Driving Pattern Variability and Impacts on Vehicle Carbon Monoxide Emissions

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An analysis of instrumented vehicle data revealed significant differences in operating mode profiles for vehicle operations in Atlanta, Georgia; Baltimore, Maryland; and Spokane, Washington. Differences in such operating mode characteristics as acceleration rates and cruise speed distributions are important in the development of new emissions models because certain vehicle and engine operating modes are proving to be significant sources of elevated emissions rates. Although not conclusive, these data indicate that the variations in operating mode fractions across cities may be related to differences in road network characteristics. A simple predictive model, based on three operating parameters (vehicle speed, engine speed, and manifold absolute pressure) was developed from data collected from eight instrumented General Motors 3.1-L vehicles and is capable of predicting elevated carbon monoxide (CO) emission rates for various vehicle and engine activities. These emission results do not apply to hydrocarbons (HC) or oxides of nitrogen (NO_x), which behave differently. The modeling technique discussed has been developed exclusively for CO. The model is used to estimate the relative CO emission differences associated with the differences in operating profiles noted from city to city (and potentially from driver to driver). This modeling approach appears capable of adequately distinguishing the CO emission effects associated with variations in engine and vehicle operations for individual vehicle makes and models. However, it should be noted that the large variability in vehicle-to-vehicle CO emission response to changes in operating modes that has been noted in ongoing studies indicates that a model based on vehicle speed and acceleration profiles alone may not provide sufficient CO emission rate predictive capabilities for the fleet.

Mobile emissions are known to be a significant source of air pollution in U.S. cities, typically accounting for more than 50 percent of the ground-level ozone and 70 to 90 percent of the carbon monoxide (CO) (*1*). It is because of this role in air pollution that federal legislation has focused on stringent motor vehicle emission standards and to a limited extent on the implementation of transportation control measures (TCMs) to control the levels of pollutants that originate from mobile sources. With over 100 metropolitan areas in violation of ozone standards and 60 in violation of CO standards (*1*), there is a significant challenge facing the United States in attaining and maintaining ambient air quality standards.

Of great importance in meeting this challenge is the development and validation of a model that can accurately estimate changes in pollutant emission rates associated with changes in transportation network, vehicle, and driver characteristics. Although existing emissions models have been in use for many years (with improvements made in each new generation of model release), these models still have serious deficiencies (*2,3*) that prevent their use in accurately assessing emission rates at the corridor level (i.e., for transportation system links). Ongoing research continues to add to an understanding of the basic phenomena associated with emissions occurring from components of the vehicle fleet. For example, several remote sensing studies have shown that a small proportion of the fleet, known as "super-emitters," may be responsible for a large proportion of the excess emissions (*4,5*). The public perception is that these super-emitters are either poorly maintained or very old vehicles. However, recent studies have shown that new, properly maintained vehicles can become high emitters under certain operating conditions, such as high load conditions (*6,7,8*). Hence, a small fraction of each vehicle's activity may be responsible for super-emissions, or a large fraction of that vehicle's daily emissions (*9*). New models must be capable of addressing the effects of both the presence of super-emitters in the fleet and the occurrence of super-emissions events associated with various vehicle operating modes.

Inherent in all the existing emissions models, and in most of the new models being developed, is the assumption that there is an average driver, or at least that the variations in driver to driver behavior is insignificant in the production of emissions from the vehicle. Average values for vehicle miles traveled and speed are used, resulting in the loss of variation inherent from vehicle to vehicle and driver to driver. Much of the research related to developing new test driver cycles (which may replace or supplement the federal test procedure cycle) for emission rates assumes typical driving in urban areas (*10*). However, if the engine mode of operation is going to become an important element of new models, there is clearly a need to better understand how driver behavior can affect the frequency of these modes. For example, given the same vehicle, are older drivers likely to drive more conservatively than younger drivers, entering into engine enrichment modes less often? Is there evidence to suggest that driving patterns are indeed different from one city to another?

This paper examines instrumented vehicle data sets from Baltimore, Maryland; Spokane, Washington; and Atlanta, Georgia, to assess first the variation in driver behavior from one city to another and to assess the potential impact this variation might have on CO emissions estimation. After the sources and limitations of the data used in this study are laid out, this paper examines the differences in the frequency of activity that leads to high CO emissions among the three urban areas. Then, two methods for estimating CO emissions as a function of vehicle and engine operating modes are presented and used to assess the potential impacts that different driving patterns may have on CO emissions estimation.

INSTRUMENTED VEHICLE DATA

A 1992 study in Spokane, Washington; Baltimore, Maryland; and Atlanta, Georgia; instrumented approximately 350 vehicles with a

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device that recorded data for three parameters: vehicle speed in meters per second, engine speed in revolutions per minute (RPM), and manifold absolute pressure (MAP) in kilopascals (kPa). The three-parameter data set yielded 213 vehicles for which valid data were recorded on all channels. In Baltimore and Spokane, a six-parameter data base contained data from 79 vehicles for the following measures: vehicle speed in meters per second, engine speed in RPM, throttle position in percentages, and one of three measures of air flow, engine coolant temperature, and the output of a wide-range oxygen sensor that monitored exhaust gas composition (i.e., air-to-fuel ratio). The six-parameter data set yielded 46 vehicles with valid data on all channels. Both studies recorded each parameter once per second, and each device continuously recorded the date and time of operation.

