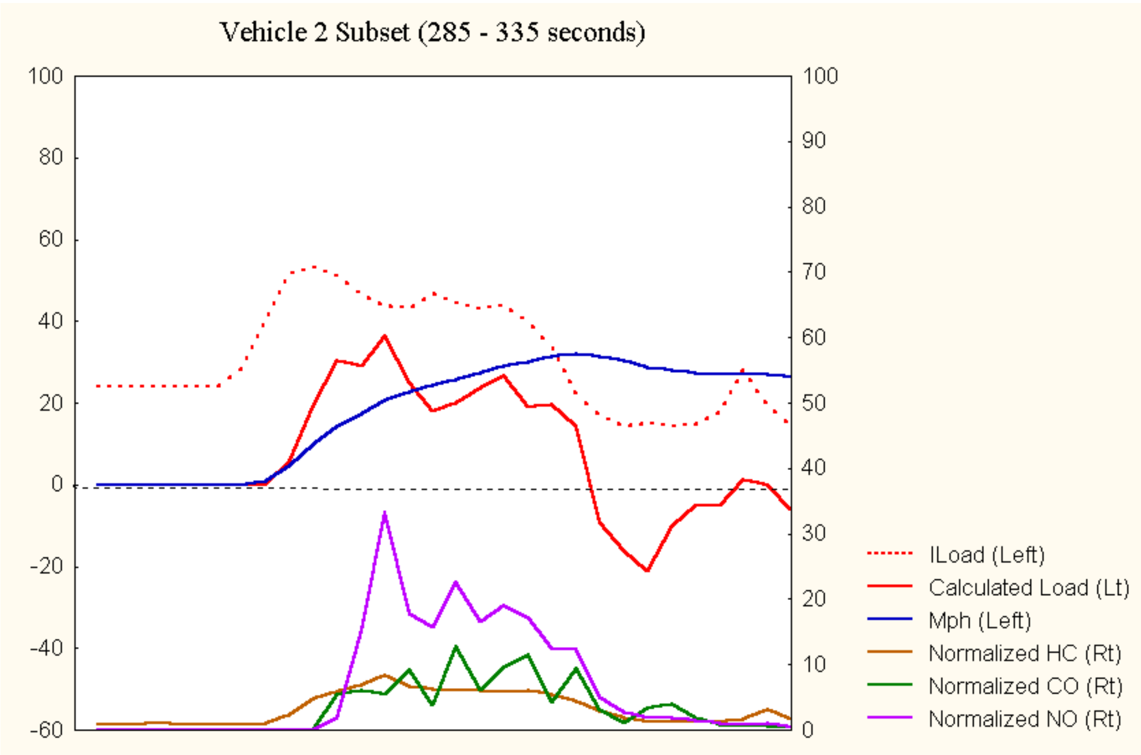

Figure 1. Comparison of load and emissions for a light-duty vehicle.

For buses and one piece of nonroad equipment, there were other data problems (fuel rate data did not match the vehicle speed, or NOx emission rates did not well match the engine load for nonroad equipment) during the time period listed in Table 1. These periods of suspect data were ignored when analyzing data.

Table 1. Estimated offset between emissions and vehicle speed and other data quality issues in dataset.

Bus	Offset (Seconds)	Data Quality Issue (For initial seconds of data)
1	1	<360 missing HC
2	0	<110 and missing HC in first trip and part of second trip
4	1	<40 and <420 missing HC
5	0	0
6	1	<90
7	1	0
8	1	0
9	4	<263 and missing HC in trip 4
10	3	<393
11	3	<429
14	1	0
15	4	<390
Bet00611	0	<106
Compactor 20947	0	0
D8landfill	0	0

Load Calculation

The engine load was expected to be the primary variable to explain emissions. However, because of concerns about the emissions offset from vehicle behavior and lagging response to load changes, microtrips beginning and end points were defined according to near steady-state load conditions. Therefore, the engine load was inferred from wheel load from the vehicle behavior accounting for rolling resistance, acceleration, grade, and auxiliary power requirements. The load was calculated using these conditions at the wheel because we could not predict the transmission efficiency over all activity. The wheel load calculation used in this work follows the equation below.

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

The coefficients a, b, and c were supplied by EPA for the light-duty vehicles in this study and are shown in Table 2, and those for a transit bus were supplied by West Virginia University (2000) also shown in Table 3. The bus "a" coefficient was provided as a function of the vehicle weight while the light-duty coefficient was not dependent on the vehicle weight. The WVU coefficients were similar in magnitude to those used by EPA (1995) for a similar weight (unloaded) Ford CL-9000 truck as shown in Table 3 converted to similar units. The "b" coefficient for light-duty vehicles was small and was ignored for the buses by both WVU (2000) and EPA (1995).

Table 2. Road load coefficients for light-duty vehicles.

Vehicle Number	a (lbf)	b (lbf/mph)	c (lbf/mph^2)
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 3. Road load coefficients for a bus (WVU) and a truck (EPA).

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

The average load over the microtrip was calculated by discounting the negative load conditions that occur during braking events. During braking events, the calculated load becomes negative yet emissions cannot depend upon the load for negative loads. For purposes of the calculation, the negative loads were zeroed to avoid skewing the average load over the cycle. It may be necessary to distinguish between idle and braking through addition of a base load (perhaps it could be thought of as a parasitic load of the engine) during idle and zero load during braking events. There may (or will) be a difference in emission rates between idle and negative loads as fuel injectors may (or will) shut off and an idling engine still produces some power to keep the engine running.

Per instructions from EPA (Koupal, 2001), the grade signal was averaged over 5 seconds prior to calculating the load at any given second of operation.

Auxiliary loads could be any load not required to keep the engine running but for practical purposes here was the air conditioning load available only for the light-duty vehicles. A rough calculation using idle periods with and without the air conditioner compressor on with vehicle 2 indicated an increase in the engine load which was converted with the rated power of the engine in that vehicle to estimate that the air conditioner compressor demanded 2.6 hp. This load was added to periods when the air conditioning compressor was recorded as in operation. This figure could be improved with further effort, and should be put on the same basis as the wheel load by including an estimate of the transmission efficiency.

Microtrip Approach

Our approach used the concept of microtrips to describe emissions during various types of vehicle operation but over longer time frames than other approaches may, some of which have attempted to estimate emissions based on second-by-second correlations of vehicle operation and emissions.

The concern about approaches that rely on 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 emissions rates. Indeed depending upon the operation of the vehicle, offsets in load and recorded emission could occur and be variable during driving operation. As shown in Figure 2, there may be an offset (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 detector response labeled “distributed response” in Figure 2.

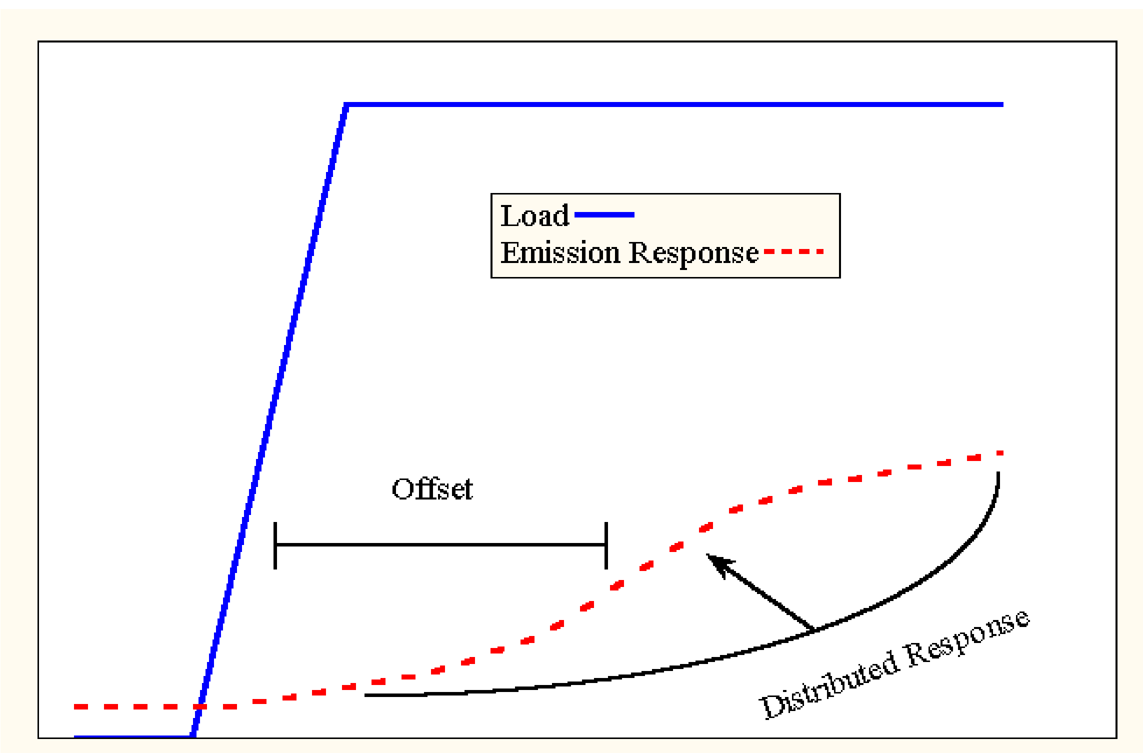

Figure 2. Expected load response of raw data.

Another reason for using a microtrip approach was to avoid any data smoothing requirements of noise signals transmitted through various speed and grade signals of vehicle behavior and emissions results. With or without a microtrip approach, data smoothing of the load and emission signals may be worth pursuing, but such raw data modification raises data integrity issues that were avoided in this work.

ENVIRON developed a microtrip search program to determine microtrips during hot running conditions. This microtrip program follows the description below including start period description, microtrip definition, and explanatory variables. Start periods were selected out and evaluated separately. The microtrips themselves were defined with minimum length and an end point criteria described below. 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 (1999). 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 during the start period. This difference was then compared to the soak time.

In the data, because each vehicle operated over several trips, the discontinuous time stamp was used to identify new vehicle trips for which the first period of time (200 seconds) after the soak was excluded from the hot running emission rates before identifying microtrips.

The start period may change depending upon vehicle type (such as certification level, age, maintenance history, etc.), soak period, and ambient conditions. ENVIRON's microtrip search program allowed for varying the start period from 0 to anytime after each discontinuous time stamp.

Microtrip Criteria

The criteria for choosing a microtrip is schematically shown in Figure 3 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 the bus in Figure 3 (Bus #10) in order to capture, for instance, the large CO increases during the initial part of the acceleration event shown.) The criteria used in this work was +/- 15 hp over 3 seconds.

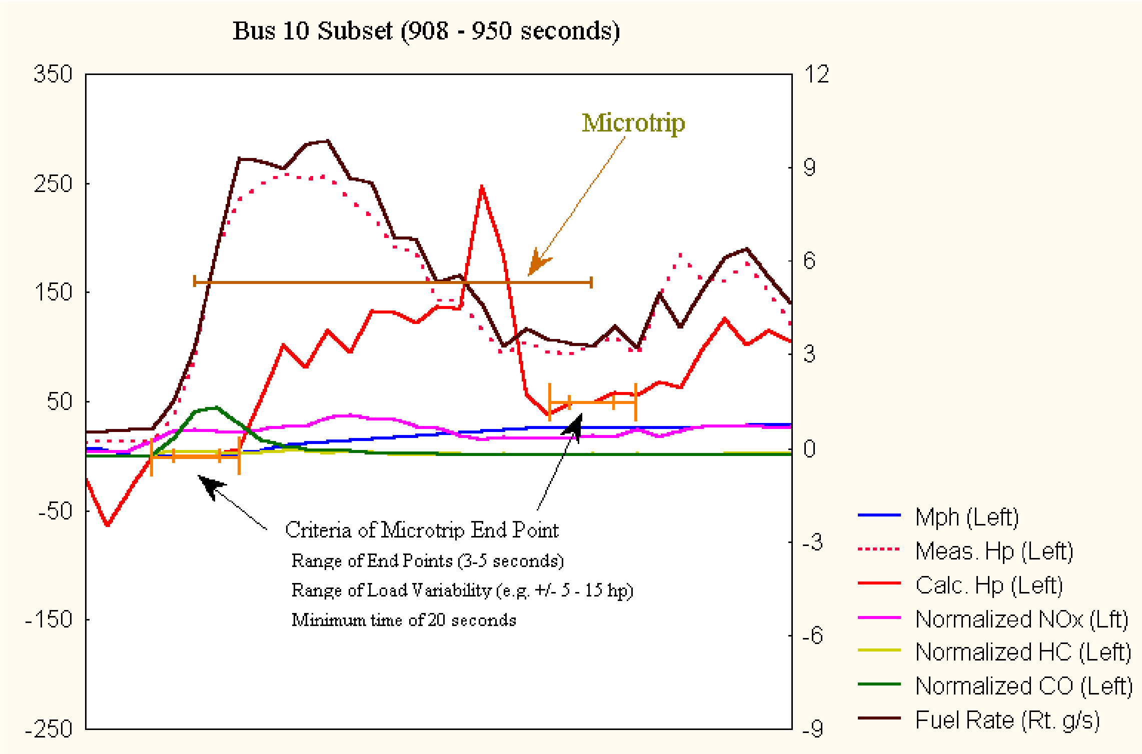

Figure 3. Comparison of load and emissions for a bus.

The load range criteria that defined the steady-state condition will depend upon the sensitivity of the emissions response to load or load changes and could be determined experimentally. If the emission response to load is strong then the constant load criteria should be set lower to avoid splitting important load changes between two microtrips. The smaller the range for the load criteria, the fewer microtrips will be identified and so longer microtrips will be identified.

The time criteria for the steady-state condition accounted for the response rate of the detector (such as from the axial diffusion in exhaust components) to step changes in load. The faster the response, the lower the number of seconds for the steady-state criteria, and could be determined experimentally. The time criteria also reduce the burden that the emissions be exactly matched in time with the vehicle behavior because the microtrip end point would be defined after some period of constant load. The time criteria was fixed to be an odd number (3, 5, 7, etc.), so the microtrip end point could be centered. As this time criterion is increased, time offsets become less important, so the 3 second criteria used in this work can tolerate offsets of 1 second. The longer the period for constant load conditions, the fewer microtrips will be identified and so longer microtrips will be identified.

Also, a minimum length of the microtrip was set at 20 seconds to reduce the importance of individual data points to a 5% weighting or less. This was an arbitrary criterion.

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. In order to test other variables, averages of these variables were compiled over the microtrips and are described in more detail below.

Load Increases

Average load was just one variable we tested. Another variable tested which was intended to describe the average load increases over the microtrip, is described in the equation below. The sum of the absolute second-by-second load changes subtracted by the difference between the end and beginning load of the microtrip was divided by the length of the microtrip. (The equation below is actually twice the average load increases. The form of the equation is such that microtrips where wheel load only decreases will result in a value of zero.)

$$Averaged\ Load\ Increases = \{SUM[ABS(\rho Load_{i-(i-1)})] - (Load_1 - Load_0)\} / \rho t$$

The reason for considering this variable was to determine the effect on emissions of acceleration or hills in the driving activity distinct from the average load over the microtrip. It was added to distinguish between highly transient driving and steady-state driving trips of similar average load. It will not distinguish from infrequent large load increases and frequent small load increases.

Previous Trip Load

We were concerned that the previous microtrip may influence the emissions of the microtrip analyzed. An example of a situation that might be described by a difference in this variable is a vehicle that begins a 30 mph cruise after aggressive freeway driving and the same cruise after an idle period. This variable was tested to determine 'memory' effects such as might be associated with the operating temperature of the engine and emission control system.

