Probabilistic Modeling of Acceleration in Traffic Networks as a Function of Speed and Road Type

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Abstract:

We propose a probabilistic approach to estimate the variation of accelerations and decelerations in traffic networks as a function of speed and road type. We model acceleration as a random variable and apply the probabilistic approach to a data set, for which we develop a probabilistic acceleration distribution for every speed range and road type. In almost all the cases, the goodness-of-fit of the modeled distribution function is acceptable, supporting the validity of the probabilistic approach. It is seen that road type has little effect on the variation of the distributions. Moreover, the standard deviation of the distributions decreases as the speed range increases. The developed model has a number of applications where only speed data are available, for example from field measurements or from a non-microscopic traffic model, and accelerations are sought. In this context, the acceleration model allows for more accurate emission modeling through the use of instantaneous emission models that require both speed and acceleration as input. The acceleration model can also be used in conjunction with speed data to model emissions as random variables and generate their distributions for various speed ranges and road types.
INTRODUCTION

Characterizing travel behavior and vehicle activity has been an important research topic that has numerous applications in traffic and emission modeling. Current travel demand models give average speeds as outputs, which are not sufficient for the increasing data needs of emissions modelers. Recent emission research recognizes that the engine mode of operation will be a significant variable in new modal emission models (1, 2, 3, 4). When modal activity exceeds specific thresholds of variables such as power, positive kinetic energy, acceleration, or idle mode, emission levels can rise significantly. Thus, there is a need to understand how driving behavior and dynamic vehicular activity affect the proportion of driving spent in different modes (idling, cruising, acceleration, deceleration, etc.). Sierra Research (5) developed representative driving cycles for different facility types and congestion levels after analyzing instrumented and chase car data. While this research was a valuable addition to the literature, it does not present a statistical methodology for generating speed and acceleration distributions, which may be necessary for applications where specific driving cycles are an insufficient tool. Moreover, driver interaction with the vehicle in terms of acceleration and (to a lesser extent) deceleration patterns is important for emission modeling. For example, high-speed, high-acceleration, and heavy braking activities are typically exhibited by young male drivers, and this in turn increases emission, while older drivers might drive more conservatively than younger drivers (6, 7). Driving patterns might also be dependent on the particular city and the nature of its transportation network, i.e. whether it is mostly dominated by local streets or freeways (8), and on the traffic and control conditions (9). For these reasons, it is important to study those aspects of driving behavior and road characteristics that may influence the statistics of acceleration and deceleration events for a given speed.

In this paper, we develop a novel approach for the quantification of acceleration and deceleration events in a traffic network. The approach models acceleration as a random variable whose distribution varies as a function of speed and road type. The basic motivation of this research is to integrate non-microscopic traffic models and instantaneous emission models, though there are other applications as well. Non-microscopic dynamic traffic assignment models are fast, applicable on a regional scale, and generally easier to calibrate than their microscopic counterparts. Their basic limitation is that they describe network conditions in terms of average link speeds, but do not provide accelerations. Load-based emission models, however, require both speed and acceleration as input. Therefore, a probabilistic acceleration model is an efficient method of overcoming the shortcomings of non-microscopic traffic models and providing the necessary link to emission models. Even in the absence of a traffic model, the acceleration model is also useful when only speed data are available in a given city from field measurements. This leads, for instance, to more accurate emission modeling using instantaneous emission models rather than average speed-based emission models (such as EPA’s MOBILE6), which in principle do not properly quantify emissions from vehicles under dynamic conditions (10) and are thus an approximation at best.

Several approaches for the quantification of acceleration and deceleration events can be found in the literature. TRANSIMS, a traffic simulator based on cellular automata modeling, uses aggregate real-world frequencies of power factor \((2*\text{speed}*\text{acceleration})\) to model the accelerations. The power factor is then used to estimate emissions (11). Microscopic traffic models assign accelerations to individual vehicles based on the interaction among vehicles and the traffic regimes. Examples of these regimes are car-following and free-flowing. Therefore, in these models, acceleration is a function of parameters such as headway distribution, the relative difference in speed between adjacent vehicles, and driver reaction time (12). In this paper, however, the focus is to develop a probabilistic approach to estimate acceleration and deceleration activity from the mere knowledge of speed, without modeling vehicular interactions at the microscopic level. The analysis is conducted using data for four main road types: interstate highways, state highways, arterials, and collectors. It is well known that the potential for accelerating or decelerating decreases as speed increases because of power and traction limitations of the vehicle. However, these limitations are usually insufficient to describe the dynamics of vehicles. It is also necessary to determine the statistical distribution of accelerations and decelerations within a given speed range on a link, which is defined by the state variables of density and flow (or average speed).
This paper is organized as follows. In the next section, we describe the data for which we develop an acceleration model. This is followed by a presentation of the approach that we developed to calibrate the model. An analysis of the results is also given. We then describe an application of the model. Finally we conclude the paper and give future research directions.

