Forecasting Dynamic Passenger Car Activity at Signalized Intersections for Enhanced Mobile Source Emission Modeling

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ABSTRACT
Current research suggests that vehicle emission rates are highly correlated with modal vehicle activity and that specific instances of load-induced enrichment may contribute a disproportionate share of motor vehicle emissions. Consequently, researchers have been developing a variety of modal modeling approaches to transportation-related air quality modeling. Modal models predict emissions as a function of specific operating modes or engine load surrogates that represent the on-road operating conditions leading to high instantaneous emissions rates, such as hard accelerations and decelerations. Such models should be much more accurate in making realistic estimates of mobile source contribution to local and regional air quality. These new models typically require that vehicle activity be input by fraction of time spent in these different operating modes. However, the ability to realistically model microscopic on-road modal vehicle activity currently limits the implementation of these models.

To provide better estimates of microscopic vehicle activity, field studies using laser rangefinding devices were undertaken to quantify actual driving patterns along signalized arterials and at signal-controlled intersections in Atlanta, Georgia. Data were analyzed to determine the fractions of vehicle activity spent in different operating modes, especially those likely to lead to high engine load and elevated emissions. Using binary recursive partitioning tree-based regression methods, analyses indicated that roadway grade, vehicle queue position, traffic volume, and distance to the downstream intersection are the most critical variables in influencing the modal activity. A significant amount of on-road activity was also found to be outside of the range of activity represented in the Federal Test Procedure. Statistical analysis of the data yielded a model for predicting link-based microscopic vehicle activity summaries based on geometric and operational characteristics of the roadway. Research results will provide the ability to estimate microscopic vehicle activity as input to both local and regional transportation-related air quality models. Findings may also enhance current methods for estimating capacity and modeling traffic flow and may have applications for intelligent transportation systems.

Keywords: Modal emissions, air quality, transportation, vehicle activity
INTRODUCTION
Because transportation sources typically contribute more than 50% of ozone precursor emissions in major urban areas, mobile source emissions modeling in an integral part of state and local air quality analysis. These agencies depend on results from motor vehicle emissions models to demonstrate progress towards conformity and to gauge the air quality impact of new transportation projects. The fate of future transportation projects and an area’s ability to demonstrate conformity may hinge on model estimates. Consequently, the ability of models to accurately predict transportation-related emissions is critical.

For at least ten years, technical, scientific, and regulatory communities have expressed concerns about the current certification cycle for automotive emissions being representative of actual driving behavior (1). Discrepancies between existing transportation air quality models and actual emissions have been identified by researchers and are related to the data input, modeling, and output of traditional mobile source air quality models (2; 3; 4; 5). Specifically, the traditional approach linking emission rates to average speeds has been challenged by current research, which suggests that vehicle emission rates correlate to specific engine operating mode. In particular, activity such as hard accelerations, high speeds, and operations on steep grades, increase engine loads leading to optimum conditions for enrichment of the air and fuel mixture. Enrichment results in significantly elevated motor vehicle emission rates compared to stable engine operation (6; 7; 8; 9; 10; 11). Rapid load reduction events, such as hard deceleration or long deceleration events, can also lead to elevated emission rates (12).

Currently, various research groups, both nationally and internationally, are working on various facets of modal modeling (13; 14; 15; 16; 17; 18; 19; 20; 21; 22; 23). To implement effective modal modeling, accurate vehicle activity profiles (by appropriate emission-related technology group) and corresponding activity-specific emission rates are required. Consequently research efforts have typically concentrated on one of these two areas.