Aggressive Load Events

Jiménez-Palacios (1999) postulated that there is a load threshold above which HC and CO emissions rates could markedly increase in light-duty vehicles. He described these events in terms of enrichment of the fuel delivery system during high load events. As explained in Appendix A, the criteria could not be determined based on the second by second data even shifted by plus or minus a second. So it was not possible to determine an enrichment condition to monitor. The reason that enrichment condition was not found may have to do with the limited testing conditions (lack of high load conditions).

Malfunction Indicator Light

The malfunction indicator light could be a measure of emission rate failure modes. The fraction of time with the MIL light on was monitored for each microtrip. This variable was only available for the light-duty vehicles due to the on-board diagnostic sensors available. It might be appropriate to consider just those sensors that might affect the exhaust emissions.

This variable was not found to be useful because the indicator occurred during operation of only Vehicle 16, and Vehicle 16 did not exhibit unusual emissions behavior. So while this may be a useful indicator in some studies, it was not used in this analysis.

Ambient Temperature and Humidity

The average ambient temperature and humidity over each microtrip was determined as it may affect the hot running emissions. However the temperature and humidity range during this testing was only over a limited range, so it may not have been a significant distinguishing variable in this dataset.

Load Vehicle Weight Relationship

Phenomenologically, the load divided by the vehicle weight might be expected to best describe vehicle-to-vehicle design differences typical of light-duty vehicles. For light-duty vehicles, the emission certification is performed on the whole vehicle, so emissions might be expected to be less dependent on the actual wheel load than the load to weight ratio. Jiménez-Palacios (1999) used this variable to better describe emissions across a fleet of light-duty vehicles.

This issue did not apply to the bus data because all vehicles were of identical design. And obviously this issue is not applicable to nonroad equipment. The CO_2 emissions for light-duty vehicles could be vehicle weight dependent, so the specific load (load/vehicle weight) could be ignored with CO_2 calculations, while other emissions may be controlled to similar rates across vehicle types.

Results

For the purposes of air quality consideration, hydrocarbon (HC) and NOx emissions would be the primary pollutants of concern for ozone. Carbon monoxide (CO) is decreasing in importance as the number of regions showing nonattainment for ambient CO levels has been rapidly decreasing. While CO_2 may be an important emission for greenhouse gas estimates, it can through fuel sales/consumption provide an independent means of verifying regional emissions estimates.

By vehicle type, light-duty vehicles are important sources for HC, CO, NOx, and CO_2 while diesel vehicles and nonroad equipment are primarily sources of NOx and CO_2 emissions. For diesel engines, CO may however be an adequate indicator of PM emissions (Clark et al., 2002), and HC may be needed for estimates of toxics.

Below is a discussion of the process and results of our investigation into the variables affecting emissions from light-duty vehicles, buses, and nonroad equipment. In all cases, the hot running emissions were predicted, and with light-duty vehicles these were compared with the start emissions to predict a start increment. 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 the mean loads of all microtrips.

<u>Light-duty Vehicles</u>

For light-duty vehicles, two separate modes were defined, idle or no load conditions (perhaps including occasional no load microtrips during coasting or braking events), and those microtrips with positive mean loads. From Figures 4 and 5 for vehicles 2 and 16, it is clear that load represents a reasonable general predictive variable for CO, NOx, and CO_2. HC results indicated more scatter, and for vehicle 2 demonstrated a curious upperlimit correlated with load. Given the low emission rates, some of the scatter in the HC could be due to noise associated with the lower detection limits or other reasons that deserves further investigation.

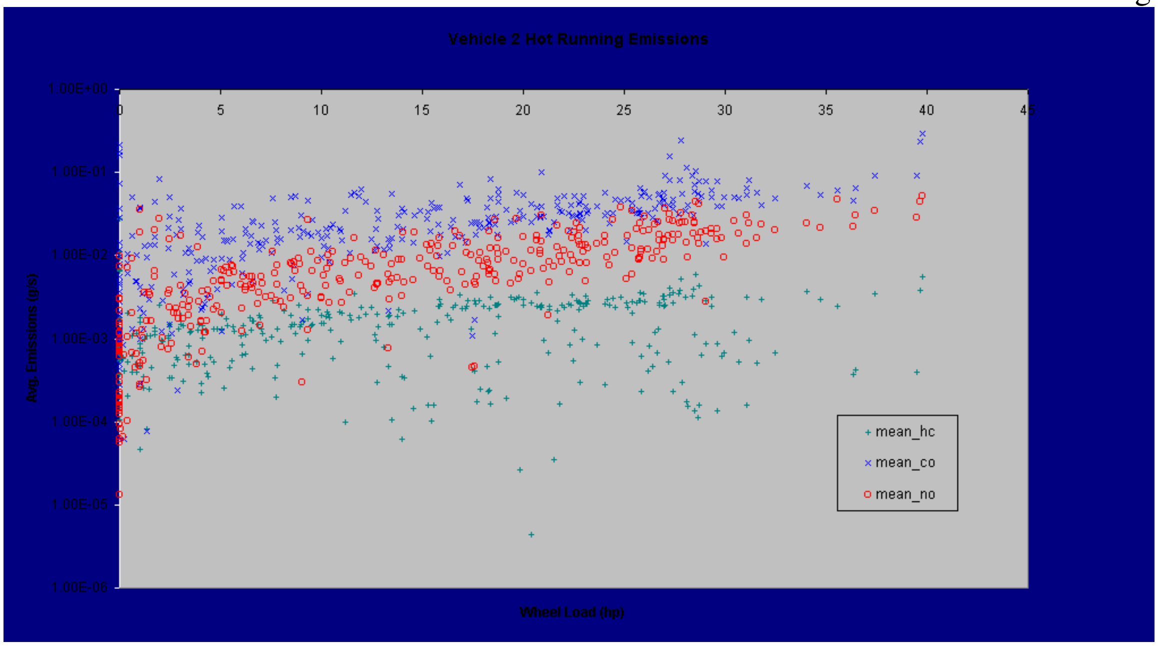

Figure 4. Vehicle 2 microtrip load and emissions

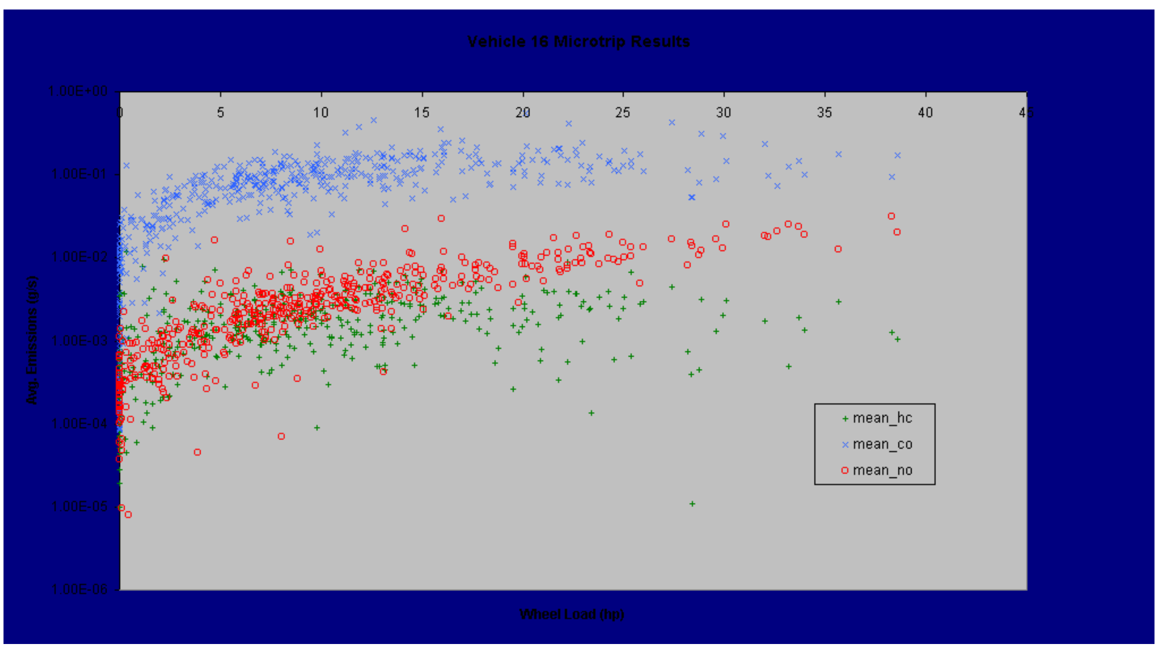

Figure 5. Vehicle 16 microtrip load and emissions.

In most microtrips, the light-duty vehicles exhibited regular behavior with load, and additional variables improved the prediction. Below are shown the overall fleet predictions by emissions levels. The specific load (wheel load divided by vehicle weight) called "spload" was used instead of load to be able to put vehicles with different designs on the same terms. Below are the equations used to best describe the emissions during the microtrips. In Table 4 are the results of the regression analysis for the hot running conditions along with the zero load emission averages. As previously mentioned the specific load should not have been used for CO_2 emission predictions, but because vehicle weights did not differ significantly this error was ignored.

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

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

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

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

Table 4. 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

The regression error was typically lower for individual vehicles than the overall predictions because of vehicle to vehicle variability were included in the overall prediction. The overall correlation included all vehicles and microtrips, so some vehicles could have greater weighting than others if only because more microtrips were defined for those vehicles. The uncertainty results of the regressions are shown in Table 5. NOx and CO_2 were well correlated (specific load was the primary explanatory variable) with overall r-squares above 0.5 for all vehicles.

Table 5. Regression uncertainty.

Car	HC rsq	CO rsq	NO rsq	CO2 rsq
11	0.46	0.65	0.73	0.94
12	0.59	0.66	0.77	0.93
14	0.60	0.65	0.75	0.74
15	0.40	0.41	0.51	0.88
16	0.20	0.59	0.77	0.89
17	0.58	0.36	0.56	0.77
18	0.38	0.57	0.83	0.89
2	0.25	0.51	0.61	0.67
5	0.48	0.10	0.61	0.82
6	0.27	0.41	0.78	0.90
7	0.31	0.31	0.83	0.80
Overall	**0.24**	**0.30**	**0.63**	**0.69**

Odometer readings may have had an effect on the CO and NOx emissions as shown by the resulting positive slopes when the coefficient and slopes above are plotted as functions of accumulated mileage. This would indicate that deterioration might have affected the regressed variables related to the overall emissions at all loads and in terms of the emission load response. However, while most coefficients increased with odometer, it was not clear if these estimates were sufficient to build an emissions model, and in some cases the results were counterintuitive with decreasing emissions with odometer, such as shown in Figure 6 for the HC regressed variables, or more typically expected as shown in Figure 7 for the NO emissions regressions.

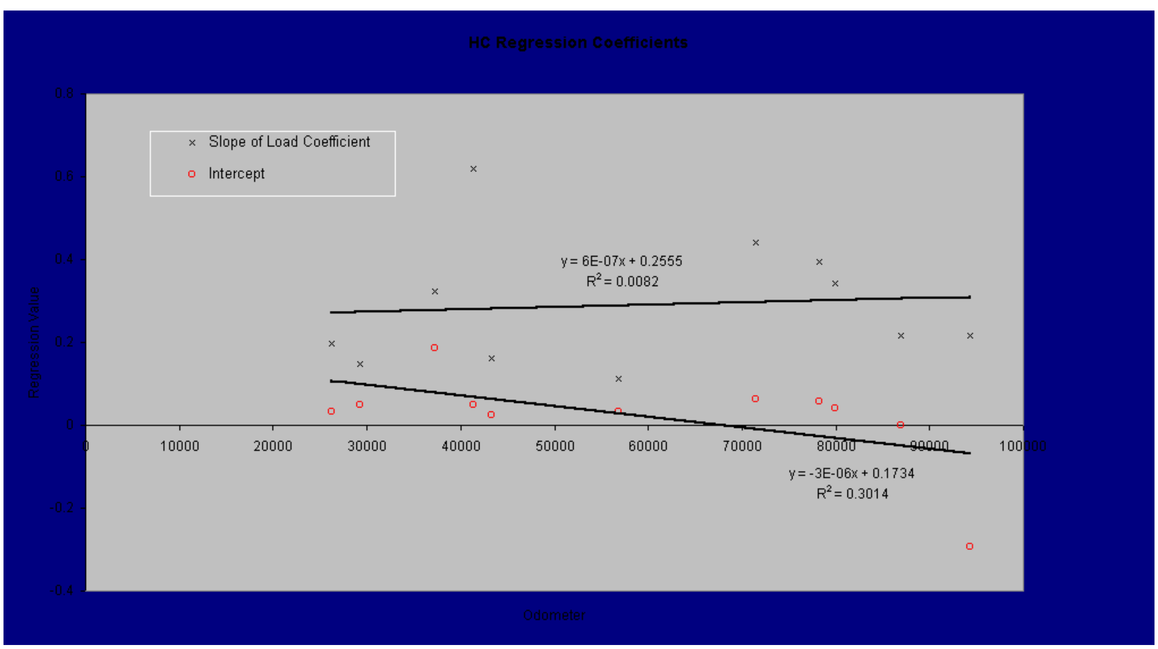

Figure 6. Effect of odometer on HC regressed coefficients

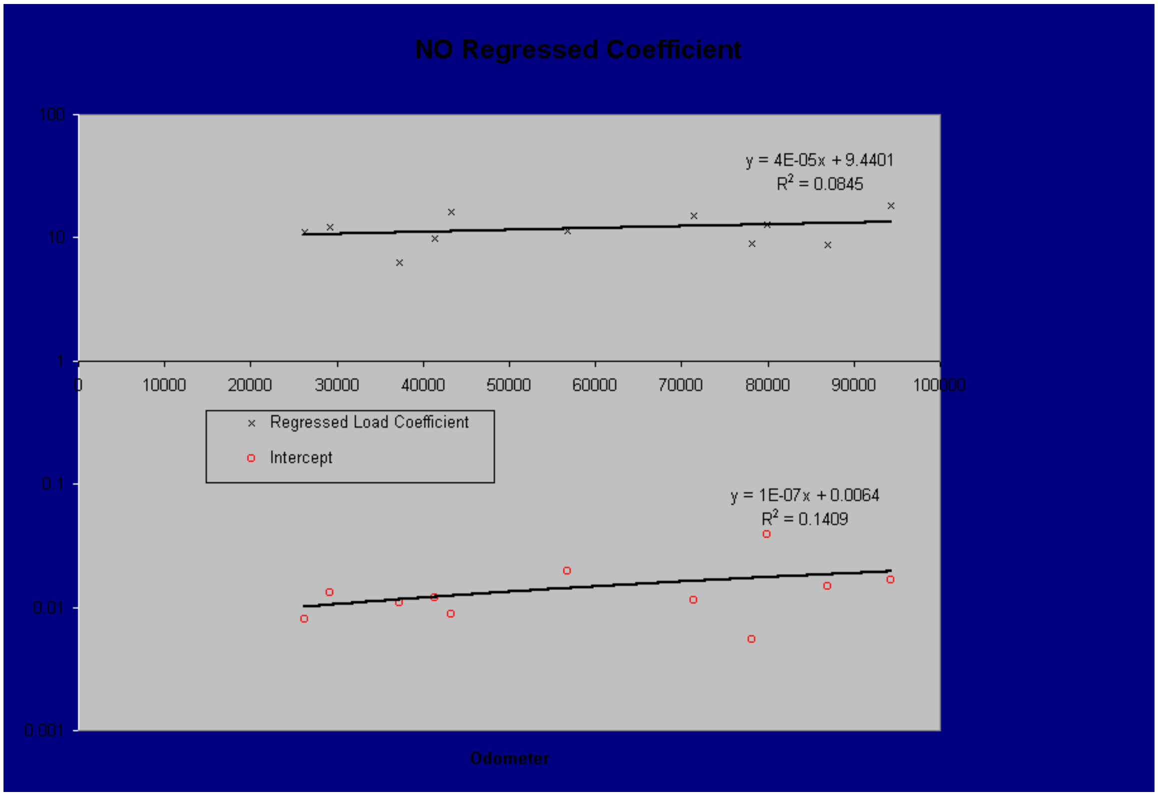

Figure 7. Effect of odometer on NO regressed coefficients

Idle or no load microtrips exhibit a range of emission rates not entirely described by the variables tested here. The higher emission rates especially should be investigated more thoroughly to determine the important components in high emission rates. High emissions for any microtrip should be investigated more thoroughly to determine the responsible vehicle behavior. For instance, other researchers have found enrichment conditions to produce short-term high emissions, but we were unable to find much evidence of those conditions within this dataset. This may be due either to limited driving or the types of vehicles tested.