Each resulting data set was subject to strict quality control procedures. More than 15 error-detection measures were used to track the wide variety of anomalous conditions that could be part of any given data set. Many of the problems detected were transient and were corrected by substituting the erroneous value with an interpolated value. Only the vehicle records containing valid data on all recorded channels for the entire study period were used in this analysis.

To avoid the emissions modeling problems associated with elevated emissions rates during vehicle warm-up (*2*), the research team used data collected only from hot stabilized engines. Engines were assumed to have achieved hot stabilized combustion, and catalytic converters were assumed to have reached light-off temperatures by the time the engine temperature reached 70°C. Thus, the six-parameter data used in developing emission rate models excluded all data from operations when the engine coolant temperatures were lower than 70°C.

Each vehicle recorded data for approximately 1 week before the instruments were removed. In the three-parameter data set used in this study, Atlanta drivers recorded over 3.0 million sec of operation from 76 vehicles, Baltimore drivers recorded 2.5 million sec of operation from 68 vehicles, and Spokane drivers recorded 1.9 million sec of operation from 69 vehicles. The six-parameter data used in this study recorded 1.6 million sec of operation from 46 vehicles.

Driver Selection

Baltimore and Spokane drivers were solicited at centralized emissions inspection centers, with vehicles instrumented at the time of solicitation (*11*). Atlanta has no centralized emission inspection. Drivers were solicited at three driver's license stations; their vehicles were instrumented later at remote sites.

Data Limitations

The six-parameter data base was limited. The sample size was small and appears biased in important respects. For example

- Only fairly new vehicles (i.e., model years between 1989 and 1991) were instrumented,
- A limited number of engine types and sizes were included,
- Young drivers are poorly represented (only 1 of the 46 drivers was under the age of 25,
- Manual transmission vehicles were underrepresented, and
- High-performance vehicles were not included in the sample.

For the three-parameter data sets in all three cities, efforts were made to select a representative sample of drivers and vehicle types from the target population. For example, the three-parameter data set was not restricted to the type or age of vehicle instrumented. Potential driver bias has not yet been examined in the three-parameter data set. However, based on the preliminary analysis of the Atlanta data set, the three-parameter data set appears less likely to be biased than the six-parameter data set.

Both data sets are somewhat limited in their usefulness because geographic positioning data or accelerometer data were not collected for use in evaluating the impacts of grade on speed, acceleration, and throttle position. Furthermore, without positional information, the data could not be directly associated with the roadway classification upon which the vehicle was operating. Hence, if the noted speed was 56 km/hr (35 mph), it was not possible to determine directly whether the activity occurred on a congested freeway or a free-flowing arterial.

Despite the potential biases and shortcomings in the data sets, the six-parameter and three-parameter data sets from these three cities still represent a rich source of information on vehicle activity. The data serve as an excellent point of departure for preliminary discussions of the potential impacts of variations in driving patterns.

DATA ANALYSIS

Vehicle speed distributions for the three-parameter data set for each city are shown in Figure 1 and indicate the proportion of total driving time spent in each specific speed range. For example, approximately 15 percent of the total driving time in Spokane occurred in the 48 to 56 km/hr (30 to 35 mph) speed range, compared with only 8 and 6 percent in Baltimore and Atlanta, respectively. If it is assumed that the speed range from 25 to 40 mph (40 to 64 km/hr) represents driving that would occur primarily on arterial highways or congested freeways, Spokane has the highest percentage of such activity in the three cities studied. In addition, Spokane has the lowest percentage of activity above 60 mph. Atlanta drivers tended to drive much faster than their counterparts in the other two cities.

If drivers in the different cities operated on uncongested freeways, the shape of the high end of the speed distributions should be the same. Because they are different, it may be because (a) the drivers in the different cities do not drive on uncongested freeways, which means that they do not have freeways, they do not drive on their freeways, or that their freeways are not uncongested, or (b) the drivers in the different cities are driving differently on uncongested freeways, which means that the freeways may be physically different, causing different responses, or that the freeways are physically similar but that there is a behavior difference between drivers in various cities. Unfortunately, with the data collected, the reason cannot be determined.

If it is assumed that the largest fraction of vehicle activity occurs on arterial highways, this activity occurs in Spokane and Baltimore in the 40 to 64 km/hr (25 to 40 mph) speed range. In Atlanta, this fraction of activity occurs in the 56 to 80 km/hr (35 to 50 mph) speed range. In addition, there appears to be a less distinctive break between the arterial highway activity fraction and the freeway fraction in Atlanta. However, depending on congestion conditions, some of the data from congested freeways may overlap data from arterial operations.