Improved Motor Vehicle Emission Rates
To improve emission rate estimates, various research efforts have focused on developing methods to relate emission output to specific vehicle activity such as a vehicle's instantaneous velocity and corresponding acceleration. Post et al. (24) tested 177 Australian light duty vehicles on a dynamometer and created matrices correlating carbon monoxide (CO), carbon dioxide (CO₂), oxides of nitrogen (NOₓ), and hydrocarbon (HC) rates with instantaneous velocity and acceleration. An et al. (14) are in the process of ongoing development of a comprehensive modal emissions model capable of predicting emissions for a wide variety of light-duty cars and trucks based on engine operating mode. At the highest resolution, the model will predict second by second vehicle trajectories (location, speed, acceleration). Approximately 320 in-use vehicles were recruited and tested on a dynamometer over three different load-inducing driving cycles. For each cycle, second-by-second emissions for CO₂, CO, NOₓ, and HC emissions were collected and analyzed for different driving conditions. Ultimately, the model will be able to predict emissions for a variety of light duty vehicles (LDVs) in different
maintenance states (properly functioning, deteriorated, malfunctioning, etc.). The model will predict emissions and fuel consumption second by second (15).

Remote sensing technology was employed in a different research effort. The technology, SMOG DOG, was used on-road to simultaneously measure emission concentrations for CO, HC, NO\textsubscript{x} and CO\textsubscript{2} in the dispersing exhaust cloud of vehicles. Instantaneous speed and acceleration of the vehicle was also collected. Analysis of the data derived a relationship between pollutant concentrations and a vehicle’s instantaneous velocity profile using regression equations for six independent variables. Of the six variables, velocity, velocity squared, acceleration squared, ambient temperature, and humidity proved to be relevant in predicting emission rates (16).

Georgia Tech researchers are in the process of developing new hydrocarbon, nitrogen oxide, and carbon monoxide emission rates, which are more representative of on-road modal activity, as part of their GIS based modal emission model, MEASURE. Regression analysis was used for a data set of more than 13,000 hot-stabilized laboratory treadmill tests on 19 driving cycles (specific velocity versus time testing conditions), and 114 variables describing vehicle, engine and test cycle characteristics. The data set represents almost two decades of in-use driving tests conducted by the EPA and CARB and compiled by the EPA’s Office of Mobile Sources for use in developing the MOBILE model (25).

**Improved Motor Vehicle Activity Estimates**

On the vehicle activity side, various models are emerging to predict either macroscopic or microscopic estimates of on-road vehicle activity. One class of models, such as CALINE4 or FLINT, macroscopically segregates vehicle activity into modal zones, which may include time spent idling, cruising, accelerating, and decelerating. For CALINE4, link length, stopline distance, cruise speed, maximum and minimum idle time, acceleration time, deceleration time, and number of vehicles per cycle entering the intersection and delayed at the intersection per cycle are input and provide an indirect measure of modal activity (26). FLINT uses a deterministic queuing algorithm to calculate queue lengths and idling time per vehicle. Roadway links are divided into zones of deceleration, idling, acceleration and cruise and then coupled with idle and cruise emissions rates from MOBILE5a. Internal multipliers are used to approximate modal emissions (27; 28).

Another group of models has utilized some manner of simulation to obtain microscopic vehicle profiles related to mode specific emission production or fuel consumption rates. As early as 1988, Al-Omishy and Al-Samarrai (29) prototyped a road traffic simulation model that predicted vehicle operation based on vehicle type, location along the roadway, velocity, and acceleration based on car-following theory to predict both HC and NO\textsubscript{x}. Matzoros (19) reports the development of a modal emission simulation model, capable of modeling the formation and dissipation of queues as well as cruise, idle, acceleration, and deceleration at different positions along a street link, including emission rates disaggregated by operating mode. In a separate effort, an analytical model using mathematical algorithms to identify inter-relationships between traffic characteristics,
signal control strategies, and roadway geometric conditions to estimate intersection fuel consumption was created to investigate the effects of signal timing on fuel consumption by Liao and Machemehl (30).

A major research effort is currently underway at Los Alamos National Laboratory to develop the TRANSIMS model, which is a simulation system for the analysis of transportation options in metropolitan areas. The base of the system is a cellular automata microsimulation model producing second-by-second vehicle positions defined by 7.5 meter cell locations. TRANSIMS is a set of integrated analytical and simulation models and supporting databases dealing with prediction and simulation of trips for individual households, residents, and vehicles as well as movement of individual freight loads (20). Given the speed binning that is inherent when vehicles move in 7.5-meter distance steps, the TRANSIMS model applies statistically-derived approximations to the traffic flow to predict operating modes.