Start emissions were determined as a difference in total grams of emissions for the microtrips within the first 200 seconds after each key-on from the emissions predicted from the hot running emissions for the same microtrips in the start period. Figures 8, 9, and 10 demonstrate the effect of soak on the calculated start increment. After 90 minutes, the start increment appeared to have leveled out with a few outlier points unnaturally affecting the regression for longer soak periods. Soak increments were then taken as a constant for soaks longer than 90 minutes.

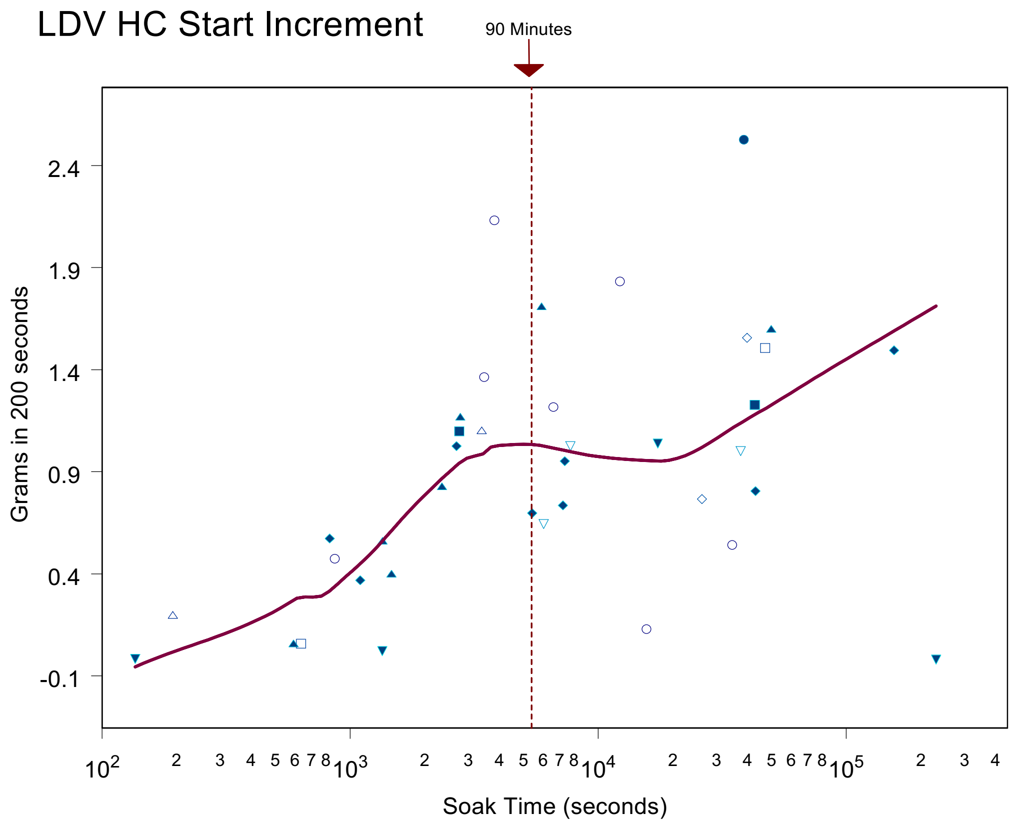

Figure 8. Incremental HC start emissions by soak time

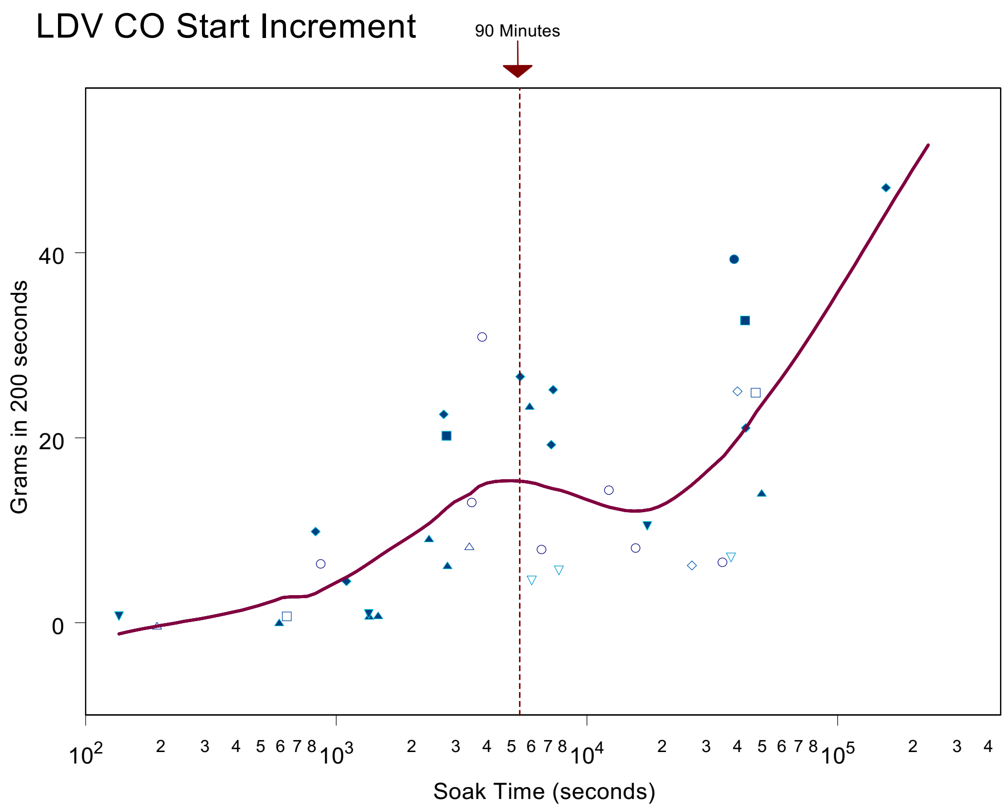

Figure 9. Incremental CO start emissions by soak time

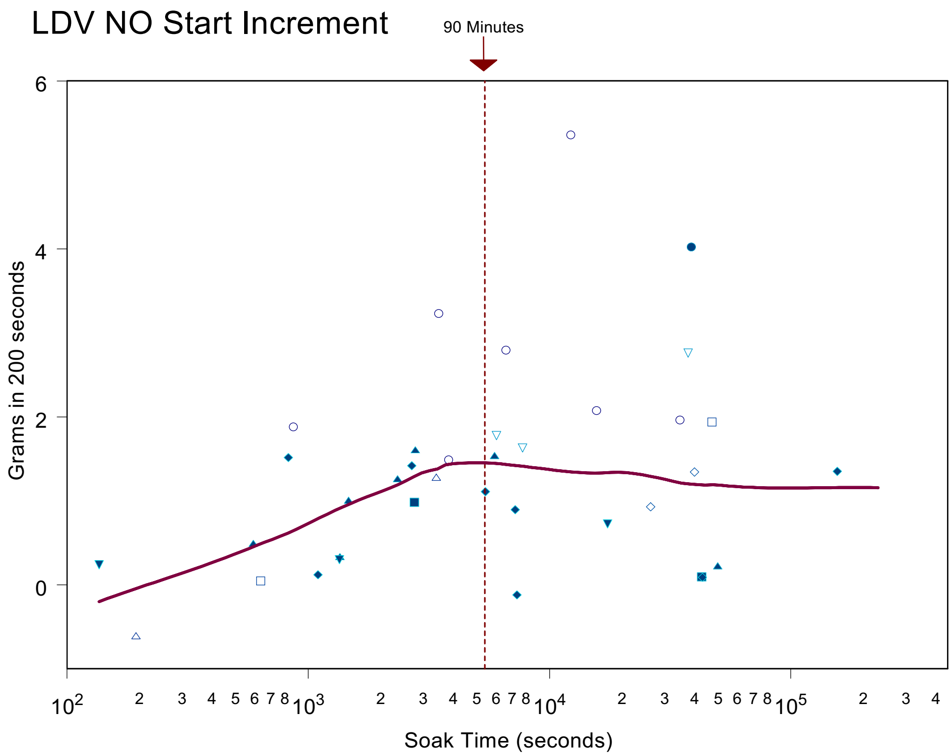

Figure 10. Incremental NO start emissions by soak time.

Table 6 shows the predictions for the unknown vehicles using an average of the dataset for light-duty vehicles. Start increments are in **BOLD** and represent the total increment for the emissions in the start above that predicted for hot running emissions. To calculated total emissions the start must be added to that calculated from the average gram per second results multiplied by the trip length.

Table 6. Predicted emissions for blind data for **Start Increment** and Hot Running (including zero load estimates in the averages shown) emissions.

Car	Trip	Trip Length	HC	CO	NO	CO2
1	2	3,373 s	**0.28 g** 0.0008527 g/s; 0.075 g/mi	**2.91 g** 0.01000 g/s; 0.88 g/mi	**0.564 g** 0.003527 g/s; 0.312 g/mi	**37.0 g** 3.107 g/s; 269.8 g/mi
3	3	1,521 s	**1.28 g** 0.0006157 g/s 0.050 g/mi	**15.60 g** 0.006999 g/s; 0.56 g/mi	**1.70 g** 0.003533 g/s; 0.285 g/mi	**82.5 g** 3.058 g/s; 233.1 g/mi
3	5	2,334 s	**0.80 g** 0.0004135 g/s 0.034 g/mi	**9.54 g** 0.002884 g/s; 0.23 g/mi	**1.16 g** 0.002555 g/s; 0.208 g/mi	**60.8 g** 2.866 g/s; 223.0 g/mi
8	2	916 s	**1.35 g** 0.001428 g/s; 0.106 g/mi	**16.54 g** 0.0186418 g/s; 1.39 g/mi	**1.78 g** 0.009516 g/s; 0.709 g/mi	**85.9 g** 3.929 g/s; 262.8 g/mi
8	4	1,106 s	**1.35 g** 0.000635 g/s; 0.054 g/mi	**16.54 g** 0.0042771 g/s; 0.36 g/mi	**1.78 g** 0.006536 g/s; 0.557 g/mi	**85.9 g** 3.558 g/s; 291.1 g/mi
8	5	1,555 s	**0.77 g** 0.000432 g/s; 0.049 g/mi	**9.12 g** 0.0029548 g/s; 0.34 g/mi	**1.12 g** 0.003800 g/s; 0.432 g/mi	**59.3 g** 2.738 g/s; 304.3 g/mi

The predicted emissions over the unknown trips are shown in Table 7. After the presentation to EPA, it was realized that the 200-second start increment had not been included in the estimates presented. Because the load during this start portion was lower than the average during the rest of the trip (as shown in Table 7), overall emissions were slightly over predicted because the hot running emissions during the start period would have been lower than during the rest of the trip. There was insufficient time to exactly correct this error, but a rough calculation estimated that the over prediction was probably less than 10% than that shown in Table 7 for all trips and pollutants.

Table 7. Predicted emissions for light-duty blind data by trip (grams) and (% from start increment).

Car	Trip	Start Load Ratio	HC	CO	NO	CO2
1	2	0.522	3.16 (9%)	36.64 (8%)	12.46 (5%)	10,516 (0%)
3	3	0.347	2.22 (58%)	26.25 (59%)	7.07 (24%)	4,734 (2%)
3	5	0.282	1.77 (45%)	16.27 (59%)	7.12 (16%)	6,749 (1%)
8	2	0.305	2.66 (51%)	33.62 (49%)	10.50 (17%)	3,685 (2%)
8	4	0.571	2.05 (66%)	21.27 (78%)	9.01 (20%)	4,021 (2%)
8	5	0.839	1.44 (53%)	13.71 (66%)	7.03 (16%)	4,317 (1%)

An estimate of the uncertainty in the light-duty vehicles was performed on the hot running emissions estimates. The approximate 95% confidence limits and the mean estimates by trip are shown in Table 8. [*These were only rough approximations to the true prediction intervals because they assumed that the regression errors were independent and normally distributed. This was not entirely true because: a) The errors were known to be only approximately normally distributed b) There was autocorrelation in predictors used in the regression (one micro trip is somewhat correlated with the next) c) No consideration was made for the fact that the error distribution varied from one vehicle to the next. It is possible that the true prediction intervals are somewhat wider than those shown here due to (b) and (c).*] The mean load emission rate estimates shown in Table 8 were somewhat different than the mean values shown in Table 6 because the transformed variables were treated differently to allow the calculation of the confidence interval. But Table 8 provides a reasonable estimate of the relative uncertainty in the mean hot running emission estimates for each of the trips.

Table 8. Hot running emissions (g/s) for light-duty blind data with 95% confidence range.

Car	Trip	HC	CO	NO	CO2
		0.000829 (high)	0.00800 (high)	0.00293 (high)	2.93 (high)
1	2	0.000823 (mean)	0.00794 (mean)	0.00292 (mean)	2.90 (mean)
		0.000818 (low)	0.00788 (low)	0.00291 (low)	2.86 (low)
		0.000589	0.00523	0.00289	2.89
3	3	0.000581	0.00515	0.00287	2.80
		0.000573	0.00508	0.00285	2.71
		0.000424	0.00268	0.00227	2.73
3	5	0.000394	0.00250	0.00226	2.65
		0.000365	0.00234	0.00225	2.57
		0.001461	0.01276	0.00693	3.58
8	2	0.001341	0.01105	0.00687	3.44
		0.001227	0.00956	0.00681	3.29
		0.000658	0.00354	0.00496	3.25
8	4	0.000582	0.00308	0.00493	3.07
		0.000510	0.00268	0.00489	2.90
		0.000437	0.00226	0.00261	2.38
8	5	0.000378	0.00199	0.00259	2.23
		0.000325	0.00174	0.00258	2.08

Transit Buses

The buses were generally well behaved in terms of emissions associated with load except perhaps for CO emissions and for HC for a few buses. Depending upon the importance of these variables and certain aspects of the measurement method, HC and CO emissions from diesel equipment may be less important in terms of overall anthropogenic emissions. The mean load best described the NOx and CO_2 emissions over any cycle with HC and CO well described by load in general but exhibiting much more variation as demonstrated for Bus 10 in Figure 11.