These results are perhaps not surprising given the different terrain and road network characteristics of the three cities. Although

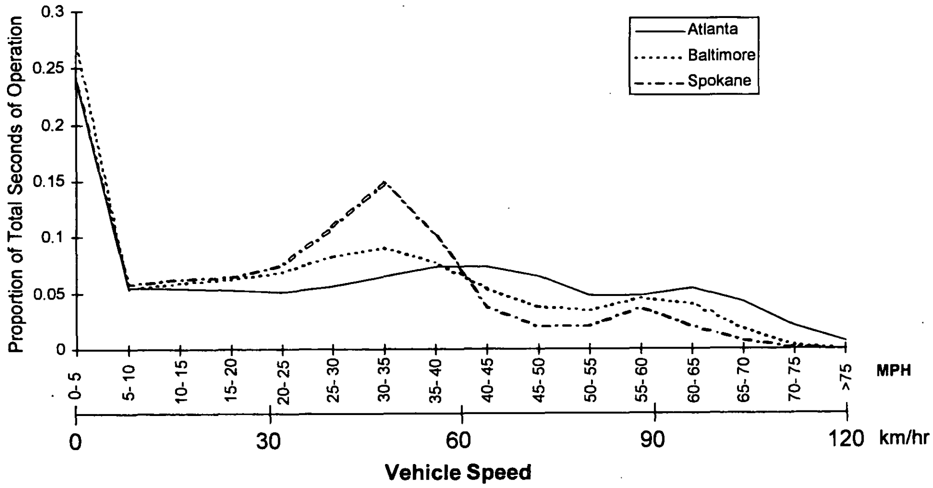

FIGURE 1 Vehicle speed distributions for three-parameter data sets. (Bin marked "5–10" refers to speeds ≥ 5 mph and < 10 mph.)

the Spokane metropolitan area includes an Interstate highway, the Interstate serves primarily as a bypass link and does not serve as a major transportation link for trips internal to Spokane. Baltimore is a more densely developed, older city than Atlanta and Spokane, with a freeway system that is more expansive than Spokane's but not as large as Atlanta's. The freeway system in Baltimore is augmented with a highly developed set of arterial highways that have traditionally served many of the internal Baltimore trips. Atlanta, on the other hand, has a newly expanded freeway system that many drivers use as the major means of reaching destinations in the Atlanta area. The freeway system is accessed by a large network of major arterial roads, many with high levels of capacity that experience high-speed activity.

Although the reasons for the noted differences are as yet unclear, the data in Figure 1 clearly indicate that there are substantial differences in vehicle speeds from one city to another. These differences are statistically significant and were substantiated through discriminant analysis, where a set of functions is derived that minimizes the variance within a group and maximizes the variance between groups (*12*). The discriminant analysis results are contained in Table 1. In this case, two functions were needed to classify each driver into the three groups. The proportion of total driving time in each of 16 speed bins for each driver was used to predict in which city the driver operated the vehicle.

If the speed profiles contained little information about the city in which a driver operated, a discriminant analysis would misclassify most of the drivers, with a success rate approaching that of chance assignment. In this case, the speed profiles worked well in determining in which city the driver operated, with a success rate of 79 percent. Atlanta drivers were most frequently correctly grouped, indicating that Atlanta drivers' speed profiles are more distinctive than those for Baltimore or Spokane. Also, no Atlanta driver was misclassified as Spokane drivers were. There is also some overlap between the driving patterns found in Baltimore and the other two cities.

TABLE 1 Results of Discriminant Analysis Based on Speed Profiles

Actual Group		Predicted Group Membership		
City	Cases	Baltimore	Atlanta	Spokane
Baltimore	68	51	10	7
		75.0%	14.7%	10.3%
Atlanta	76	13	63	0
		17.1%	82.9%	0.0%
Spokane	69	13	2	54
		18.8%	2.9%	78.3%

However, Figure 1 does not allow for observations about the style or aggressiveness of driver behavior (which could also be related to the characteristics of the road network). For the purposes of this paper, aggressive is defined to indicate higher acceleration rates. If each data set was segregated into subsets by driver according to the proportion of driving in arterial or highway modes, previous research indicates that the acceleration distributions would not be distinctly different for these subsets (*13*). That is, drivers who spend most of their driving time at freeway speeds are not more likely to drive more aggressively in any speed range than the drivers who spend most of their driving time at arterial speeds. However, one possible measure of driver aggressiveness is the distribution of acceleration across all speed ranges.

To examine the potential differences in acceleration profiles across cities, the standard deviation of the acceleration and deceleration values was calculated for 8 km/hr (5 mph) bins for each of the cities (Figure 2). A larger standard deviation implies a larger number of vehicles with greater acceleration or deceleration values, or both, in that speed group, a phenomenon of great interest in estimating emissions related to engine load or power enrichment. By this measure, Atlanta drivers were more aggressive in most speed ranges.