Other related simulation based activity models include INTEGRATION, which combines a traffic simulation model with an emission module. The model uses car-following and lane changing logic to estimate velocity and headway. Acceleration is modeled as a by-product of car-following logic, resulting in unrealistic values which are then constrained via a linear acceleration decay function that decreases the vehicle's acceleration as a function of its velocity (21). In another study, the microsimulation model TRAFFNETSIM, used to model urban roadways, and the microsimulation model INTRAS, used for modeling freeways, were used to develop a modeling framework for prediction of vehicle activity in regional areas for improved emission estimates (22). Output from the simulation modules was used to develop relationships between basic link characteristics and the time spent in each operating mode. Derived relationships were incorporated into a post processor from the Urban Transportation Planning Software (UTPS) four-step planning model so that region-wide estimates of vehicle activity could be applied with the existing state-of-practice in regional modeling. Field data using instrumented vehicles for a freeway segments were used to validate model results (22).

In addition to simulation models created specifically to model transportation air quality, general traffic simulation and optimization models such as TRANSYT-7F, INTEGRATION, FREQ, NETSIM, and INTRAS also have incorporated modules for estimating emissions. These modules were structured to be sensitive to modal model output but none of the models were developed based on on-road emission or vehicle activity data (16).

Transportation-related air quality models with macroscopic measures of vehicle activity are only able to generalize modal components of vehicle activity. Consequently, their ability to accurately link activity-specific emission rates with estimates of vehicle activity is limited. Microscopic activity models are one step closer in being able to capitalize on the advantages of modal modeling because they typically are able to model individual vehicle profiles along a specific street segment. The instantaneous velocity and acceleration output from the simulation models can then be related to corresponding modal emission rates. The ability to model at this level of detail is attractive, as mode-
specific emission estimates require that actual vehicle activity be highly disaggregated. The main disadvantage to simulation model output is that each successive movement of an individual vehicle (velocity and acceleration) is controlled by car-following logic with unrealistic accelerations estimates constrained by decay functions or upper limit velocity-acceleration ranges. As a result, vehicle activity output is not based on actual patterns of vehicle profiles for specific activities, such as accelerating from a stop, nor do they represent actual distributions of data. While simulation models adequately model velocity and traffic volumes for a variety of scenarios, limitations exist in their ability to accurately describe the specific velocity-acceleration combinations that are crucial for use with modal emission rates (31; 16).

ON-ROAD VEHICLE ACTIVITY ESTIMATES
Because emission rates for emerging modal transportation-related emission models are sensitive to specific combinations of velocity and acceleration, the activity input must be as representative as possible of real world conditions. Even with high-resolution emission rate models, estimates from modeling efforts will only be as accurate as the vehicle activity input to the model. As discussed, earlier, the majority of modal emissions models base vehicle activity on either generalized estimates of the time spent in a mode such as idling or rely on output from simulation models, which may not be statistically representative of on-road vehicle activity.

Consequently, the main purpose of the research described in this paper was to further the understanding of on-road vehicle operation, which will in turn lead to estimates of vehicle activity. This paper describes a new methodology that will more accurately forecast individual vehicle activity along signalized street segments in Atlanta. Actual on-road vehicle profiles were collected at various intersections and served as the model base. Research was conducted as part of a cooperative grant with the U.S. Environmental Protection Agency and the Federal Highway Administration. This work parallels recent efforts undertaken by Grant (17) and Roberts et al. (18) aimed at statistically relating observed velocity/acceleration characteristics on freeways as a function of vehicle class, traffic flow, and geometric highway parameters using laser rangefinders. Both approaches used aggregate measures of flow and roadway geometry to predict the important load-related measures of flow. In particular, Grant derived regression models that related the fraction of activity exceeding a critical threshold, such as percent accelerations >= 3.0 mphs. Roberts et al. (19) utilized a similar approach with hierchial based regression tree analysis (HBTR) as the statistical methodology.