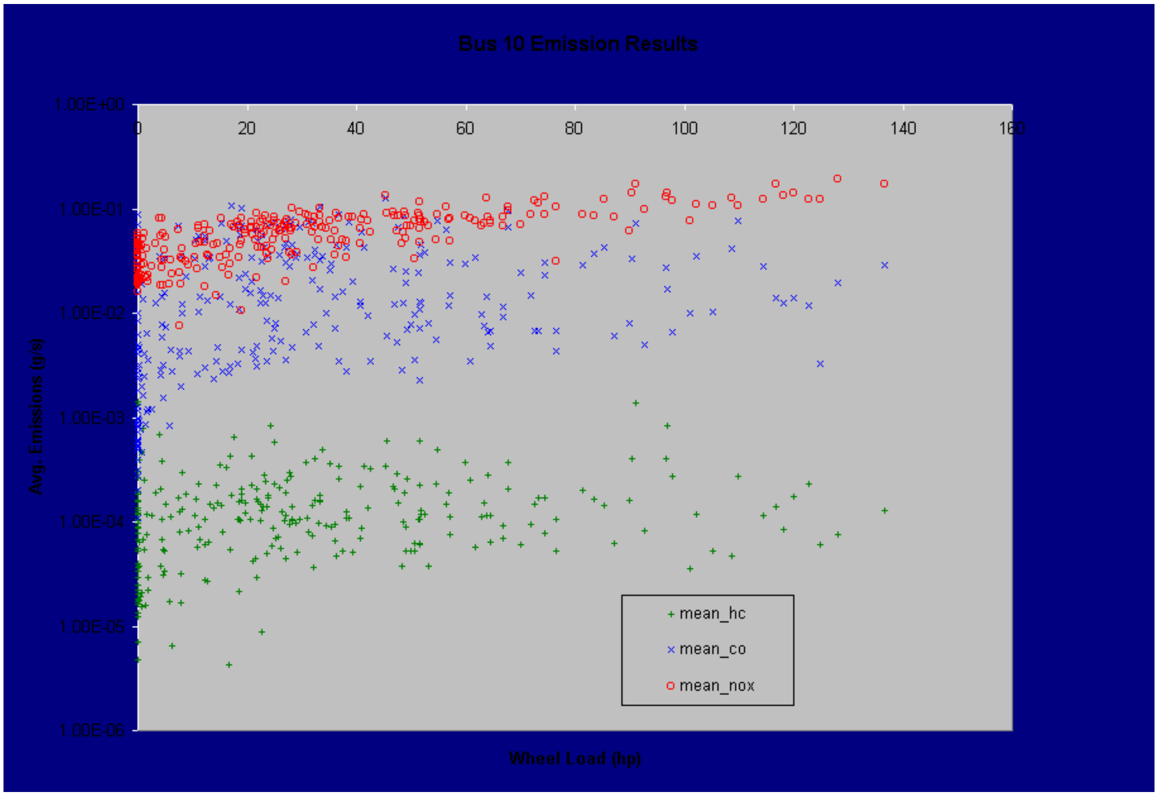

Figure 11. Bus 10 microtrip load and emissions.

As demonstrated in Figure 3 for Bus 10, high CO emissions appeared to be associated with acceleration events after idle, but not during accelerations at speed. The variables tested here, previous mean load and load changes, only partially explained this phenomena. Additional work to better define this high emission driving behavior is warranted especially if CO is used to apportion particulate emissions across driving trips.

HC emissions from diesel engines are notoriously difficult to measure given the type of compounds measured. For instance, some high HC emissions may be due to either heavy oils or unburned fuel or to lighter components and measurement instruments may respond differently depending upon how sample integrity (heated lines etc.) is maintained. HC emissions from diesels were found to be quite low perhaps approaching the detection limits of the system.

The regression coefficients and the zero load mean emission rates are shown in Table 9. As shown in Table 10 for correlation variables, the NOx and CO_2 regressions were well explained by the variables used here, while HC and CO were not as well described. Very few buses had any data on start emissions, so it was considered to be not appropriate to model starts separately without a complete fleet data set. Therefore, HC and CO predictions may be low without including a start emissions increment.

$$lm\ sqrt(mean.hc) = intercept + A * sqrt(mean.load) + B * load.changes + C * sqrt(prev.mean.load) + D * mean.humid + E * mean.temp$$

$$lm\ sqrt(mean.co) = intercept + A * sqrt(mean.load) + C * sqrt(prev.mean.load)$$

$$lm\ sqrt(mean.nox) = intercept + A * sqrt(mean.load) + B * load.changes + C * sqrt(prev.mean.load) + D * mean.humid + E * mean.temp$$

$$lm\ sqrt(mean.co2) = intercept + A * sqrt(mean.load) + C * sqrt(prev.mean.load)$$

Table 9. Regression coefficients for bus microtrips above zero load and zero load rates.

Pollutant	Intercept	A	B	C	D	E	Zero Load (g/s)
HC	0.0496	0.0005	0.0001	-0.0001	-0.0004	0.0001	0.000671
CO	0.1272	0.0145	---	-0.0085	---	---	0.003976
NOx	0.2903	0.0297	0.0001	-0.0011	-0.0010	-0.0036	0.032602
CO_2	1.1815	0.3287	---	-0.0528	---	---	1.345467

Table 10. Regression uncertainty.

Bus	HC rsq	CO rsq	NOx rsq	CO_2 rsq
1	0.55	0.35	0.82	0.88
2	0.41	0.36	0.68	0.78
4	0.08	0.34	0.84	0.88
5	0.05	0.40	0.83	0.91
6	0.26	0.51	0.80	0.85
7	0.56	0.26	0.90	0.94
8	0.29	0.43	0.84	0.93
9	0.48	0.09	0.63	0.34
10	0.25	0.16	0.61	0.67
11	0.09	0.30	0.79	0.88
14	0.01	0.32	0.79	0.86
15	0.11	0.13	0.57	0.60
Overall	**0.27**	**0.37**	**0.65**	**0.83**

The predicted emission rates for the bus trips are shown in Table 11 and overall trip emissions are shown in Table 12. As with the light-duty vehicles, the start period was mistakenly excluded from the calculations but there was insufficient time to correct this error. This error would affect the prediction of bus 3 trip 3 and bus 12 trip 3 most markedly because the start period load was much lower than the remainder of the trip, while not affecting bus 3 trip 4 and bus 13 trip 3 much because the start period load was equivalent to the load in the remainder of the trip.

Table 11. Predicted emissions for blind bus running emissions data.

Bus	Trip	Trip Length	HC	CO	NOx	CO2
3	3	2,032 s	0.001850 g/s; 0.356 g/mi	0.02808 g/s; 5.40 g/mi	0.1352 g/s; 25.99 g/mi	9.082 g/s; 1746 g/mi
3	4	1,650 s	0.001634 g/s; 0.488 g/mi	0.02586 g/s; 7.73 g/mi	0.0972 g/s; 29.03 g/mi	6.572 g/s; 1963 g/mi
12	2	1,722 s	0.001888 g/s; 0.435 g/mi	0.02677 g/s; 6.17 g/mi	0.1321 g/s; 30.43 g/mi	8.051 g/s; 1855 g/mi
12	3	1,827 s	0.002016 g/s; 0.386 g/mi	0.02852 g/s; 5.46 g/mi	0.1477 g/s; 28.28 g/mi	8.828 g/s; 1690 g/mi
13	2	1,970 s	0.001786 g/s; 0.534 g/mi	0.02789 g/s; 8.34 g/mi	0.1198 g/s; 35.82 g/mi	7.676 g/s; 2294 g/mi
13	3	1,343 s	0.001859 g/s; 0.633 g/mi	0.02800 g/s; 9.54 g/mi	0.1229 g/s; 41.85 g/mi	7.589 g/s; 2585 g/mi

Table 12. Predicted emissions for blind bus running emissions data by trip (grams).

Bus	Trip	Start Period Load	HC	CO	NOx	CO2
3	3	0.20	3.76	57.06	274.7	18,455
3	4	1.09	2.70	42.67	160.4	10,844
12	2	0.78	3.25	46.10	227.5	13,864
12	3	0.06	3.68	52.11	269.9	16,129
13	2	0.42	3.52	54.94	236.0	15,122
13	3	1.10	2.50	37.60	165.1	10,192

Nonroad Equipment

Because equipment load and engine speed were included in the data set to be predicted for emissions, it was not necessary to determine the load through equations. The microtrips were defined according to the exhaust flow instead of load.

As shown in Figure 12, the D8 dozer results showed a clear relationship between exhaust flow and the emissions. As shown in Figure 13, the roller\compactor showed interesting relationships between exhaust flow and emissions with a two-tiered situation with exhaust flow, as if some baseline measurement or calibration had changed. The remaining piece of nonroad equipment, the scraper showed that CO_2 is well correlated, but NOx emissions showed more scatter in the results as shown in Figure 14.

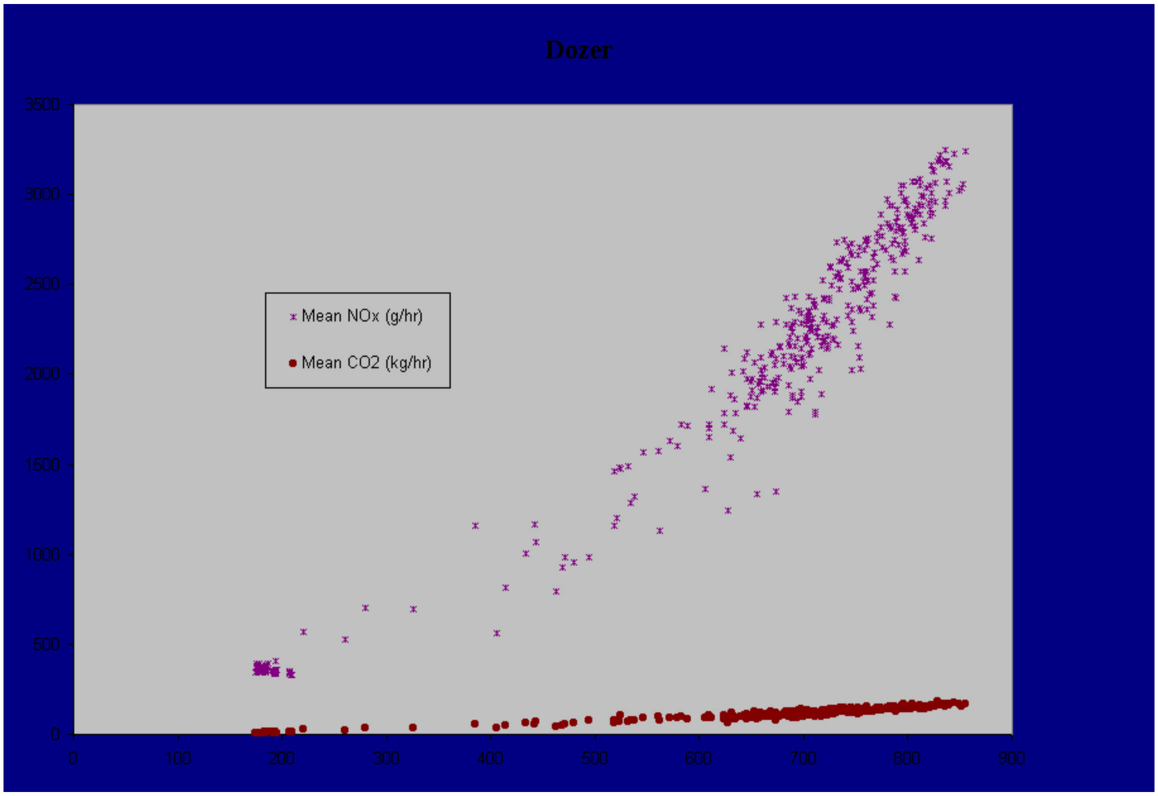

Figure 12. Load response for the dozer.

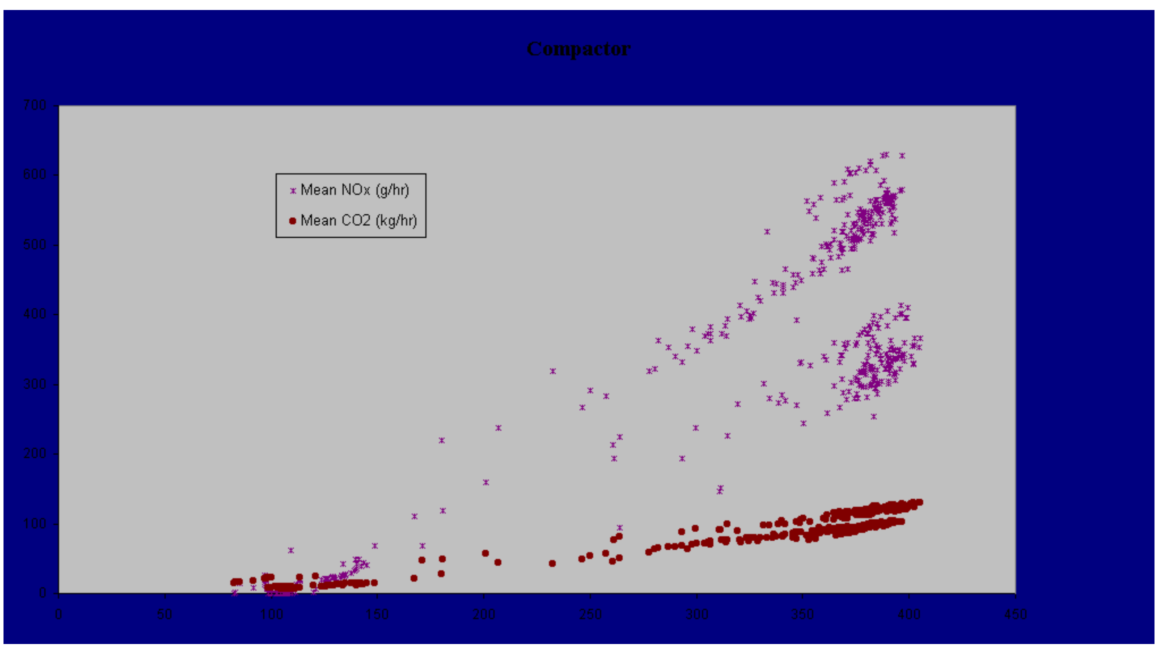

Figure 13. Load response for the compactor.

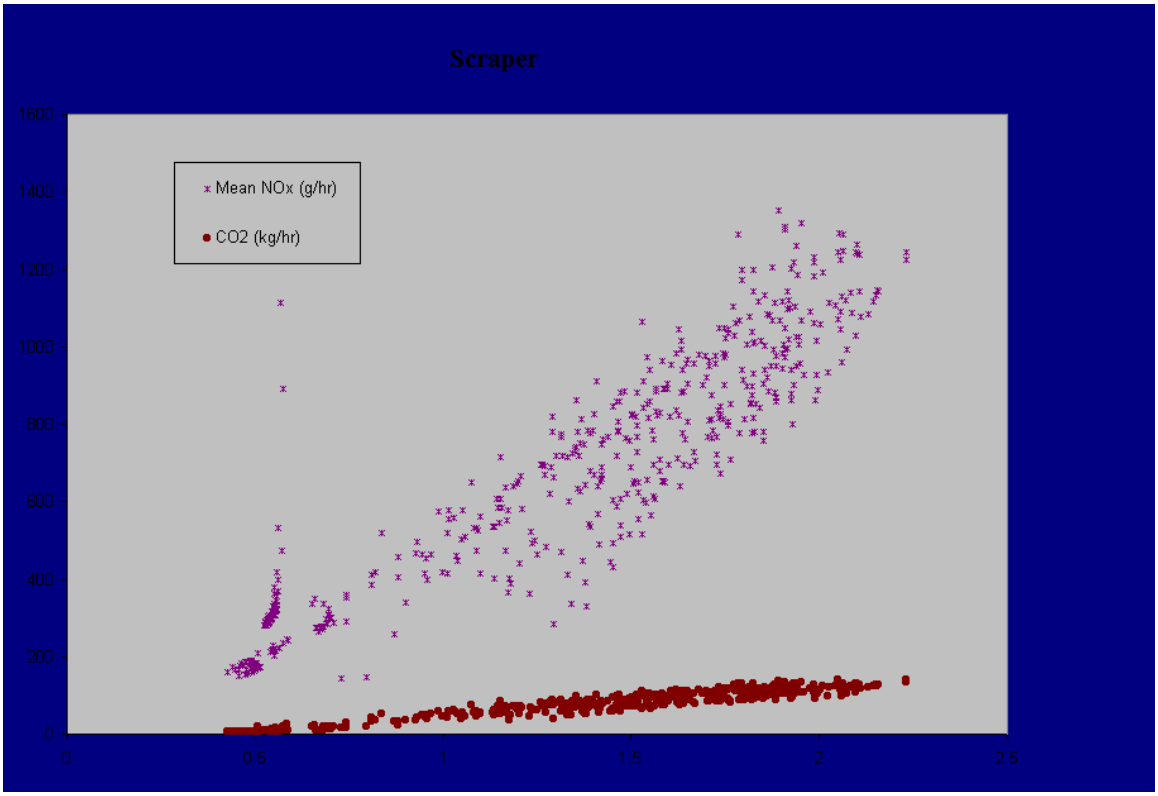

Figure 14. Load response for the scraper.