The acceleration profiles were also examined by using discriminant analysis, and the results are better than those obtained using only the speed profiles. The analysis grouped the drivers into their correct cities 85 percent of the time, with Atlanta drivers grouped properly 88 percent of the time.

The results of the discriminant analysis clearly show that the driving patterns are significantly different across the three cities. It may be that particular transportation network characteristics are the most important parameter. For example, higher levels of acceleration changes could be explained by a larger number of opportuni-

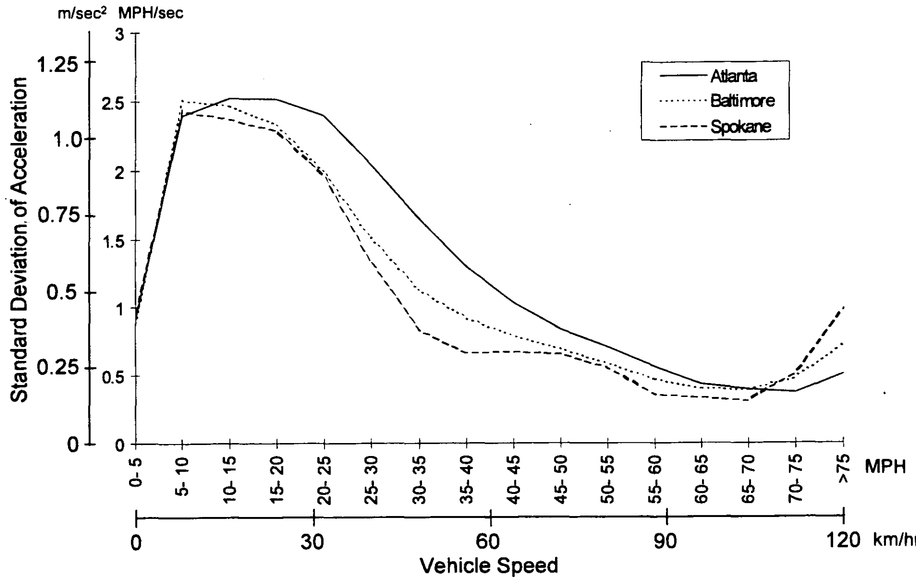

FIGURE 2 Standard deviation of acceleration distributions for three-parameter data sets. (Bin marked "5–10" refers to speeds ≥ 5 mph and < 10 mph.)

ties in a road network to accelerate or decelerate (e.g., stop signs or traffic signals). This could certainly be one explanation for the differences in the lower speed ranges (such traffic controls are not found on freeways). The greatest differences in acceleration standard deviations between Atlanta and the other two cities occur in the 24 to 72 km/hr (15 to 45 mph) speed ranges. This suggests that the greatest variation in acceleration behavior may occur on arterial highways (or congested freeways). One possible contributing factor is that the Atlanta arterial road network covers a much larger geographic area than that of the other two cities, often providing drivers with greater distances before signal interruptions. This may not only allow greater speeds but also account in part for the distinct differences in acceleration activity. Perhaps the transportation system characteristics have conditioned drivers to drive in the manner noted for each city. That is, drivers may simply respond to various infrastructure characteristics, such as lane width or presence of highway barriers, in terms of speed and acceleration profiles.

However, demographic differences or vehicle sample could also account for some of these characteristics. It may be that driver characteristics are responsible for the differences noted across the cities. Perhaps the age distribution or previous driving experiences play a role in modal profiles. Perhaps the vehicles themselves are an important explanatory variable or an interaction term with driver characteristics. It may even be that local law enforcement habits play a role in these differences. There are no clear reasons why such differences in vehicle activity occurred. But the Georgia Institute of Technology has undertaken additional studies to explain these differences. In future studies, vehicle characteristics, driver characteristics, and infrastructure characteristics will be controlled during data collection so that statistical analyses are more likely to reveal the factors that appear to affect these activity differences (*14*).

In summary, an examination of instrumented vehicle data sets from three U.S. cities indicated that there are significant differences among the cities in vehicle activity profiles. These differences may be caused by the characteristics of the road networks or the driving styles found in separate regions of the United States. The importance of this finding is that it suggests the existence of potentially substantial differences across cities in mobile emissions estimates, depending on the relative contribution of modal emissions to the overall emissions inventory. To examine the potential impacts of these activity differences, two simple predictive models for CO emissions, derived as functions of vehicle and engine parameters, were developed from the data collected during the six-parameter study. These models were then used to examine the relative CO emissions from the cities, given the different speed-acceleration distributions found in each city.

POTENTIAL EMISSIONS IMPACT OF DRIVER BEHAVIOR VARIABILITY

CO emissions can be estimated from variables contained in the six-parameter data set. By coupling the wide-range oxygen sensor (which detects the exhaust air-to-fuel ratio) reading with mass air flow and assumed catalytic converter efficiency, the CO emissions rate can be estimated. The development of this method was covered extensively in a previous work (*15*) and is not repeated here.