DATA

The data sets of this research are obtained in conjunction with an intelligent cruise control study sponsored by the US Department of Transportation and conducted in South Eastern Michigan from July 1996 to September 1997 by the University of Michigan Transportation Research Institute (7). The model developed in this paper is built on real-world driving data collected during the first week of the study, during which the intelligent cruise control was not functional. 108 randomly-chosen drivers from eight counties of South Eastern Michigan were selected to drive in metropolitan and rural areas of the state, using the same type of vehicle: an instrumented 1996 Chrysler Concorde.

Drivers were classified into five categories according to their driving behavior:

- Ultraconservative: means an unusual tendency towards far (‘far’ means large gap between leading and following vehicle) and/or slow driving.
- Planner: means an unusual tendency towards far and/or fast driving.
- Hunter/tailgater: means an unusual tendency towards fast and/or close driving.
- Extremist: means that the driver satisfies more than one of the above tendencies.
- Flow conformist: means that the driver satisfies none of the above tendencies. A flow conformist tends to travel at the same speed as other cars and at approximately the median headway time-gap.

A sub-sample of eighteen drivers, each conducting 20 to 60 trips, was used to develop the model presented in this paper. Most trip durations were less than 30 minutes. The eighteen drivers belong to the following categories: two planners, three extremists, five hunters, four ultraconservatives, and four flow conformists. The model does not capture differences in driver aggressiveness because the intent is to isolate road type as the only independent variable.

Roads were classified into the following types: high-speed ramp, interstate highway, state highway, arterial, collector, light duty, alley or unpaved, unknown, and low-speed ramp. Only four road types (interstate highways, state highways, arterials, and collectors) are considered in the present study because of data availability. Moreover, these road types cover most road types in a transportation network (except for on-ramps and off-ramps).

The distribution of acceleration and deceleration data points, aggregated from all drivers on every road type, is shown in Table 1. These observations correspond to second-by-second combinations of velocity and acceleration.

CALIBRATION

In this section, we describe the approach that we followed to develop an acceleration model corresponding to the data described above. The same procedure can be used in general to derive statistical acceleration distributions from any given acceleration data set though the fitted distributions might vary from one data set to another.

The first five trips have been eliminated from every driver’s record to remove some of the "novelty factor" bias that might be present at the beginning of the test since drivers might not be accustomed to their new vehicles. The remaining data are divided into four subsets, one for each considered road type, to see whether acceleration and deceleration distributions are dependent on road type. The data in each subset are further divided into two groups: acceleration data (strictly positive values) and
deceleration data (zero or negative values). Acceleration and deceleration are considered separately since in general they may not be similarly distributed. In the case of arterials, we have divided the data into two subsets, \( S_C \) for calibration and \( S_V \) for validation. For the other road types, we did not validate the model because of the lack of a sufficient number of observations for those road types.

Consider one data group, for example, accelerations (strictly positive values) on road type \( r \). The statistical distribution analysis is conducted for 10 km/h speed ranges. For each speed range \( v \), we would like to find a probability distribution that fits the acceleration distribution obtained from the sample for that particular speed range. Plotting the sample acceleration values suggests a distribution similar (with a scale factor) to the density of a half-normal distribution with zero mean \( \mu = 0 \), and a standard deviation to be determined (see Fig. 1).