Load in the form of exhaust flow was found to be the only variable that could be consistently used to model NOx and CO_2 emissions with engine speed (rpm) only added for the scraper. Table 13 presents the results of the regressions and a low load emission rate was used for the dozer. Below are the correlation coefficients shown in Table 14, and the predicted emissions in Table 15 for the unknown activity following the equations shown below.

Dozer

$$sqrt(mean.nox) = intercept + A * mean.load$$
$$sqrt(mean.co2) = intercept + A * mean.load$$

Compactor

$$sqrt(mean.nox) = intercept + A * mean.load$$
$$sqrt(mean.co2) = intercept + A * mean.load$$

Scraper

$$mean.nox = intercept + A * mean.load + B * mean.rpm$$
$$mean.co2 = intercept + A * mean.load + B * mean.rpm$$

Table 13. Running emissions coefficients for the equations above.

Pollutant	Intercept	A	B	Low Load (<200 SCFM)
Dozer NOx	1.0097	0.0653	---	9.625
Dozer CO_2	0.1338	0.0151	---	357.7
Compactor NOx	-3.3740	0.0643	---	---
Compactor CO_2	0.5443	0.0257	---	---
Scraper NOx	-41.8751	2.4847	-0.2366	---
Scraper CO_2	-34.3846	0.2612	-0.0075	---

Table 14. Regression uncertainty.

Bus	NOx rsq	CO2 rsq
Dozer	0.83	0.81
Compactor	0.86	0.95
Scraper	0.86	0.94

Table 15. Predicted emissions for blind data **Start** and Hot Running.

Equipment	Trip Length	NOx	CO2
Dozer	3,600 s	1547.5 g/hr 1547.5 grams	78.07 kg/hr 78.07 kg
Compactor	3,441	359.9 g/hr 344.0 grams	87.69 kg/hr 83.8 kg
Scraper	3,599	597.3 g/hr 597.1 grams	65.34 kg/hr 65.32 kg

Conclusions

This work does not purport to have discovered all variables that affect emissions and further investigation into additional variable terms is needed to provide insight into the depth and breadth of vehicle emissions behavior. The vehicle load (which combines speed, acceleration, grade, and auxiliary equipment) appears to perform as a good indicator of overall emissions from vehicles and nonroad equipment; however, it does not explain all of the variability in the data. The mean load was overwhelming the most important variable for explaining emissions and other variables were added with slight improvement in the statistical result.

High emission microtrips deserve further attention to distinguish these from other similarly loaded microtrips. Such high emission microtrips will provide additional vehicle and equipment behavior that can be further confirmed with the larger data set. These high emission segments of the microtrips may affect some or all microtrips and afford a method to reduce the microtrip to microtrip variability in the predictions. For example, one instance was discovered where high relative CO emissions occurred with accelerations from idle for buses but was only partially accounted for in this analysis.

A sensitivity test of the microtrip criteria should be included in any future work. In Appendix B, the microtrip length distribution shows that the microtrip length was heavily skewed toward our minimum trip length of 20 seconds indicating that the criteria that we used (+/- 15 hp over 3 seconds) was relaxed. This criteria could be made more strict, further reducing carryover of emissions from one microtrip to the next.

The start period should be investigated more thoroughly possibly through the addition of an exhaust or catalyst temperature sensor to accurately identify the end of the start period. In this data set a period longer and shorter than the assumed 200 second interval after the key on should be investigated to determine if the 200 second interval was appropriate. Bus and nonroad equipment starts should be analyzed to determine if there was a start increment to be added to the emission estimates.

In this analysis we did not distinguish between braking an idle microtrips because we could not define a load criteria for idle conditions without auxiliary load. To determine whether braking had different emissions from idle, we looked and zero load microtrips with and without positive speeds to determine that in general emission rates were about the same between braking and idle, but certain idle events had much higher emissions than braking events. Braking and idle emissions rates are described in more detail in Appendix C.

RECOMMENDATION FOR THE ROLE OF ALTERNATE EMISSION DATA

The use of on-board data presents a departure from the traditional methods of developing emission factor models and poses some concerns about data viability for the New Generation Mobile Source Model (NGM). EPA has historically estimated emissions for a wide variety of end uses and needs to describe the effect of transportation and activity modifications as well as vehicle/equipment emissions behavior associated with use or emission control devices. The NGM model seeks to improve not only the performance of the emission estimation, but also provide more flexibility in determining the emission effects.

For instance, MOBILE estimates emissions for a variety of transportation network effects that are inferred through the use of speed correction factors to be applied to specific facility type in MOBILE6. Also, MOBILE estimates the effect on emissions of various fuels, emission control devices, and the emitter status of the vehicles. However, transportation and air quality planners have sometimes sought more enhancements than the MOBILE model could provide. A list of the currently available and desired model enhancements is shown below.

List of Effects Available In MOBILE6 or NONROAD

- Ambient conditions (Temperature, Humidity, Cloud Cover, Sun Hours and Peak, Altitude, others)
- Fuel conditions (sulfur, oxygen, others)
- Engine/Vehicle conditions (vehicle class/type, emission standards or model year, age distribution, mileage accumulation, technology type, emitter status, others)
- Activity conditions (speed, facility, soak condition, and others)
- Nonroad engines uses (average load, by end use, and others)

List of Effects Not Available In MOBILE6 But Typically Desired

- Project level estimates (e.g. signal timing, congestion improvement, link-based estimates)
- Estimates other than average speed to understand speed/acceleration effects on emissions
- Grade (affecting load)
- Congestion level (affecting average load or speed and load/speed variability) of service
- Nonroad equipment/activity types

Based on the limited results of this study, vehicle behavior can be described by the portable emissions monitors (PEM). Based on the limited response, conditions well described by the in-situ analysis are those related to the load and emissions response. The vehicle load describes most activity conditions, including desired effects of grade and air conditioning load.

For other activity conditions, such as project, link, or congestion level, the burden is on the response of vehicles to these situations rather than the direct measurement of emissions under these conditions. As such, vehicle load response to these conditions becomes more important factors than testing emissions under all these situations. However it is necessary that the emission testing cover the entire range of important vehicle activity. More study should identify all important variables that affect emissions, and determine the range of these variables through activity studies before performing a testing program to measure emissions. When a testing program begins, all vehicles need to be driven in such a manner as to cover the range of important activity.

Ambient (altitude, humidity, and temperature) and fuel conditions appear to be clear situations where alternative data would be most appropriate for alternative emissions studies. The effect of these variables should be determined to be an adjustment to the larger PEMs data set through selected studies that can determine if the effect on emissions of these situations is in similar proportion over all vehicle behavior (i.e. for all loads) or if the effect varies under different conditions. For instance, does the fuel oxygen affect primarily the emissions under high load or other types of instantaneous load conditions or does it affect emissions for all loads in the same proportion? Likewise it will be necessary to determine whether the effect is similar across vehicle types. Once the emission effects of these parameters are determined, they may be used to adjust the larger PEMs field dataset.

Because of the vast amount of historic data generated using the standard FTP test cycle on a wide variety of vehicles, how might this data be used in context with the data generated from PEMs is of interest. Microtrips can be defined over the FTP test cycle and historic data can be compared with the results of the analysis of the PEMs data to determine adjustment factors for either the FTP or the PEMs data. However, the driving behavior over the FTP cycle may not include all of the types of driving behavior that exists on the roadways, so FTP data may need to be limited to predicting emissions from older vehicle types that cannot be identified for PEM's testing.

Historic FTP data may be appropriate for determining adjustment factors for fuel and ambient conditions. It may be advisable to determine if these adjustment factors can be identified over hot running conditions (Bags 2 and 3) distinct of start emissions.

RECOMMENDATION FOR ON-BOARD TESTING AND SAMPLING METHODOLOGY

Testing Conditions

It is not sufficient to merely affix the PEMS to a random set of vehicles and drivers and average emissions across all vehicles, driving, or other conditions. Without a proper consideration of the testing methodology, results may be biased under certain conditions or vehicle types. Because emissions models, such as MOBILE, are used under an extremely wide range of conditions, attention must be paid to all possible, even odd, situations.

When testing vehicles, each vehicle should be tested over the full range of operation so that the data set does not become biased for certain conditions. For instance, if only a subset of vehicles were measured under high load conditions (such as on a high speed highway with grade), then the emissions estimates for high load conditions would be entirely dependent upon only that subset of vehicles, which may not be representative of all vehicles. Other conditions that might also apply would be soak conditions or ambient conditions.

An example of the range of conditions that could be considered was the load and the previous load shown in Figure 15 for vehicle #2. The maximum load tested in this dataset was 37 hp though the wheel load for this vehicle at 75 mph and a 5% grade would be nearly 70 hp. (The rated power for this vehicle was 145 hp.) Therefore, the testing on this particular vehicle would be unable to be incorporated into the predicted vehicle emissions under high load conditions, with sparse activity above 30 wheel horsepower. So while the testing program may initially chose a random set of vehicles, unless all conditions have been incorporated, the emissions under certain conditions may, perhaps unknowingly, be determined by a bias set of vehicles.

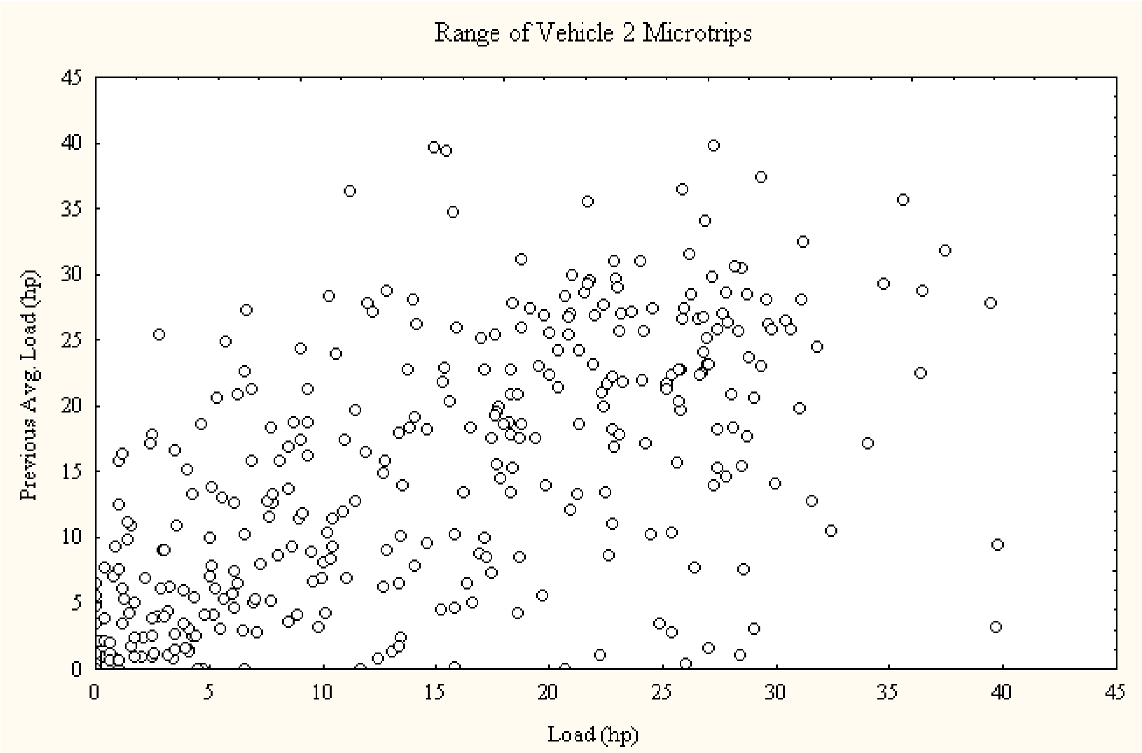

Figure 15. Range of microtrip results for Vehicle 2.

More study should be performed to identify and define all the important variables that affect emissions. It would be tragic to begin testing and realize halfway through that an additional variable should be recorded to either explain emissions or be adjusted for in the dataset with alternative datasets. Our work with this dataset identified load as the primary variable with previous trip load and load increases as variables with a possible effect on some emissions, and identified situations where more variables should be investigated to better explain the data.

One additional variable that we recommend recording is the exhaust and/or the catalyst temperature to better define the start period. With this dataset, only an inference based on the emissions rate might have been used to define the start period, but absent a clear methodology the start period was defined in this work from historical work.

If high emissions modes can be determined, then testing should seek to preferentially test these modes (for instance high load modes) to better define overall emissions. Because the high emissions modes disproportionally affect the overall emissions, the estimates of emissions during these modes demand greater attention.

Activity Correspondence

One approach to identify PEMS emissions data needs is to determine the activity data to be used for emissions estimates. For example, if highway vehicle emissions are determined with VMT data associated with average speed and level of service, then studies must be performed to determine the range of activity (such as that range of vehicle load and other driving behavior) during these conditions of facility, average speed, level of service or other input variables. Chase car study data, the PEMS data, or some other instrumented engine/vehicle data may be sufficient to identify the operating modes which are included in each such category of activity.

The PEMS emission data would then need to record data over the sufficient range of operating modes covered by the activity data. This approach would define the categories of micro-trips so that they map into the required operating modes provided these fully describe the emissions behavior.

Though our experience with raw GPS data leads us to estimate that this information will not typically be useful for identifying facility type, it may under the right conditions (for instance more vigilant recording of the routes) the PEMS data may provide sufficient GPS information to determine the facility type, and, coupled with time of day and local transportation planners, the level of service may be estimated to determine the range of vehicle operation for a selected facility such as a freeway.

Off Portable Emission Monitor (PEMS) Estimates

It will be necessary to determine adjustment factors for certain sets of conditions, primarily related to ambient and fuel differences between datasets derived from PEMS monitoring. For instance the humidity correction factor on tailpipe emissions could now be decoupled from the air conditioner load through the use of the information on compressor load.

REFERENCES

Clark, Nigel N., Justin M. Kern, Christopher M. Atkinson, and Ralph D. Nine. (2002), "Factors Affecting Heavy-Duty Diesel Vehicle Emissions," J. Air & Waste Manage. Assoc. 52:84-94, January 2002.

EPA (1995), Personal communication with D. Bruce Harris, EPA RTP, May 31, 1995.

Jiménez-Palacios, José Luis. (1999), "Understanding and Quantifying Motor Vehicle Emissions with Vehicle Specific Power and TILDAS Remote Sensing," Thesis for a Doctor of Philosophy in Mechanical Engineering at the Massachusetts Institute of Technology, February 1999.

Koupal. J. (2001), Personal communication with John Koupal, EPA, December 15, 2001.