Using the methodology developed previously (*15*), two alternative engine-specific models were developed from the largest subset of the six-parameter data available, eight General Motors vehicles with 3.1-L engines that were equipped with MAP sensors. The eight vehicles in this subset made 350 trips, and emissions were modeled on a per-trip basis. Two different models were considered: a speed-acceleration model and a speed-MAP-RPM model. These parameters were chosen because the three-parameter data included these variables. These models could likely be improved if throttle position were also used as a predictive variable, because many engine control units base commanded enrichment logic on throttle position (as well as other factors not included in the model) and because throttle position is controlled directly by the driver.

The speed-acceleration model initially considered six zones of operation (Figure 3). The characteristics of the zones are

1. Speed and acceleration combinations within the bounds of the FTP test,
2. Speeds less than the maximum FTP speed of 92 km/hr (57 mph) and acceleration rates higher than the FTP maximum for any given speed,
3. Speeds less than the maximum FTP speed and deceleration rates higher than the FTP maximum for any given speed,
4. Speeds greater than the maximum FTP speed and acceleration rates greater than 0.45 m/sec^2 (1 mph/sec),
5. Speeds greater than the maximum FTP speed, acceleration rates less than 0.45 m/sec^2 (1 mph/sec), and deceleration rates less than 0.45 m/sec^2 (1 mph/sec),
6. Speeds greater than the maximum FTP speed of 92 km/hr (57 mph) and deceleration rates greater than 0.45 m/sec^2 (1 mph/sec).

Of these six zones, the two deceleration zones (Zones 3 and 6) were not found to be statistically significant. Zones 3 and 6 were merged with the FTP zone. The functional form of the regression equation is

$$\text{CO(g/sec)} = 0.050514 + 0.094067 * (\text{HI\_SPEED}) + 0.642077 * (\text{LO\_ACCEL}) + 0.823341 * (\text{HI\_ACCEL})$$

where

HI_SPEED = the proportion of each trip with speeds greater than 92 km/hr (57 mph) and acceleration rates less than 0.45 m/sec^2 (1 mph/sec) (Zone 5),
LO_ACCEL = the proportion of each trip with speeds less than 92 km/hr (57 mph) and accelerations greater than those found on the FTP (Zone 2), and
HI_ACCEL = the proportion of each trip with speeds greater 92 km/hr (57 mph) and accelerations greater than 0.45 m/sec^2 (1 mph/sec) (Zone 4).

The R^2 for this model is fairly poor at 0.29, with an F-statistic of 46.9 and a standard error of 0.035 g/sec.

The speed-MAP-RPM model is based on the concept that engine parameters govern commanded enrichment and will better predict modal emissions for a single engine type. When the CO emissions rate is plotted across MAP and RPM, four zones were defined to account for different engine modes. These four zones were defined arbitrarily as operations with

- MAP $\leq$ 70 kPa and RPM $\leq$ 3,500, corresponding to normal driving;
- MAP > 70 kPa and RPM $\leq$ 3,500, corresponding to high-load conditions, such as climbing a steep hill;
- MAP $\leq$ 70 kPa and RPM > 3,500, corresponding to a high-RPM, low-load condition, which rarely occurs; and
- MAP > 70 kPa and RPM > 3,500, corresponding to high-load conditions that are often associated with both commanded enrichment and high-mass air flows.

Each of these four zones was then examined for variance with respect to vehicle speed. With the exception of the rare high-RPM, low-load condition, the CO emission rates in each zone varied similarly with speed. Each zone showed the lowest emission rates when speed was less than 16 km/hr (10 mph). Emission rates then became speed-invariant to approximately 113 km/hr (70 mph). In light of this, each of the four engine zones was divided into three speed zones: less than 16 km/hr (10 mph), between 16 and 113 km/hr (10 and 70 mph), and greater than 113 km/hr (70 mph).

This model required fine tuning as well. The high-RPM, low-load zone had very little data and did not exhibit a clear relationship with vehicle speed; thus, the three zones were merged into a single zone. The high-load, zone with RPM less than 3,500 had insufficient data to support separate groups for moderate and high speeds, and these two zones were merged as well. No data points included activity at speeds less than 10 mph and with both high MAP and RPM.

The resulting regression equation displayed much better results than the model based only on speed and acceleration with an R^2 value of 0.56, an F-statistic of 62.8, and a standard error of 0.029 g/sec.