DATA COLLECTION
One of the primary research goals was to develop representative distributions of vehicle activity at signalized intersections as a function of both geometric (grade, lane width, etc.) and operational (volume, percent heavy vehicles, etc.) characteristics. Vehicles are hypothesized to behave differently depending on the roadway conditions around them. For example, the acceleration capability of a vehicle on a 9% grade will be constrained by gravitational forces acting against the vehicle’s forward movement. As a result, a vehicle accelerating from rest on a 9% grade is expected to behave differently than a vehicle accelerating from rest on a flat grade. Likewise, the range of vehicle velocity and
acceleration may be markedly different as roadway volumes increase. As more and more vehicles occupy the roadway, each vehicle’s activity is likely to be more constrained by surrounding vehicles. The potential for interactions between vehicles, such as being forced to slow down or brake, increase as volumes increase.

To identify those variables most likely to influence the fractions of time that vehicles spend in different operating mode, intersection data collection sites were selected to represent a diversity of both geometric (grade, lane width, etc.) and operational (volume, percent heavy vehicles, etc.) characteristics. The Highway Capacity Manual (32) and Traffic Engineering Handbook (33) identify several variables commonly shown to affect traffic operation. It was hypothesized that the same variables affecting traffic operation would also affect individual vehicle activity leading to different distributions of velocity and acceleration. A list of variables considered in the site selection process is presented in Table 1.

Table 1: Operational and Geometric Factors Represented in Data Collection

<table>
<thead>
<tr>
<th>Factor</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade</td>
<td>Geometric</td>
</tr>
<tr>
<td>Number of Lanes</td>
<td>Geometric</td>
</tr>
<tr>
<td>Lane Width</td>
<td>Geometric</td>
</tr>
<tr>
<td>Distance Between Intersections</td>
<td>Geometric</td>
</tr>
<tr>
<td>Geographic Location (CBD, Suburban, etc)</td>
<td>Geometric</td>
</tr>
<tr>
<td>Speed Limit</td>
<td>Geometric</td>
</tr>
<tr>
<td>Vehicle Mix</td>
<td>Operational</td>
</tr>
<tr>
<td>Volume to Capacity (V/C)</td>
<td>Operational</td>
</tr>
<tr>
<td>Level of Service</td>
<td>Operational</td>
</tr>
</tbody>
</table>

Individual activity profiles were collected in the field through measurement of speeds and accelerations of vehicles with laser rangefinders (LRF), also called “laser guns”. Advantage Laser Rangefinders, manufactured by Laser Atlanta Optics, were used in this effort. The LRF is a portable, handheld devices capable of measuring the distance to an object at a high sampling frequency (238.4 distance measurements per second) with a manufacturer’s accuracy specification of 0.1 feet (rms) over 2,500 feet (34). The maximum effective range is 2,500 feet. Actual range was governed by practical considerations such as the type of vehicle, sight constraints, and interference between the vehicle "tracked" and surrounding vehicles. In all cases the actual range was less than the maximum range of 2,500 feet. Because water droplets affect readings, the units cannot be used in the rain.