Singer, B.C., et al. (1999), "A Fuel-Based Approach to Estimating Motor Vehicle Cold Start Emissions," J. Air and Waste, Feb. 1999.

WVU (2000), Personal Communication with Mridul Gautam, Professor at West Virginia University, September, 2000.

Appendix A

Command Enrichment Variable

Command Enrichment Variable

In order to efficiently stratify observed emission levels from the vehicle data set, ENVIRON attempted to identify onset of command enrichment mode. According to Feng and Ross (Feng, 1995), air-fuel mixture enrichment is controlled via either the throttle position or equivalently, the intake manifold pressure. Correspondingly, the result of the enrichment can be observed by monitoring the level of tailpipe CO normalized by the fuel rate. Thus both throttle position and fuel-specific CO data are required in order to identify the onset of command enrichment.

Sufficient data were provided for only four vehicles in the data set, vehicles 5, 6, 15 and 16 (Figures 1 – 4). Plots of the fuel-specific CO emission rate as a function of the throttle position are presented below. An examination of these plots seems to indicate that command enrichment is not present in the data for vehicles 5 and 6. However, vehicles 15 and 16, (Figure 3 and Figure 4) may be evincing signs of rich operation above 60% of wide-open throttle.

For the remaining vehicles, the load (as a percent of the maximum) is used in place of throttle position as the operational parameter to identify the command enrichment mode. If command enrichment is present, high fuel-specific CO observations are expected at high loads. The plots do not indicate this to be so for vehicles 2, 11, 17 and 18 (Figures 5 – 8). Vehicles 7, 12 and 14 (Figures 9 – 11) seem to indicate relatively higher normalized CO above 75-80% of maximum load. Because of the lack of data at these higher loads, it is difficult to state for certain if the observations point toward rich operation.

Also, even if command enrichment were occurring during these high load conditions, the limited time spent at high load within this dataset would not have affected aggregate emissions significantly.

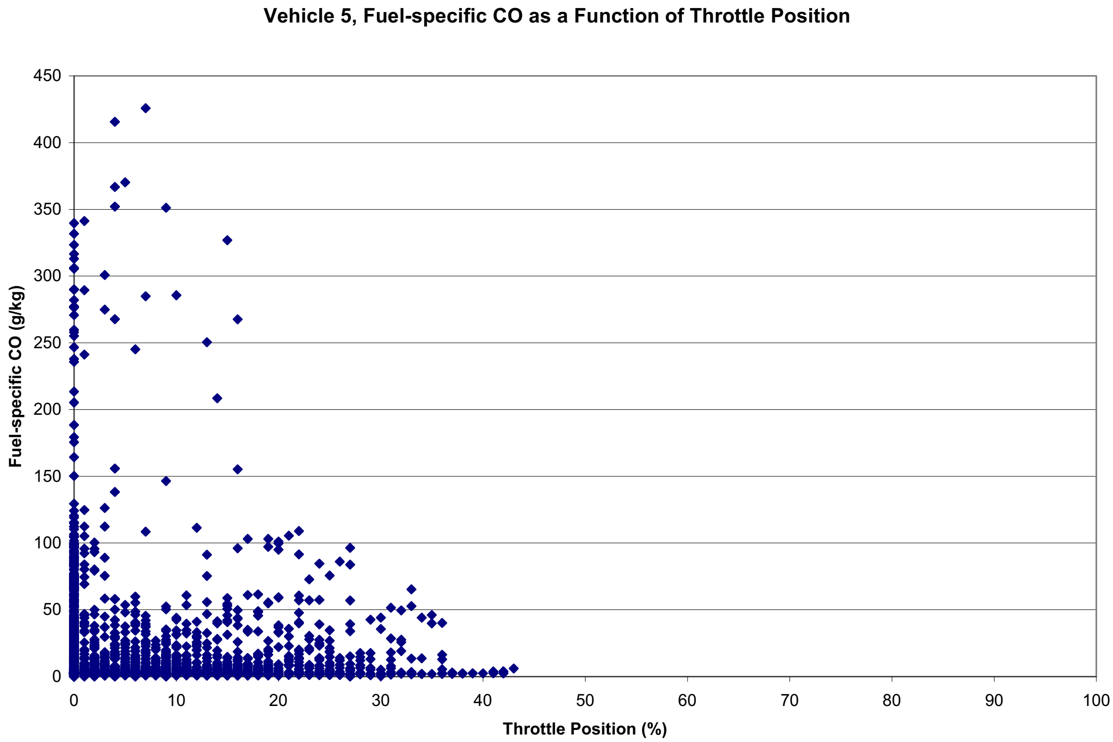

Figure 1.

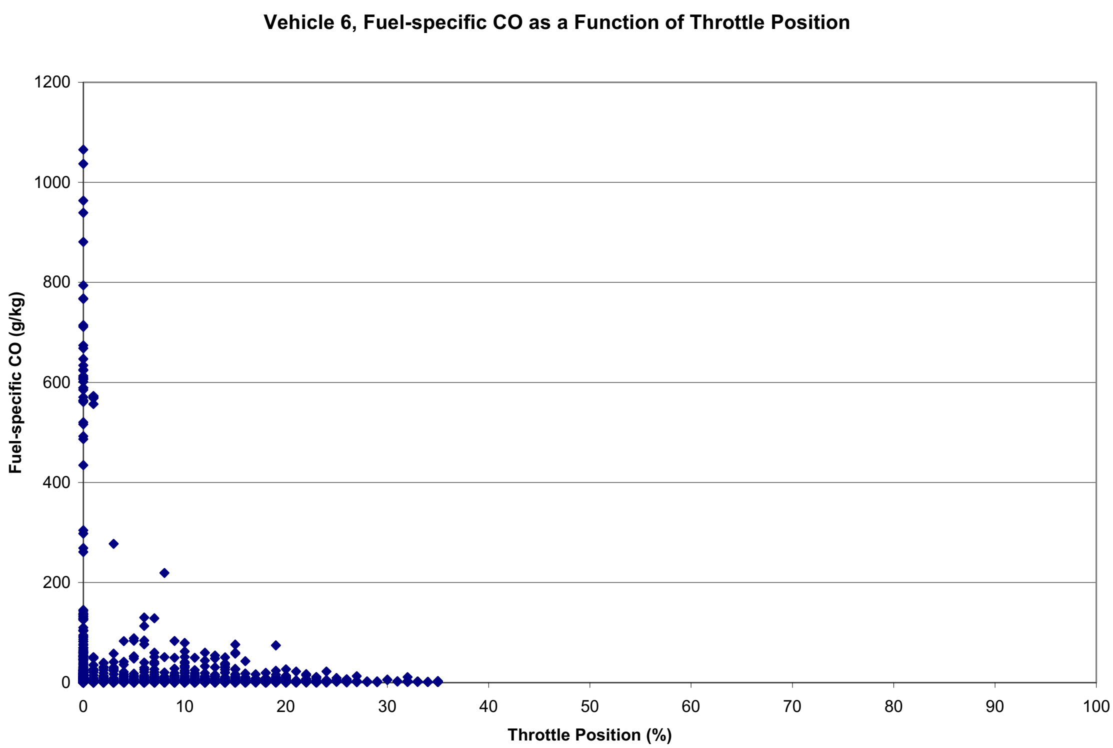

Figure 2.

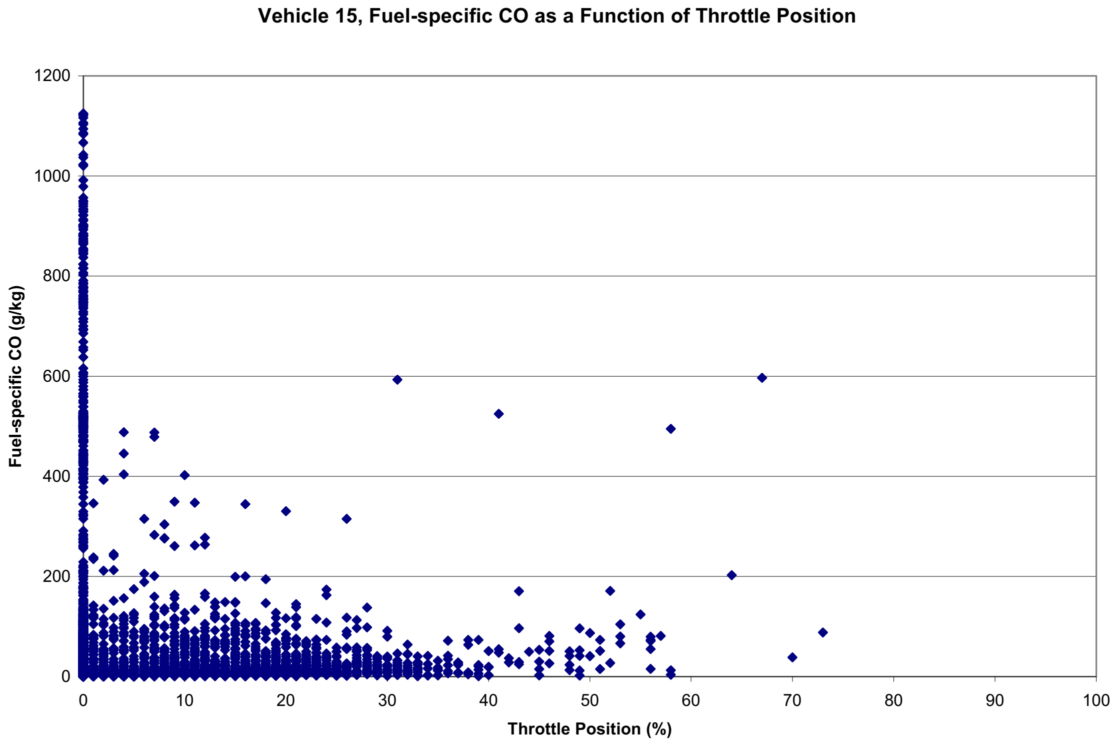

Figure 3.

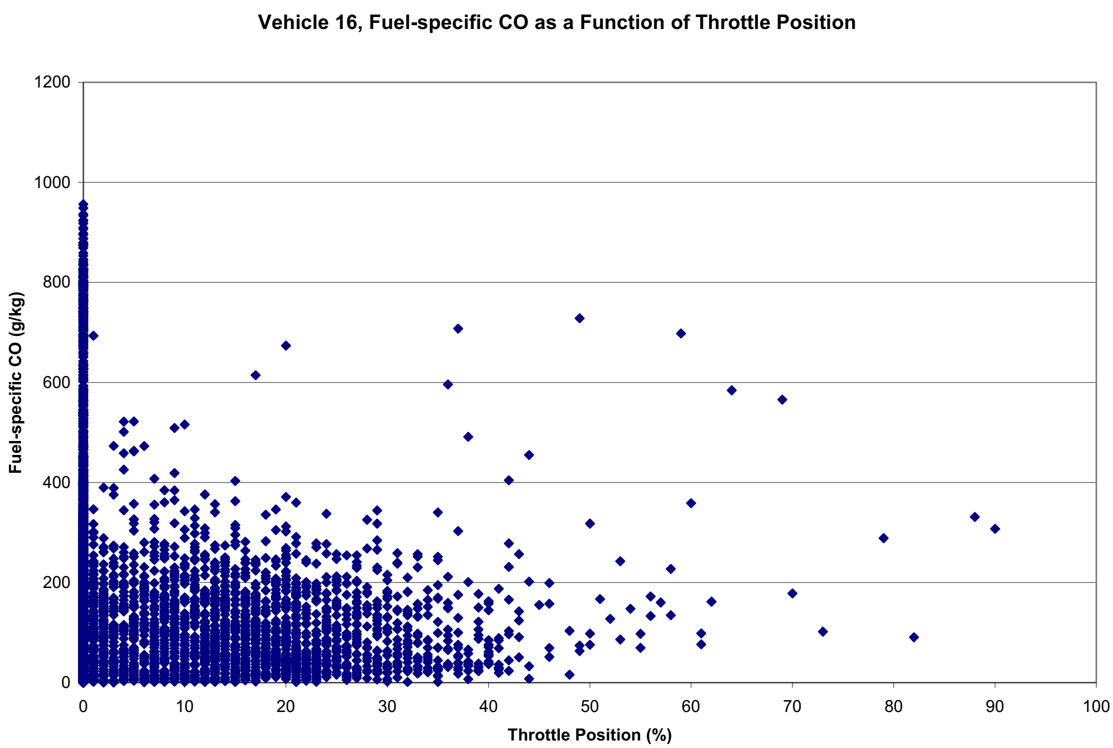

Figure 4.

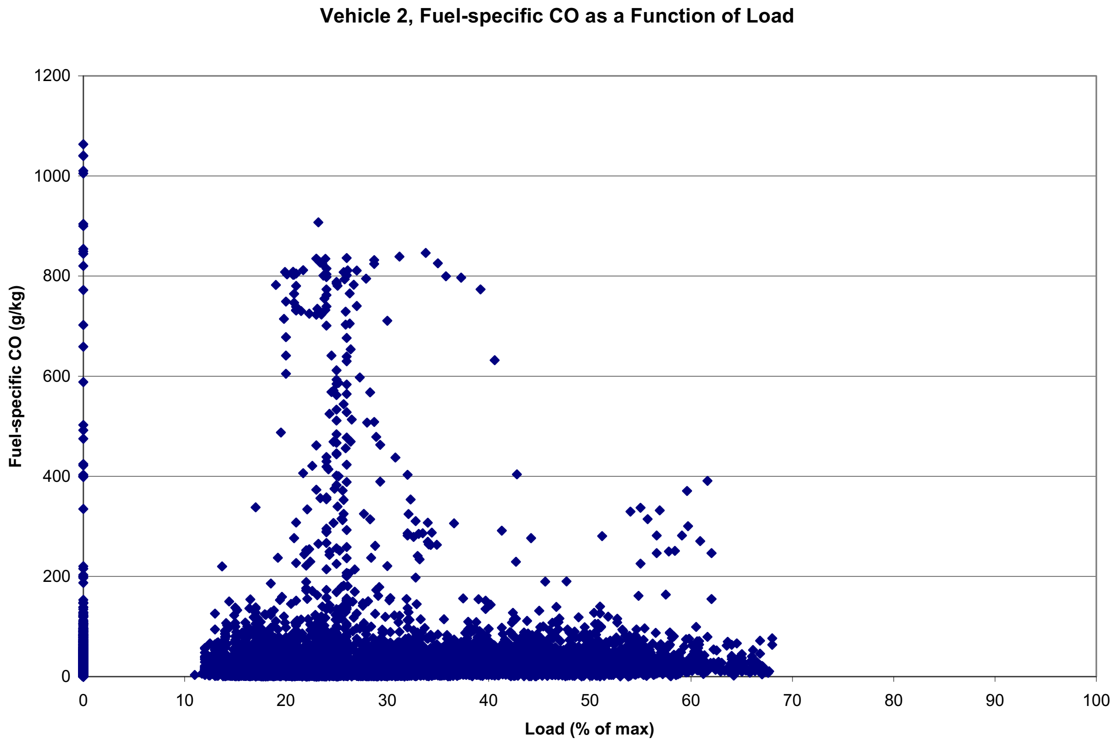

Figure 5.