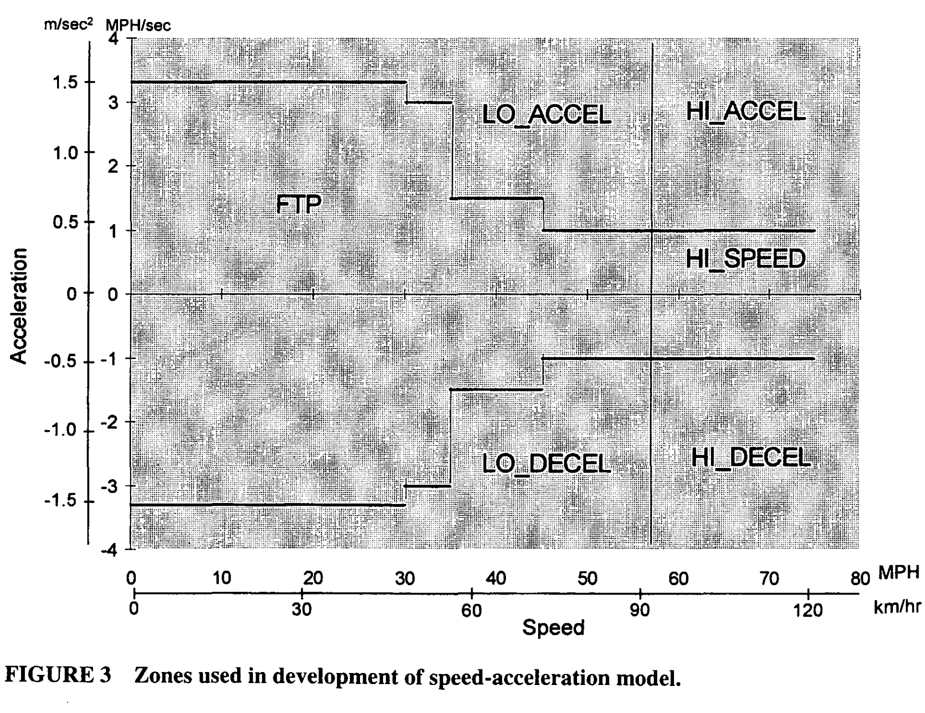

FIGURE 3 Zones used in development of speed-acceleration model.

The engine-based model clearly explains more of the variation in the CO emission rates of vehicles equipped with 3.1-L engines than does the speed-acceleration model. This is because the engine control unit (on-board computer) commands enrichment based largely on monitored engine parameters. A given speed-acceleration combination does not directly determine these engine parameters. (Note, however, that the linear acceleration variable, change in speed per change in time, used in the model did not include acceleration due to grade.)

Throttle position is another potentially significant variable because it is monitored by the on-board computer system and appears to be used by many vehicles in commanded enrichment algorithms. Preliminary analyses indicate that emission rate variation for specific vehicle makes and models can be comparably explained by a model based solely on RPM and throttle position. Because throttle position appears to be only partially correlated with engine load expressed as MAP (a Pierson correlation coefficient of roughly 0.75 for the six-parameter data examined), variation in throttle position may be in part due to the individual differences in how the driver uses the throttle to interface with the engine.

It is important to keep in mind, however, that other studies have indicated that the vehicle-to-vehicle variations in emissions response to various operating modes and loads (i.e., modes that may cause commanded enrichment) appear to be large (*9*). Hence, an engine-parameter model developed from single or limited engine types may be inappropriate when applied to other vehicles.

The speed-acceleration and speed-MAP-RPM models were then re-derived using the entire six-parameter data set. The three-parameter data set was not used because engine sizes were not recorded. In the case of the Spokane and Baltimore data, even the vehicle type was unknown. It is theoretically possible to derive engine size data from the vehicle identification number, but this was not attempted. In future analyses, it would be ideal to use some measure of differences among vehicles, particularly engine size, when extending this type of model. As expected, the models did not perform as well when they were derived from data collected for several vehicles with different engine types and control strategies taken together. In the case of the speed-acceleration model, the R^2 dropped from 0.29 to 0.17, with the standard error rising from 0.035 to 0.056 g/sec. The speed-MAP-RPM model did not suffer as severe a degradation, with the R^2 dropping from 0.56 to 0.37, which is a better fit than the speed-acceleration model was able to manage over a single vehicle type. However, the standard error is also fairly high at 0.050 g/sec. The proportion of each trip spent at low speeds and normal engine operation was taken as the regression constant because this region would usually correspond to idle and was found to be statistically insignificant. The regression equation, where the value of each variable is the proportion of each trip that fell into a given zone is

$$
\begin{aligned}
\mathrm{CO(g/sec)} = {} & 0.029854 + 0.034631(\mathrm{NOR\_MED}) \\
& + 0.196595(\mathrm{NOR\_HI}) \\
& + 1.304044(\mathrm{HI\_RPM}) \\
& + 0.029155(\mathrm{HI\_MAP\_LO}) \\
& + 0.273061(\mathrm{HI\_MAP\_MEDHI}) \\
& + 3.228802(\mathrm{HI\_LOAD\_LOMED}) \\
& + 22.74787(\mathrm{HI\_LOAD\_HI})
\end{aligned}
$$

where

NOR_MED = activity at speeds between 16 and 113 km/hr (10 and 70 mph) and normal engine parameters;
NOR_HI = normal engine parameters where speed > 113 km/hr (70 mph);
HI_RPM = all activity at high RPM and MAP < 70 kPa;
HI_MAP = activity at high MAP, but RPM < 3,500, with the speed divisions as above; and
HI_LOAD = activity where MAP and RPM are both high.