To physically collect data, operators were located along the right of way at the signalized intersection being studied. Vehicles were randomly selected and the operator “locked” onto the back of the vehicle, following it until line of sight with the vehicle was compromised by interference with other vehicles or the operator lost lock. Each vehicle trace was stored in a unique datafile. Vehicle attributes such as type of vehicle (passenger vehicle versus type of heavy truck), queue position, etc. were also noted for the individual vehicle. Vehicle activity profiles were calculated for each vehicle from
raw distance measurements using a program with a smoothing algorithm, which output
instantaneous velocity, acceleration, and distance. Site attributes were also collected,
such as link volume, grade, or distance to the nearest downstream or upstream signalized
intersection, or calculated from field attributes, such as level of service (LOS). Vehicle
and roadway attributes were attached to individual second by second vehicle activity
profiles. Consequently, data could be sorted by position along the roadway, queue
position, or by any roadway attribute. Data collectors were positioned either to collect
activity as vehicles accelerated off the intersection stopline or as vehicles decelerated into
the intersection. Vehicles proceeding through the intersection without encountering a
‘red’ signal were also recorded. For acceleration, vehicles were tracked up to 800 feet
downstream of the stopline depending on interference with roadside objects and other
vehicles. For deceleration, vehicles were tracked for up to 600 feet upstream of the
signalized intersection.

A total of 26 locations in the Atlanta, Georgia metropolitan area were sampled in the data
collection process. A total of 4,097 passenger vehicles were sampled resulting in a total
of 29,673 seconds of passenger vehicle activity available for data analysis. The
designation “passenger vehicle” includes standard passenger cars as well as passenger
vans, light duty trucks, and sport utility vehicles. Data for heavy trucks were also
collected but are not included here. For the locations sampled, a variety of conditions
were represented. The range of conditions for each variable considered in selection of
data collection locations is shown in Table 2.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum Value</th>
<th>Maximum Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level of Service</td>
<td>A</td>
<td>F</td>
</tr>
<tr>
<td>Volume to Capacity</td>
<td>0.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Distance to Nearest Upstream</td>
<td>756</td>
<td>4,118</td>
</tr>
<tr>
<td>Intersection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to Nearest Downstream</td>
<td>300</td>
<td>5,544</td>
</tr>
<tr>
<td>Intersection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upstream Per Lane Volume</td>
<td>143</td>
<td>924</td>
</tr>
<tr>
<td>Downstream Per Lane Volume</td>
<td>143</td>
<td>1,159</td>
</tr>
<tr>
<td>Grade</td>
<td>-9</td>
<td>9</td>
</tr>
<tr>
<td>Percent Trucks</td>
<td>1%</td>
<td>35%</td>
</tr>
<tr>
<td>Number of Lanes</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Speed Limit</td>
<td>30</td>
<td>45</td>
</tr>
<tr>
<td>Lane Width</td>
<td>9 feet</td>
<td>12 feet</td>
</tr>
<tr>
<td>Geographic Position</td>
<td>Suburban, Commercial, Industrial, CBD</td>
<td></td>
</tr>
<tr>
<td>Queue Position</td>
<td>1</td>
<td>15</td>
</tr>
</tbody>
</table>

**ANALYSIS AND RESULTS**

The following sections discuss the results of data analysis. The main research
goal was to identify variables that were noted to affect vehicle operation. This way,
activity data can be segregated by the influential variables so that mode-specific emission rates can be applied. Regression tree analysis was the statistical tool used for this analysis. A brief description of the analysis is presented below. A more in-depth discussion of the analytical procedure and statistical results was beyond the scope of this paper. Because a large amount of actual on-road field data were collected, they can also be used to show the fractions of actual vehicle activity spent outside the range of activity included in the Federal Test Procedure. Finally, the data summaries are presented illustrating the relationship between velocity and acceleration distributions.

Regression Tree Analysis Results

The purpose of the statistical modeling was to determine which variables influence vehicle activity behavior so that the data can be stratified by those variables and 3-dimensional matrices of velocity and acceleration created for input into Georgia Tech’s mobile source emission model, MEASURE. As discussed previously, linear regression analysis was used to develop improved emission rate models based on vehicle fleet characteristics (fuel injector type, transmission type, etc.) as well as modal (velocity, acceleration, and the product of the two) characteristics (25). The emission rate regression equations identified specific zones of modal activity that were correlated with elevated emission production for HC, NOx, and CO. For example, the aggregate modal model in MEASURE employs fraction of total activity where acceleration is greater than or equal to 3.0 mph/s or fraction of total activity where deceleration is less than or equal to –2.0 mph/s as input variables (23, 25).