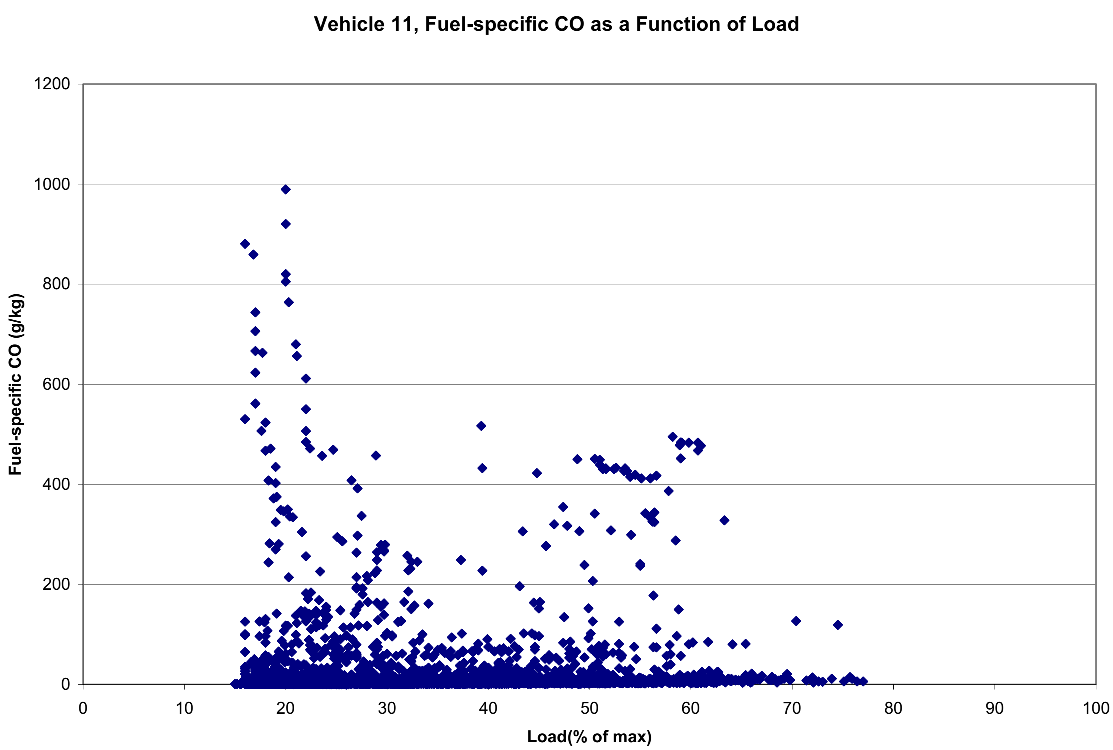

Figure 6.

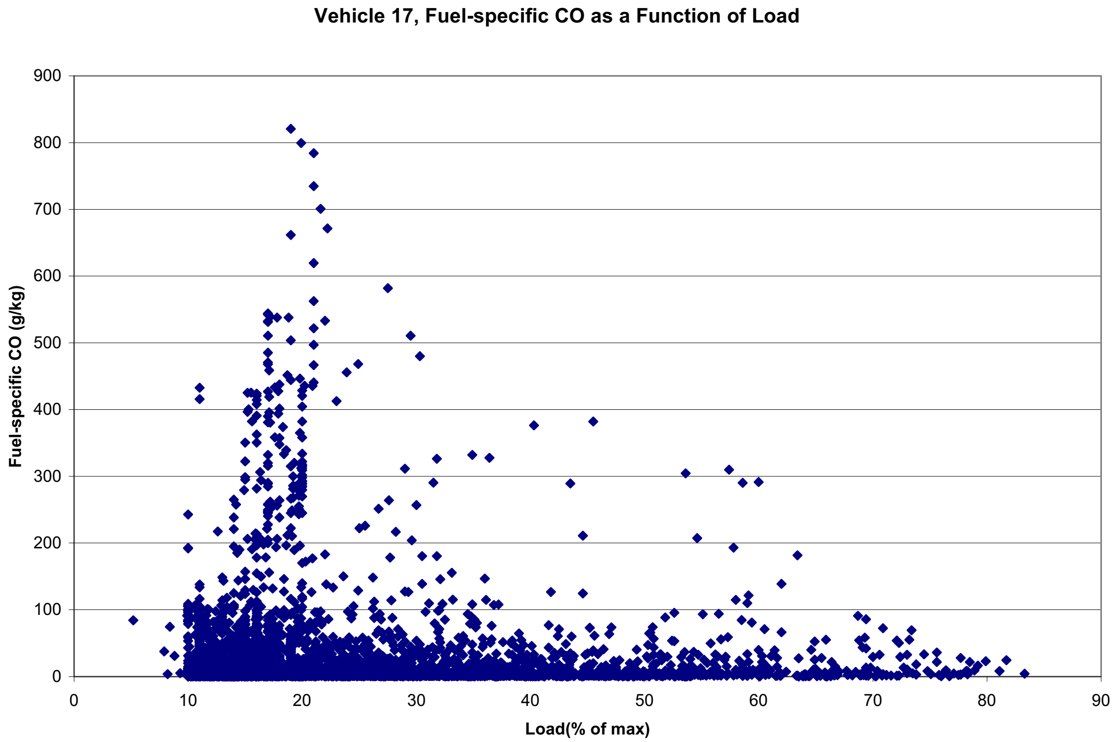

Figure 7.

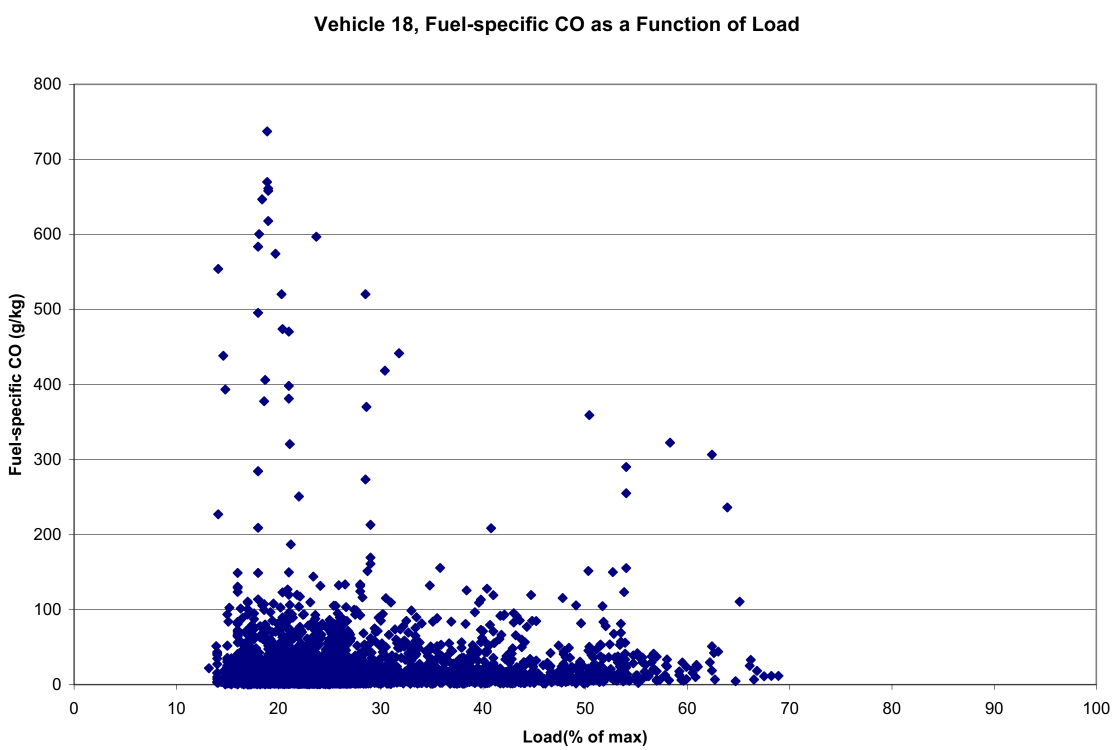

Figure 8.

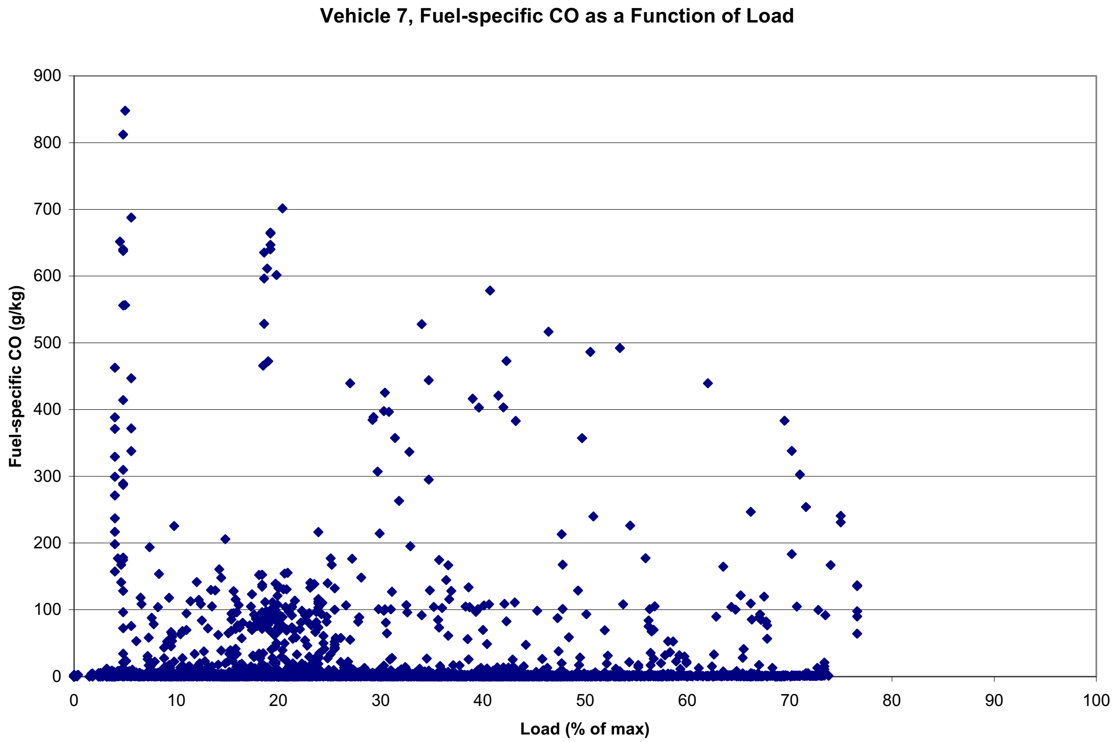

Figure 9.

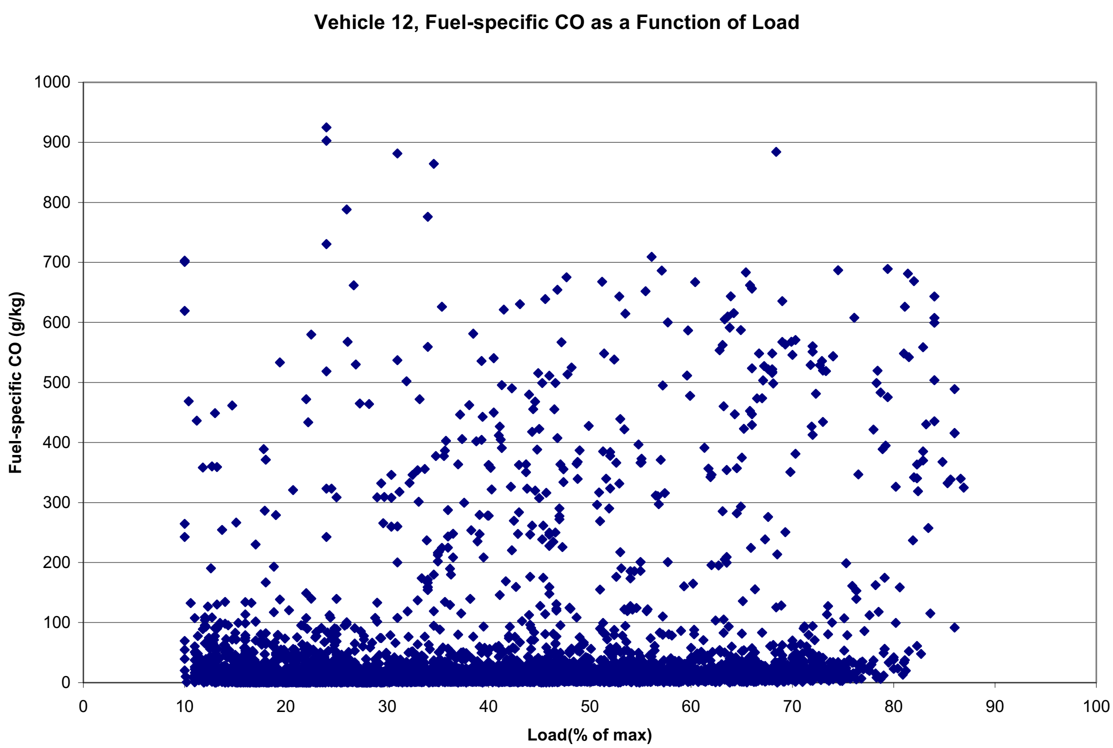

Figure 10.

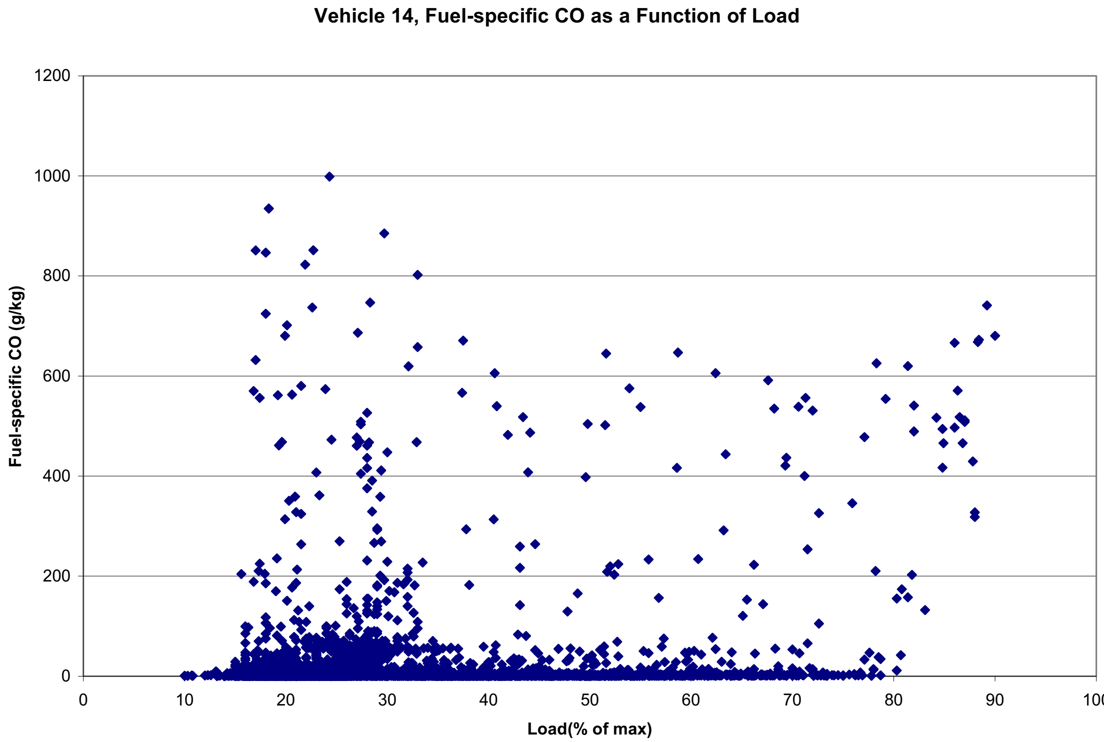

Figure 11.