Let \( N_{r,v}^+ \) be the total number of acceleration observations aggregated from all drivers driving on a road type \( r \) in a speed range \( v \). Let \( Q_{r,v}^+ (a) \) be the sample probability of observing a certain value of acceleration \( a \), where \( a \) belongs to an acceleration interval of length 0.2 m/s\(^2\) (e.g., [0.2,0.4],[0.4,0.6]...). If \( a \) belongs to an acceleration interval \([a_1,a_2]\), we define \( T_{r,v}^+ (a) \) as the total number of acceleration observations that are in the interval \([a_1,a_2]\). Then \( Q_{r,v}^+ (a) \) is given by:

\[
Q_{r,v}^+ (a) = \frac{T_{r,v}^+ (a)}{N_{r,v}^+}.
\]

The sample standard deviation is given by the expression:

\[
\sigma_{r,v}^+ = \sqrt{\sum_{a \in A} (a-\mu)^2 Q_{r,v}^+ (a)} = \sqrt{\sum_{a \in A} (a-0)^2 Q_{r,v}^+ (a)} = \sqrt{\sum_{a \in A} a^2 Q_{r,v}^+ (a)}
\]

where \( A \) consists of all the acceleration values in the data set, taken at 0.2 m/s\(^2\) intervals.

The half-normal probability density function, fitted to the acceleration data, is given by:

\[
f_{r,v}^+ (a) = \frac{1}{\sqrt{2 \pi \sigma_{r,v}^+}} \exp \left[ -0.5 \left( \frac{a-\mu}{\sigma_{r,v}^+} \right)^2 \right] = \frac{2}{\sqrt{2 \pi \sigma_{r,v}^+}} \exp \left[ -0.5 \left( \frac{a}{\sigma_{r,v}^+} \right)^2 \right]
\]

where \( \sigma_{r,v}^+ \) is the standard deviation obtained from the acceleration sample, as given by expression (2).

The half-normal distribution is truncated at some maximum acceleration value \( a_+^+ \), so as to avoid predicting unrealistic high accelerations. The truncated distribution is then normalized so that the area under the resulting density function is one. The resulting density function is given by:

\[
f_{\text{normalized},r,v}^+ (a) = \frac{f_{r,v}^+ (a)}{\int_0^a f_{r,v}^+ (a) \, da}
\]

An error term \( \varepsilon_{r,v}^+ \), defined as the sum of the squares of the difference between the cumulative sample probability \( F_{r,v}^+ (a) \) and the cumulative truncated and normalized half-normal density function \( F_{\text{normalized},r,v}^+ (a) \) is used to test the goodness-of-fit of the obtained distribution:

\[
\varepsilon_{r,v}^+ = \sum_{a \in A} \left[ F_{\text{normalized},r,v}^+ (a) - F_{r,v}^+ (a) \right]^2
\]
Low values of the error term $\epsilon^e_{vr}$ indicate a good fit, while high values suggest that the proposed distribution does not explain well the variation in acceleration. This procedure was applied for every road type and speed range in the acceleration data.

The maximum acceleration values at which the distributions are truncated are approximately equal to the maximum experimental values of acceleration and deceleration for every speed range, and they are given by: $a^+_a = 5$ m/s$^2$ for speed ranges from (0-10) to (71-80) km/h, $a^+_a = 2.5$ m/s$^2$ for speed range (81-90) km/h, $a^+_a = 1$ m/s$^2$ for speed range (91-100) km/h, $a^+_a = 0.75$ m/s$^2$ for speed range (101-110) km/h, and $a^+_a = 0.5$ m/s$^2$ for speed range (111-120) km/h.

The steps described above to estimate accelerations are applicable to the deceleration data for every road type and speed range.

The density function $f^+_r(a)$ of the combined distribution of acceleration and deceleration corresponding to road type $r$ and speed range $v$ is obtained by weighing the truncated and normalized distribution with the probability of occurrence of acceleration and deceleration, respectively:

$$f^+_r(a) = \begin{cases} 
0 & \text{for } a \leq 0 \\
\frac{P^-_{r,v} f^-_{r,v}(a)}{\int_0^{a^+_r} f^-_{r,v}(a) da} & \text{for } a > 0
\end{cases} \tag{6}
$$

where $P^+_{r,v}$ and $P^-_{r,v}$ are the probabilities of a deceleration realization and an acceleration realization, respectively, obtained from the sample data for road type $r$ and speed range $v$. The other terms in expression (6) are as previously defined.

In the remainder of this paper, we refer to the truncated normalized distribution as the “half-normal distribution.”