Regression tree analysis was used to identify which of the variables considered in data collection were statistically relevant in influencing on-road vehicle activity. With regression tree analysis it was possible to not only identify variables but also to quantify the statistical relevance of the variables. The modal variables defined by the emission rate regression equations described above were utilized as response variables for the data analysis.

To identify the variables most likely to influence individual velocity-acceleration profiles, data were segregated by distance upstream or downstream of the intersection stopbar, by queue position, and by the variables listed in Table 2 to form datasets of vehicles with homogenous characteristics. For example, a single dataset might contain data for vehicles with the following vehicle or street segment characteristics:

- first vehicle in the queue
- 5% grade approach
- intersection operating at LOS C
- 45 mph speed limit
- 5% heavy vehicles
- suburban location

With data divided in this manner, fractions of activity in each of the modal zones identified in the emission rate models were calculated and regression tree analysis performed. The most influential variables determined through regression tree analysis were as follows:
Location

Vehicle activity varied depending on the physical location of the vehicle in relationship to its position upstream or downstream of the intersection stopline. Intuitively, vehicles will behave differently as they accelerate off the stopline than they will even a few hundred feet downstream. Figures 1 through 4 shows three-dimensional (tri-variable) joint probability density functions of velocity, acceleration, and the joint probability for a given velocity-acceleration bin for vehicles that were first in the queue at intersections operating at LOS C with flat approaches. The vehicle profiles trace vehicle activity from the initial intersection downstream along a street segment to a second signalized intersection downstream. Figure 1 illustrates activity for vehicles accelerating off the stopline to a point 200 feet downstream and the same vehicles downstream for a distance of 200 to 400 feet. Figure 2 shows data for the location along the link that is 400 to 600 feet downstream of the vehicles initial point and 600 to 800 feet downstream. In Figure 3, midblock activity where vehicles have reached their ‘cruise’ speed is shown along with the segment from 600 to 400 feet upstream of the second intersection where the vehicles begins to decelerate. Figure 4 illustrates activity for the segment from 400 to 200 feet upstream of the second intersection and from 200 feet upstream to the point where the vehicle is stopped by the traffic signal at the second intersection. Note that as the vehicle accelerates off the stopline at the first intersection, speeds are lower, but a wide distribution of accelerations is represented. As the vehicles proceed down the street segment, speeds increase and the range of acceleration activity decreases. Midblock, speeds are at their highest point and the distribution of acceleration is fairly narrow. As the vehicles begin deceleration, speeds decrease and the range of accelerations again increases.

Grade

Grade was influential in affecting vehicle activity. In general vehicle operation on negative grades have significantly different activity profiles than vehicle activity on positive grades. Figure 5 illustrates frequency profiles for vehicle activity by grade. Data shown are percent activity in each velocity or acceleration range. Data are from all queue positions for the first 400 feet of operation off the stopline. Profiles are shown for data collected on a –9% grade, flat grade, and +9% grade. As noted the profiles differ by grade for both the velocity and acceleration profiles.

Queue Position

The vehicle’s position in queue at the intersection stopline proved to be highly relevant in influencing vehicle activity. Variations were noted in the first, second, and third queue positions, which were shown to typically be dissimilar while queue positions, including the fourth and higher, did not appear to be significantly different. Figure 6 illustrates the percent of time spent in particular acceleration modes by queue position. The modes correlate to three of the vehicle activity zones found to be relevant in the linear regression models derived for the various pollutants described previously (35). Data are shown for vehicle activity from the point of queue downstream 500 feet. As shown, the first vehicle in the queue, consistently spends a higher fraction of operating time in extreme modal activity than any other queue position with the exception of percent of activity in deceleration <= -2.0 mph/s where the first and second queue
From queuing point at 1\textsuperscript{st} intersection downstream 200 feet to 400 feet downstream of 1\textsuperscript{st} intersection.