The smaller degradation of the engine model may be because any engine is likely to be in enrichment at high MAP and RPM, and to some degree at high MAP independent of RPM. However, the frequency of high-load activity for any vehicle will vary as a function of engine size and vehicle weight (i.e., load is associated with the power-to-weight ratio). Engine size appears from other studies to be an important causal variable (*9*), and engine size and vehicle weight were not used as explanatory variables in the derived models. That these variables are not included is a limitation in the derivation and application of these two models. Note, however, that engine size may not be a sufficient discriminant variable—the GM 3.1-L vehicles equipped with MAP sensors behaved differently from the GM 3.1-L engines equipped with LV8 sensors, and there were significant differences between these and the 3.0-L Ford.

It is important to note that the estimate of the CO emissions rate does not include measure of startup or cold-operation emissions because these data were not used in the analyses. In addition, as noted earlier, the six-parameter data base is limited to only a few engine types of a limited manufacture date range. Large engines, sports cars, manual transmissions, and young drivers are all underrepresented in this data set. Any values obtained by extrapolation to the three-parameter data should not be considered an accurate estimate of overall CO emissions for a particular vehicle, only as a preliminary indication of emission rate differences associated with differences in vehicle activities. A much larger study would be necessary to obtain enough data to accurately predict the emissions rates for the general population. Applying the models developed using the six-parameter data to the three-parameter data sets is not ideal. The application was intended to explore only the capability of the three-parameter data to distinguish among different driving patterns and to see whether the differences in speed and acceleration behavior have a possible impact on emissions. As such, these models are taken as a common metric that should be used for comparative purposes only.

These models based on the six-parameter data produce interesting results when applied on a trip-by-trip basis to the three-parameter data sets. There were 4,354 trips recorded in Atlanta, 3,701 trips in Spokane, and 3,641 trips in Baltimore. The speed-acceleration model tended to predict a much smaller variability than the speed-MAP-RPM model (Figure 4). The speed-acceleration model yielded a median CO emissions rate (on a per-trip basis) of 0.078 g/sec for Atlanta drivers, 0.067 g/sec for Baltimore drivers, and 0.064 g/sec for Spokane drivers. The speed-MAP-RPM model yielded a median CO emissions rate of 0.102 g/sec for Atlanta drivers, 0.087 g/sec for Baltimore drivers, and 0.079 g/sec for Spokane drivers (Figure 5). These results are not surprising when compared with the overall behavior patterns found using speed and acceleration profiles. (Spokane drivers exhibited the lowest average speeds and the lowest acceleration rates, the Baltimore drivers were in the middle, and the Atlanta drivers exhibited the highest speeds and acceleration rates.) This trend is replicated in the results of these two models. Interestingly, the speed-acceleration model shows little difference between the median emissions rates of Spokane and Baltimore drivers, in contrast with the results of the speed-MAP-RPM

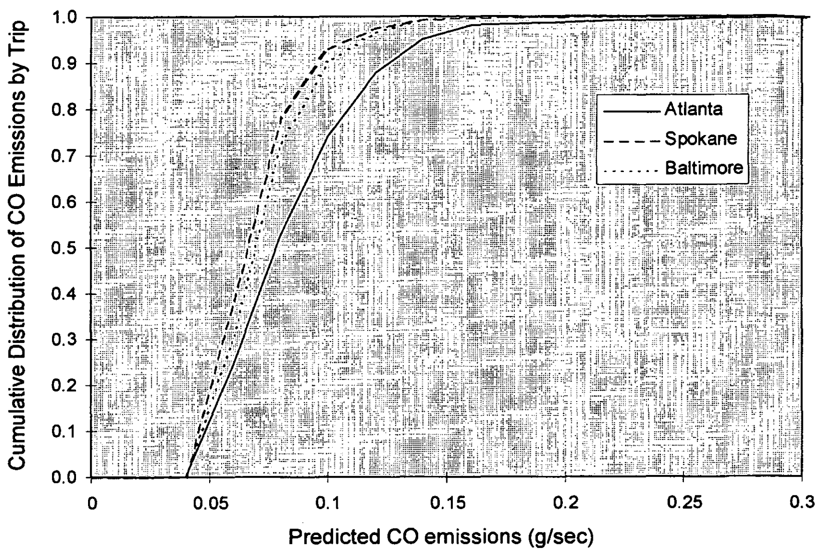

FIGURE 4 Cumulative distribution of predicted CO emissions by trip for speed-acceleration model.

model, which predicts larger differences between median emission rates in these cities.

At this time, it is unclear whether the relatively poor performance of the speed-acceleration model is due to inherent flaws in attempting to model emissions based solely on speed and acceleration, lack of control over the grade variable, or inadequate model specification (i.e., only four activity zones were used in this model), or whether poor performance is an artifact of the potential biases within this particular data set. Nevertheless, this initial work indicates that the speed-MAP-RPM model may provide greater sensitivity to changes in driving patterns.