**ANALYSIS OF RESULTS**

**Comparison of Observed Distributions to Fitted Half-Normal Distributions**

The error terms $\epsilon$ obtained upon fitting half-normal distributions (with zero mean and the standard deviations obtained from the sample) to the observed values of acceleration and deceleration are shown in Table 2 (part a) for the four road types. These error values are satisfactorily low. They support the validity of the hypothesis that the accelerations and decelerations are probabilistically distributed, with the fitted distribution in this case being half-normal with zero mean and a standard deviation that decreases as the speed increases. Note that the error term values of deceleration distributions are in most cases lower than those of acceleration distributions because of the availability of more deceleration data and the absence of any acceleration value in the interval [0,0.2]. However, error term values are similar among different road types although there is an uneven distribution of data points among the road types.

Fig. 2 shows the cumulative sample probability $F_a(a)$ and the cumulative modeled distribution function $F_2(a)$ for accelerations (part a) and decelerations (part b), respectively, on arterials in subset $S_c$. 

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for the speed range \((0 – 10)\) km/h. The goodness-of-fit is better for the deceleration data than for the acceleration data due to lack of a sufficient number of observations in the interval \(\{0,0.2\}\), as stated above.

**Validation**

Validation of the half-normal distributions was done only for the data of arterials because it contained enough observations to allow for both calibration and validation. For every speed range, the same half-normal distribution that was fitted to the acceleration data in subset \(S_c\) was compared to the acceleration data of subset \(S_v\) to test whether the distributions developed from a certain sample can be applied to another sample for the same road type. Validation was also done for the deceleration data on arterials. In both cases, the error terms obtained were acceptable, supporting the adoption of probabilistic models to estimate accelerations and decelerations. Fig. 3 shows the cumulative sample probability of the acceleration data (part a) and deceleration data (part b) in subset \(S_v\) and the cumulative distribution corresponding to the modeled density function (which was derived from the calibration data set \(S_c\)) on arterials for the speed range \((0-10)\) km/h. The error terms for all speed ranges are shown in Table 2 (part b).

**Variation of Standard Deviation of the Distributions with Speed Range and Road Type**

Fig. 4 shows the variation of standard deviation of acceleration (part a) and deceleration (part b) distributions among speed ranges for the four road types. Beyond a certain speed threshold, the standard deviations decrease with speed because at lower speeds, there is a higher probability of achieving high values of acceleration and deceleration than at larger speeds. This diversity of acceleration and deceleration at lower speeds is an important phenomenon in estimating emissions related to engine load or power enrichment. This phenomenon is violated for the first speed range, where the standard deviation increases when moving from \((0 – 10)\) km/h to \((11 – 20)\) km/h. The reason for this phenomenon could be that the maximum power available to vehicles at very low speeds is lower than what drivers desire as acceleration. This observation might also be due to the common "lurch" (sudden positive variation in acceleration) that follows a light change, or stop and go traffic, and might be made pronounced by the inexperience of the drivers with a new vehicle throttle. This effect was also observed in (8).

Road type is seen to have little effect on the variation of acceleration and deceleration distributions, as shown in Fig. 4. While it is expected that stop and go conditions, characteristic of collectors and arterials, might lead to higher acceleration and deceleration values, the results actually indicate that highways have similar standard deviations to those of arterials and collectors, and in some cases have even higher variations. Note that higher speeds can be reached on highways than on arterials and collectors.

**MODEL APPLICATION**

In this section, we describe a general procedure for a possible application of the acceleration model. Then we depict one instance where the procedure has been applied. This application has been motivated by the integration of a non-microscopic traffic model and an instantaneous emission model.

**General Procedure**

The probabilistic nature of the acceleration model leads to a novel approach for emission modeling. Since accelerations are modeled as random variables, emission factors which are functions of speed and acceleration will themselves be random variables. Therefore, an instantaneous emission model combined with a probabilistic acceleration model can generate, for every road type and speed range, a probabilistic emission distribution from which one can obtain multiple moments of emissions (expected value, standard deviation, etc.).

The approach summarized in the previous paragraph is documented in more details in (13). For a given emission species \(i\), vehicle category \(c\), speed range \(v\), and road type \(r\), an expected emission factor
\( \bar{\tau}_{i,c,v,a} \) is calculated based on the probability of occurrence of every acceleration and deceleration, and is given by:

\[
\bar{\tau}_{i,c,v,a} = E \left[ e_{i,c,v,a} \right] = \int_{a_1}^{a_2} e_{i,c,v,a} \cdot f^{+}_{c,v,a} \, da
\]  

(7)

In expression (7), \( e_{i,c,v,a} \) is the emission factor, obtained from any instantaneous emission model, for emission species \( i \), vehicle category \( c \), speed \( v \), and acceleration \( a \). \( a_1 \) and \( a_2 \) are the highest deceleration and acceleration realizations, respectively, in speed range \( v \), as obtained from the sample data. \( f^{+}_{c,v,a} \) is given by expression (6).