**Figure 1**: Vehicle activity path from queuing point at 1\textsuperscript{st} intersection to queuing point at 2\textsuperscript{nd} intersection (continued in Figure 2).
400 to 600 feet downstream of 1\textsuperscript{st} intersection

600 to 800 feet downstream of 1\textsuperscript{st} intersection

Figure 2: Vehicle activity path from queuing point at 1\textsuperscript{st} intersection to queuing point at 2\textsuperscript{nd} intersection (continued in Figure 3)
Midblock 600 to 400 feet upstream of 2nd intersection

Figure 3: Vehicle activity path from queuing point at 1st intersection to queuing point at 2nd intersection (continued in Figure 4)
400 to 200 feet upstream of 2\textsuperscript{nd} intersection

200 feet upstream to queuing point at 2\textsuperscript{nd} intersection

Figure 4: Vehicle activity path from queuing point at 1\textsuperscript{st} intersection to queuing point at 2\textsuperscript{nd} intersection
position are similar. Also note that percent time spent in extreme modes is more consistent among subsequent queue positions (i.e. data for the first and second queue positions are more similar than for the first and third).

**Traffic Volume**
The link per lane volume was also influential in affecting vehicle activity. Link per lane volume was calculated by dividing the total link volume by the number of lanes. The most notable difference in vehicle activity was for speed. As per-lane volume increased, the average speed decreased.

**Other Variables**
The posted speed limit and distance to the nearest upstream or downstream signalized intersection also appeared to be influential variables. Because posted speed limits are highly correlated with roadway functional class, it is theorized that the speed limit may be acting as a surrogate for other variables associated with functional class. For example, major arterials in an urban area may have a posted speed limit of 45 mph while minor arterials are posted at 40 mph and collector roads are posted at 35. Consequently if vehicle activity is shown to be different for a posted speed limit of 45 mph than for 40 mph, the significant factor affecting vehicle activity may simply be the whether the vehicle is operating on a major or minor collector. Volume to capacity and level of service were also shown to be influential in affecting vehicle activity. However, they were highly correlated both with per lane volume and were correlated to each other. Because level of service and V/C are both more computationally difficult to determine, only per lane volume was included in the final analysis.

**Activity Outside of FTP**
One of the main criticisms of the traditional transportation-related air quality modeling approach is that range of activity embodied in the Federal Test Procedure does not adequately represent the actual range of vehicle activity found on-road. Several other studies have indicated that a significant amount of on-road driving activity occurs outside the range of activity represented in the Federal Test Procedure (6,8).

A comparison of the total activity collected for passenger cars by percent of total activity in each speed/acceleration range is presented in Table 3. The data represent the total activity collected over all intersections for passenger cars. For a total of 29,673 seconds of data collected, 6,922 seconds of data fall outside the FTP (shaded area of the table). This represents 23% of total recorded activity, indicating that a significant portion of on-road vehicle activity occurs in activity ranges outside those represented by the FTP.

**Distribution of Vehicle Activity by Speed Range**
Finally, the data are presented illustrating the relationship between velocity and acceleration distributions. Figure 7 illustrates the distribution of acceleration values within each speed bin (activity in each speed category sums to 1). This shows the
Figure 5: Comparison of frequency distribution of vehicle activity by grade (acceleration and velocity)
Figure 6: Fractions of total vehicle activity spent in extreme modes by queue position for 250 feet before and 250 feet after point of queue
variation in acceleration activity by speed range. As shown, significant variety exists in the data for accelerations across all speed ranges. As noted, the largest variation in acceleration ranges occurs at the lower speed ranges (0 to 35 mph). The wide distribution of acceleration rates also indicates that simplistic relationships currently imbedded in simulation models will not adequately represent on-road modal activity.