References

An, Feng, Ross, Marc, "Carbon Monoxide Modeling for High Power Episodes." Presented at the Fifth Annual CRC On-road Vehicle Emissions Workshop, 1995.

Appendix B

Microtrip Length Distribution

Microtrip Length Distribution

The microtrip length distribution for light-duty vehicles and buses are shown in the Figures below for the criteria that we used (+/- 15 hp over 3 seconds). Few microtrips were much above the minimum microtrip length criteria of 20 seconds. Making the end point criteria more strict, either tightening the length of time to 5 or 7 seconds or the constant load criteria to less than 15 hp, would lengthen the microtrips by choosing fewer end points. The length criteria affects whether the offset in emissions and load have been assumed in the microtrip, the longer the offset the longer the required length criteria. The constant load criteria accounts for the between microtrip endpoint by keeping the emissions within a certain range for a fixed period of time. The 15 hp criteria was chosen as ~10% of the light-duty full power. Ideally, the results of the modeling should inform how important this criteria was by determining overall emissions as a function of load and calculating an emissions criteria to avoid carrying over emissions from one microtrip to the other through offsets or lags in response. Such a sensitivity analysis was not performed due to lack of time.

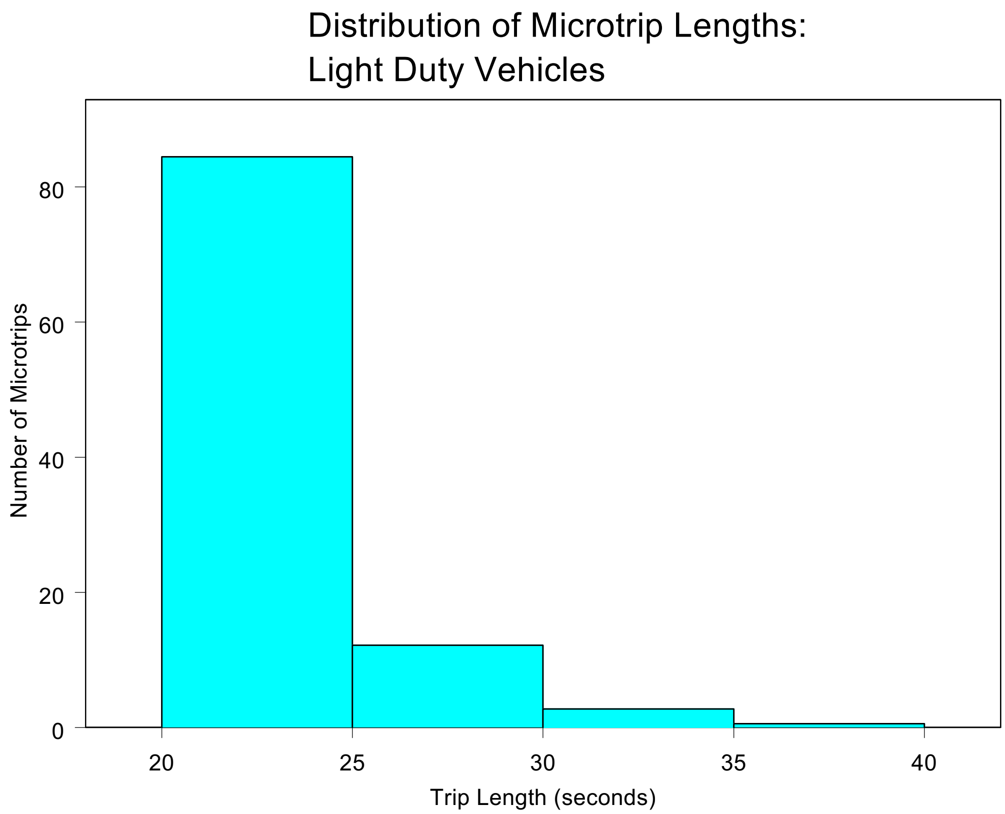
Distribution of Microtrip Lengths:
Light Duty Vehicles
Number of Microtrips
0
20
40
60
80
20
25
30
35
40
Trip Length (seconds)

Figure 1.

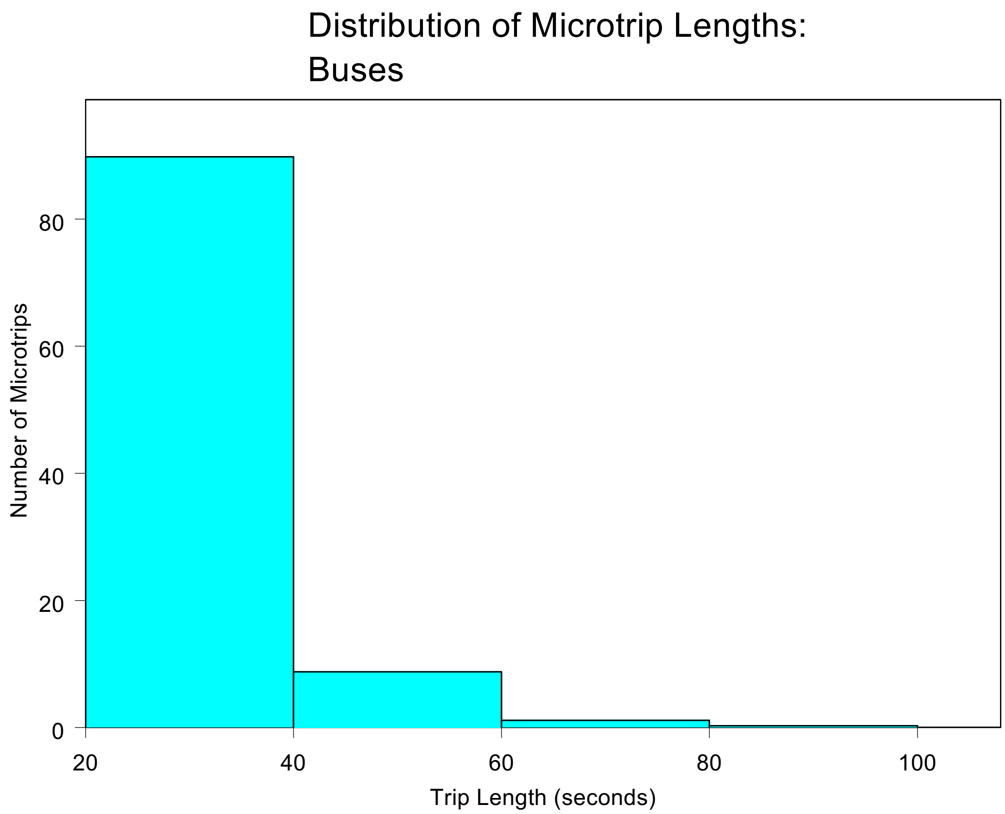
Distribution of Microtrip Lengths:
Buses
Number of Microtrips
0
20
40
60
80
20
40
60
80
100
Trip Length (seconds)

Figure 2.

Appendix C

Braking or Idle Microtrip Emissions

Braking or Idle Microtrip Emissions

Braking and idle microtrip emissions for light-duty vehicles are shown in the figures below. They indicate that idle (zero speed) microtrips could have higher emissions than braking events. More study may discern why some microtrips could have high emissions.

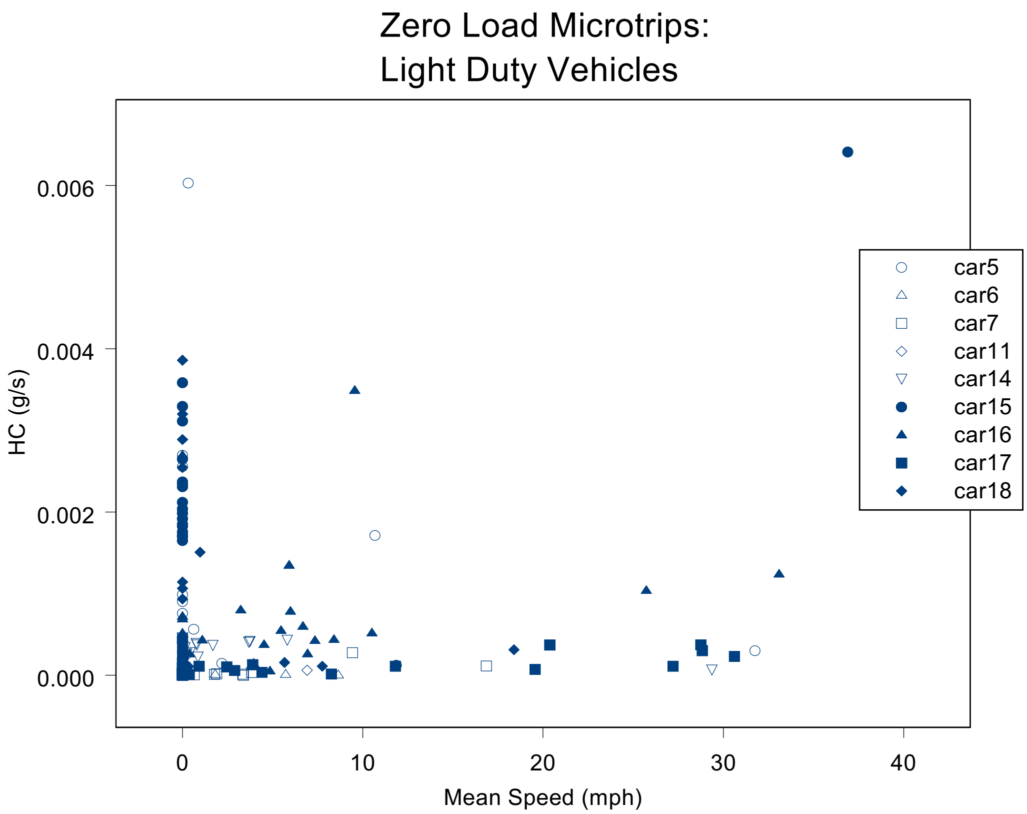
Zero Load Microtrips:
Light Duty Vehicles
HC (g/s)
0.000
0.002
0.004
0.006
Mean Speed (mph)
0
10
20
30
40
car5
car6
car7
car11
car14
car15
car16
car17
car18

Figure 1.

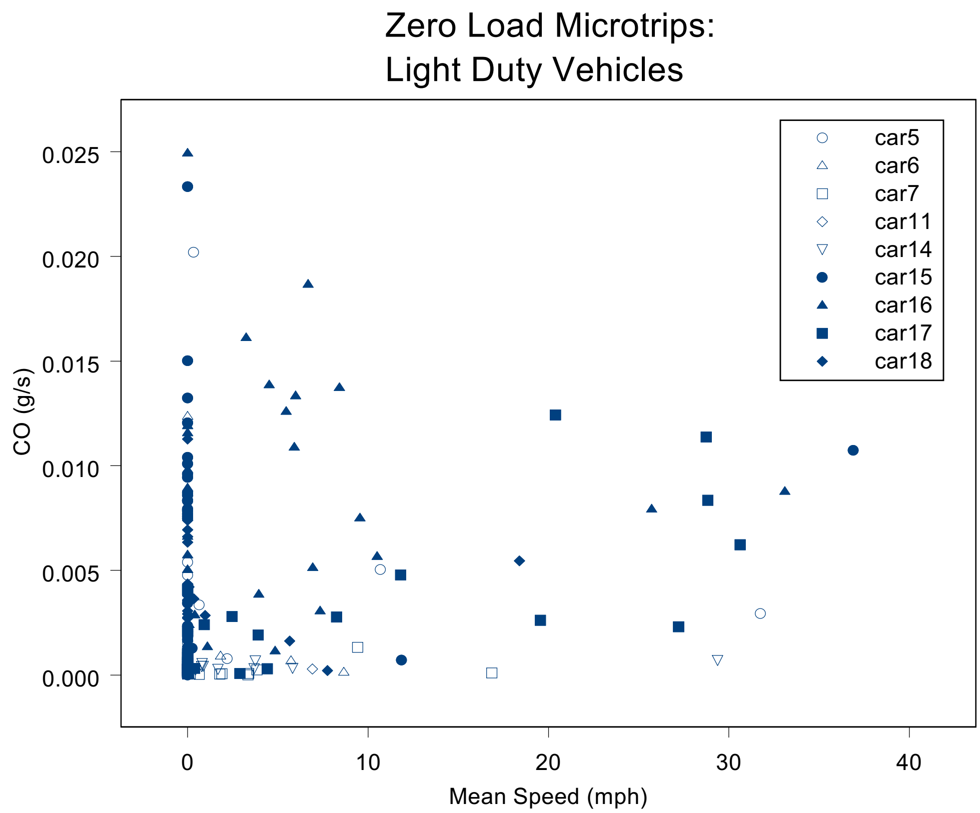
Zero Load Microtrips:
Light Duty Vehicles
CO (g/s)
0.025
0.020
0.015
0.010
0.005
0.000
0
10
20
30
40
Mean Speed (mph)
car5
car6
car7
car11
car14
car15
car16
car17
car18

Figure 2.

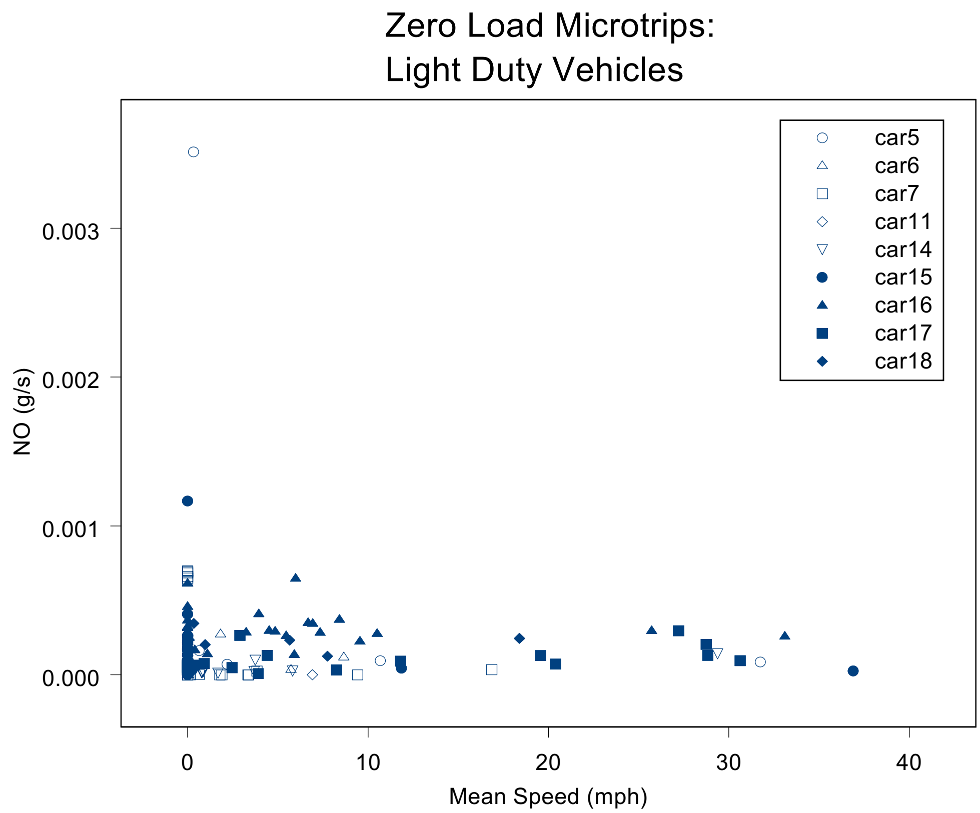
Zero Load Microtrips:
Light Duty Vehicles
NO (g/s)
0.000
0.001
0.002
0.003
0
10
20
30
40
Mean Speed (mph)
car5
car6
car7
car11
car14
car15
car16
car17
car18

Figure 3.