The expected emission factor is obtained by discretizing acceleration and deceleration values in the interval \([a_1, a_2]\). Its expression is:

\[
\bar{\tau}_{i,c,v,a} = \sum_{a \in S_a} e_{i,c,v,a} \pi_{r,v,a}(a)
\]  

(8)

In the latter expression, \( S_a = \{a_1 - h/2, a_1 + h/2, ..., a_2 - 3h/2, a_2 - h/2\} \) is the discretization interval, and \( h \) can be set to any desired value. Here it is set to 0.1 m/s\(^2\). \( \pi_{r,v,a}(a) = \int_{a-h/2}^{a+h/2} f^{+}_{c,v,a} \, dx \), which is the probability that the acceleration belongs to the interval \((a-h/2, a+h/2)\).

This general procedure can be employed in two types of applications. First, it is useful for the integration of non-microscopic traffic models and emission models. In this case, the expected emission factors can be applied to the average speeds which are output by the traffic model in order to predict emissions. A specific application of this type is shown below. Second, the procedure can be used to enhance the accuracy of emission models’ predictions in cases where speed is obtained from field measurements, for example through loop detectors, and used as input to the acceleration model which would generate acceleration distributions for a given road type. Any instantaneous emission model would then be able to predict emission distributions (or moments of emissions), given the speed and acceleration (as well as other vehicle and roadway-related factors). Therefore, the acceleration model allows the deployment of more refined and detailed emission models in practice, as it allows the determination of acceleration, which is a quantity not measured in practice, via the measurement of speed only.

**Application Example**

Below we describe a specific application where expected emission factors have been generated based on speed data obtained from field measurements. The acceleration model has been used in (13) in conjunction with EMIT (EMIssions from Traffic), a recently developed emission and fuel consumption model. We provide a brief description of EMIT, show results of expected emission factors derived from EMIT, and describe the integration of EMIT with a non-microscopic traffic model.

EMIT is a simple statistical model for instantaneous tailpipe emissions (\( CO_2, CO, HC \), and \( NO_x \)) and fuel consumption of light-duty composite vehicles. In order to realistically reproduce the behavior of the emissions, the explanatory variables in EMIT have been derived from the load-based approach, using some simplifying assumptions. The model is calibrated for a set of vehicles driven on standard as well as aggressive driving cycles, and is validated on another driving cycle in order to assess its estimation capabilities. The preliminary results indicate that the model gives reasonable results compared to actual measurements as well as to results obtained with CMEM, a well-known load-based emission model (see Fig. 5). The goodness-of-fit of EMIT varies with different emission species (see Table 3), but the model has in general a reasonable predictive accuracy. Furthermore, the model, due to its simple structure, is relatively easy to calibrate and requires less computational time than detailed load-based models. A detailed description of EMIT can be found in (13, 14).

Expected emission factors have been calculated in advance (off-line), according to the general procedure outlined above. The speed data used to compute expected emission factors are obtained from the data set described in this paper. Fig. 6 and Fig. 7 show the calculated expected emission factors of \( CO_2 \),
CO, HC, and NO as well as fuel rates for vehicle category 9 (defined in 13) as a function of speed on arterials and highways, respectively. In general, the expected emission factor (g/s) increases with speed because of the increase in fuel consumption rate. The expected emission factors are also compared with the facility-specific emission rates from MOBILE6. Note also that expected emission factors would in general be different for different vehicle categories.

An integration component is designed to apply the expected emission factors to the output (i.e. time-dependent link speeds) of a mesoscopic traffic model, developed in (15), to predict total emissions as well as their spatial and temporal variations. The combined model allows the evaluation of various traffic management strategies and their effectiveness in reducing traffic congestion, air pollution, and fuel consumption. For instance, in (13) various scenarios of traffic conditions (with and without an incident) are considered to assess the impact of dynamic route guidance (an Intelligent Transportation Systems traffic management method) on travel time, emissions, and fuel consumption.