**FORECASTING VEHICLE ACTIVITY AS A FUNCTION OF INTERSECTION GEOMETRY AND OPERATIONS ATTRIBUTES**

One of the main goals of this research was to develop a model to predict modal vehicle activity at signalized intersections and along signalized roadway segments using actual field data. Ideally, the model should be able to predict vehicle activity based on those operational and geometric characteristics, shown to influence vehicle activity. The model could then be used to predict microscopic vehicle profiles at signalized intersections and serve as input to regional or microscale transportation-related air quality modeling efforts that employ modal emission rates. To accomplish this, representative distributions of vehicle activity at signalized intersections as a function of vehicle attributes, physical roadway characteristics, or roadway operating characteristics were developed. Once the significant predictor variables are identified, data can be stratified creating a ‘driving cycle’ (vehicle activity trace) based on known segment length, volumes, queue length, delay, and signal timing. An ‘driving cycle’ illustrating a vehicle’s activity profile as it moves along a signalized arterial is illustrated in Figure 8.

Once activity is forecast for individual vehicles or for groups of vehicles that behave similarly, all vehicle traces are summed to reflect the total number of vehicles on the link. The statistical analysis described briefly above, indicated which of the independent operational or geometric variables of the study locations were relevant in influencing vehicle activity. The final output of the statistical model is a three-dimensional (tri-variable) joint probability density function of velocity, acceleration, and the joint probability for a given velocity-acceleration bin. Laser gun data provided second by second sampling of the velocity and acceleration trace for each vehicle along a specified path (or run), such as a vehicle's trajectory from the point of queuing to some point downstream. The 3-dimensional matrices are created by allocating activity from the second by second vehicle traces into the matrix of velocity and associated accelerations bins. Once data are binned, the probability of any bin can be calculated by dividing its frequency by the sum of the frequencies of all bins. For each given geometric and operational condition that is investigated, the frequency of activity in a specific speed-acceleration bin is the number of seconds of operation in a given bin divided by the total number of seconds of activity. Examples of empirical 3-dimensional matrices are shown in Figures 1 through 4. Such matrices provide the fraction of vehicle activity on a link represented in a specific operating mode (such as idle or hard acceleration). Link volume estimates can be multiplied by these fractions and then tied to modal emission rates to estimate emissions. The matrices can, therefore, serve as input to Georgia Tech’s MEASURE model or as input to other activity-specific microscale models.
Table 3: Comparison of seconds of FTP versus non-FTP activity for passenger vehicles (shaded area is FTP)

<table>
<thead>
<tr>
<th>Velocity (mph)</th>
<th>0</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>30</th>
<th>35</th>
<th>40</th>
<th>45</th>
<th>50</th>
<th>55</th>
<th>60</th>
<th>65</th>
<th>70</th>
<th>75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration (mph/s)</td>
<td>-12 +</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td></td>
<td>-11</td>
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<td>0</td>
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<td>0</td>
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Figure 7: Acceleration distribution (mph/s) by speed ranges (mph)
CONCLUSIONS
Because emission rates for emerging modal transportation-related emission models are sensitive to specific combinations of velocity and acceleration, the activity input needs to be representative of real world conditions. Even with high resolution emission rate models, estimates from modeling efforts will only be as accurate as the vehicle activity input to the model. However, many of the methods currently used for vehicle activity profiles are based on generalized estimates of modal activity or based on the output of simulation models. Neither method provides data that are necessarily representative of on-road vehicle activity.

To better understand and represent on-road vehicle operation in modal emission models, vehicle activity data were collected at signalized intersections using laser range finders for passenger vehicles. Presentation of field data illustrated a wide distribution of vehicle activity. Additionally, regression tree analysis indicated that vehicle activity profiles are related to specific roadway or operational characteristics. In particular, grade, queue position, per lane volume, speed limit, and street segment distance between traffic signals are relevant.

Analysis of the data also indicates that a significant portion of vehicle activity at signalized intersections is outside the range of activity represented in the FTP. For a total of 29,673 seconds of data collected, 6922 seconds of data fall outside the FTP. This represents 23% of total recorded activity outside the FTP.

REFERENCES


Figure 8: Sample vehicle trace from stopping point at first signalized intersection to stopping point at second signalized intersection


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