One factor that has not yet been discussed is long-term modeling implications of speed-acceleration models versus speed-MAP-RPM models. When a CO emission rate model is developed, the challenge that remains is to quantify the activity that must be used in the modeling process. That is, if a speed-acceleration model is used, the vehicle activity on a transportation link must be quantified in terms of speed and acceleration profiles. If a speed-MAP-RPM model is used, the vehicle activity on a transportation link must be quantified in terms of speed, MAP, and RPM profile. This is clearly not a simple modeling issue. Whereas the identification of speed and acceleration profiles is fairly straightforward and likely to be independent of the vehicle subfleet characteristics operating on the link, the RPM and MAP profiles are totally dependent on the characteristics of that vehicle subfleet. Hence, the potentially higher explanatory power of engine-based models may be compromised if

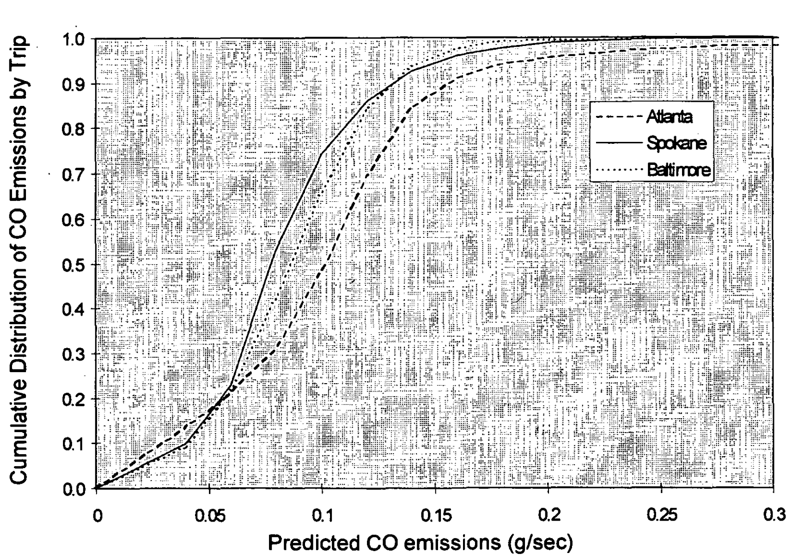

FIGURE 5 Cumulative distribution of predicted CO emissions by trip for speed-MAP-RPM model.

highly uncertain vehicle MAP and RPM distributions are linked with the emission rates. Clearly, in constructing long-term emissions models, a difficult balance must be reached.

CONCLUSIONS

Mobile source emissions are dependent on vehicle type, vehicle activity, and possibly transportation network or driver characteristics, or both. Important and statistically significant differences in vehicle activity profiles have been found among the three cities studied. It is unclear from this data set whether network characteristics explain these differences completely or whether other characteristics of these cities also play a role. A study looking for differences and similarities between drivers in cities with similar transportation networks would be necessary to test this hypothesis.

The differences noted in vehicle activity profiles suggest that emissions models must adequately incorporate these variations into the modeling regime if they are to be applied across a variety of metropolitan areas. An emissions model using engine operating parameters could provide a basis for newer, state-of-the-art transportation models where fleets of vehicles are modeled based on the characteristics of driving conditions and engine modal operations. These models can account for differences in driving habits and possibly point out locations on the transportation network (such as on-ramps) where high-emissions driving would occur. However, such an application requires accurate vehicle and engine operating profiles to be developed for the vehicle fleet for the emission rate algorithms to be applied. Note that these results should not be extrapolated to HC or NO_x.

A model that uses only the speed and acceleration distributions for a given roadway segment can be developed and applied. However, this approach initially appears to be much less sophisticated than the engine-based approach. It should be noted, however, that the model tested in this research used linear acceleration and did not account for grade effects. Once grade effects are included in net acceleration, the speed-acceleration model may provide significantly improved explanatory power. Also, the effects of grade may be more significant at higher speeds than at lower speeds. In addition, the speed-acceleration model developed used only four activity zones, and improvements in explanatory power may result from a more refined model. Although a model based only on speed and acceleration may not perform as well as an engine parameter model, the activity data are likely to be more easily and accurately measured and modeled. Hence, the approach may simply be more practical than an engine model.

Perhaps most important, this paper highlights the need for further research on variation in driving behavior. As emissions modeling research continues to develop new approaches on emissions prediction based on engine modal operation, the transportation community needs to know more about the characteristics of drivers that would cause these vehicle-and engine-operating distributions to occur. Driving patterns vary from one city to the next; hence, it is not enough to collect statistically valid vehicle data within a single city. At the very least, this would suggest that an important input variable for emissions models may be a driving behavior factor that represents the driving style and trip cycles found in that particular city, perhaps as a function of infrastructure, fleet characteristic, and demographics. Additional research is necessary to define better the different characteristics of this driving factor.

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