CONCLUSION

In this paper, a probabilistic approach that models acceleration activity as a random variable has been developed. Statistical acceleration and deceleration distributions have been developed as a function of real-world data of vehicle speeds and road types. As the speed range increases, the standard deviation of the acceleration and deceleration distributions decreases because at higher speeds only a limited range of accelerations and decelerations can be achieved due to power and traction limitations. This observation was consistent among all road types. Moreover, the standard deviations are similar among road types, which might suggest that road type has little effect, if any, on acceleration and deceleration variation. However, this effect should be studied further with more data from other cities, since there is reason to believe that driving behavior differs from city to city, especially those that have more hills (8).

For every road type and speed range, and for both acceleration and deceleration, a half-normal distribution having the same mean and standard deviation as the original data was fitted to the observations. The fitted distribution was truncated at some maximum acceleration value in order to consider only physically feasible accelerations. In almost all cases, the fit was very close as indicated by low error term values. This implies that the half-normal distribution well approximates the acceleration and deceleration activity distributions for the given data. The specific parameters of the distribution might have to be calibrated separately for each city since there might be other factors, not captured by our model, that affect these distributions. Moreover, the distribution that would fit other acceleration and deceleration data from different regions might not be half-normal. However, the same methodology developed in this paper can be used to develop other acceleration probability distributions.

A general procedure was given to illustrate an application of the probabilistic modeling approach. Then specific results were provided where the acceleration model was used in conjunction with EMIT (13, 14), an instantaneous emission model, to generate expected emission factors for the purpose of integration with a non-microscopic traffic model.

For further research, it would be useful to apply the methodology developed in this paper to other data sets (namely the Sierra chase car data) to investigate further the nature of the fitted distributions as well as the effect of road type on these distributions. It would also be important to quantify the activity from freeway ramps. Moreover, it would be interesting to disaggregate this model to assess the impact of driver aggressiveness and vehicle type on the variation of acceleration and deceleration distributions.
ACKNOWLEDGEMENTS

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REFERENCES


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### TABLE 1. Number of Observations by Road Type.

<table>
<thead>
<tr>
<th>Road Type</th>
<th>Interstate Highway</th>
<th>State Highway</th>
<th>Arterial</th>
<th>Collector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration</td>
<td>5,597</td>
<td>3,633</td>
<td>20,580</td>
<td>5,804</td>
</tr>
<tr>
<td>Deceleration</td>
<td>12,569</td>
<td>6,074</td>
<td>31,586</td>
<td>11,043</td>
</tr>
</tbody>
</table>
TABLE 2 *. Error Terms of Half-Normal Distributions Fitted to the Sample Acceleration and Deceleration Distributions, Obtained from Calibration on All Road Types (Part a) and Validation on Arterials (Part b).

<table>
<thead>
<tr>
<th>Speed Range (km/h)</th>
<th>Acceleration</th>
<th>Deceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Interstate Highway</td>
<td>State Highway</td>
</tr>
<tr>
<td>0-10</td>
<td>0.00895</td>
<td>0.00891</td>
</tr>
<tr>
<td>11-20</td>
<td>0.00588</td>
<td>0.00844</td>
</tr>
<tr>
<td>21-30</td>
<td>0.00374</td>
<td>0.00419</td>
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<td>31-40</td>
<td>0.01215</td>
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</tr>
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<td>41-50</td>
<td>0.01061</td>
<td>0.01659</td>
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<tr>
<td>51-60</td>
<td>0.02055</td>
<td>0.02580</td>
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<td>0.03146</td>
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<td>71-80</td>
<td>0.04769</td>
<td>0.05109</td>
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<td>81-90</td>
<td>0.06232</td>
<td>0.07095</td>
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<td>91-100</td>
<td>0.11171</td>
<td>0.10081</td>
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<td>101-110</td>
<td>0.13349</td>
<td>N/A</td>
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<tr>
<td>111-120</td>
<td>0.15056</td>
<td>N/A</td>
</tr>
</tbody>
</table>

* N/A indicates that not enough data were available to calibrate a model for the corresponding speed range and road type.

Part b

<table>
<thead>
<tr>
<th>Speed Range (km/h)</th>
<th>Acceleration</th>
<th>Deceleration</th>
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<td>Interstate Highway</td>
<td>State Highway</td>
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<td>0.00194</td>
</tr>
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<td>11-20</td>
<td>0.01018</td>
<td>0.00265</td>
</tr>
<tr>
<td>21-30</td>
<td>0.03033</td>
<td>0.00927</td>
</tr>
<tr>
<td>31-40</td>
<td>0.04087</td>
<td>0.04906</td>
</tr>
<tr>
<td>41-50</td>
<td>0.05469</td>
<td>0.09007</td>
</tr>
<tr>
<td>51-60</td>
<td>0.05512</td>
<td>0.03233</td>
</tr>
<tr>
<td>61-70</td>
<td>0.05648</td>
<td>0.00599</td>
</tr>
<tr>
<td>71-80</td>
<td>0.07844</td>
<td>0.03284</td>
</tr>
<tr>
<td>81-90</td>
<td>0.10668</td>
<td>0.06501</td>
</tr>
</tbody>
</table>
Table 3. R-square ($R^2$) Between the Measured and the Predicted Emission (or Fuel Consumption) Rates from EMIT. Part a: Results for Calibration. Part b: Results for Validation. (from (13)).

<table>
<thead>
<tr>
<th>Part a</th>
<th>CO₂</th>
<th>CO</th>
<th>HC</th>
<th>NOₓ</th>
<th>FR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine-out module, category 7</td>
<td>0.98</td>
<td>0.87</td>
<td>0.58</td>
<td>0.86</td>
<td>0.97</td>
</tr>
<tr>
<td>Tailpipe module, category 7</td>
<td>0.98</td>
<td>0.84</td>
<td>0.53</td>
<td>0.79</td>
<td></td>
</tr>
<tr>
<td>Engine-out module, category 9</td>
<td>0.97</td>
<td>0.90</td>
<td>0.63</td>
<td>0.87</td>
<td>0.97</td>
</tr>
<tr>
<td>Tailpipe module, category 9</td>
<td>0.97</td>
<td>0.88</td>
<td>0.58</td>
<td>0.67</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Part b</th>
<th>CO₂</th>
<th>CO</th>
<th>HC</th>
<th>NOₓ</th>
<th>FR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine-out module, category 7</td>
<td>0.96</td>
<td>0.46</td>
<td>0.25</td>
<td>0.83</td>
<td>0.94</td>
</tr>
<tr>
<td>Tailpipe module, category 7</td>
<td>0.96</td>
<td>0.36</td>
<td>0.22</td>
<td>0.63</td>
<td></td>
</tr>
<tr>
<td>Engine-out module, category 9</td>
<td>0.95</td>
<td>0.50</td>
<td>0.22</td>
<td>0.83</td>
<td>0.95</td>
</tr>
<tr>
<td>Tailpipe module, category 9</td>
<td>0.95</td>
<td>0.43</td>
<td>0.32</td>
<td>0.53</td>
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</tbody>
</table>
FIGURE 1: Acceleration Distribution for the Calibration Data Set on Arterials for the Speed Ranges 21-30 km/h (Part a), 51-60 km/h (Part b), and 81-90 km/h (Part c).
FIGURE 2: Cumulative Sample and Half-Normal Distribution Functions for the Acceleration Data (Part a) and the Deceleration Data (Part b) Used for Calibration on Arterials for the Speed Range 0-10 km/h.
FIGURE 3: Cumulative Sample and Half-Normal Distribution Functions for the Acceleration Data (Part a) and the Deceleration Data (Part b) Used for Validation on Arterials for the Speed Range 0-10 km/h.
FIGURE 4: Variation of Standard Deviation of Acceleration Distributions (Part a) and Deceleration Distributions (Part b) Among Different Speed Ranges and Road Types.
FIGURE 5. Category 9 - FTP bag 2. Second-by-Second Engine-Out (EO) and Tailpipe (TP) Emission Rates of CO₂ and CO. Thick light line: measurements (calibration data); dark line: EMIT predictions; thin line: CMEM predictions. The top plot represents the speed trace. (from (13))
FIGURE 6. Expected Emission Rates in g/s (on the left) and in g/km (on the right) for Road Type Arterial and Vehicle Category 9. The expected emission rates in g/km of CO, HC, and NOX are compared with the facility-specific emission rates from MOBILE6 (thin line). (from (13)).
FIGURE 7. Expected Emission Rates in g/s (on the left) and in g/km (on the right) for Road Type Highway and Vehicle Category 9. The expected emission rates in g/km of CO, HC, and NOX are compared with the facility-specific emission rates from MOBILE6 (thin line). (from (13)).