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Using Instantaneous Speed and Acceleration Levels to Estimate Vehicle Fuel Usage and Emissions

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Abstract: This research presents a number of hybrid regression models that forecast hot stabilised vehicle fuel consumption and emission rates for light-duty cars and light-duty trucks. Instantaneous vehicle speed and acceleration readings are important input parameters for these models. The fuel consumption and emission rate measurements (CO, HC, and NOx) for five light-duty vehicles and three light-duty trucks as a function of the vehicle's instantaneous speed and acceleration levels were recorded at the Oak Ridge National Laboratory (ORNL). This data was used to fuel the energy and emission models that were described in this paper. When compared to the ORNL data, the fuel consumption and emission models are shown to be extremely accurate, with coefficients of determination ranging from 0.92 to 0.99. These models are able to assess the environmental effects of operational-level projects including intelligent transportation systems since they use the vehicle's instantaneous speed and acceleration levels as independent variables. To further highlight their significance and use in the transportation industry, the models created for this study have been included into the INTEGRATION microscopic traffic simulation model. These models have also been used to assess the energy and environmental effects of field operations at the operational level in conjunction with GPS speed readings.

CE Database keywords: Fuel consumption; Vehicles; Emissions; Speed; Acceleration.

Introduction

Problem Definition

Two important factors that are taken into account throughout the transportation planning process for highway facilities are vehicle fuel consumption and pollution. According to recent studies, automobile emissions may be directly responsible for up to 45% of the pollutants that are emitted in the United States (National Research Council 1995). With an emphasis on energy and emission metrics of efficacy, the introduction of intelligent transportation systems (ITS) presents a compelling case for comparing different ITS and non-ITS expenditures. The advantages of ITS technology in terms of emissions and energy use have not yet been extensively measured. Modern, cutting-edge models calculate car emissions using normal urban driving patterns. The majority of these models use streamlined mathematical formulas to calculate fuel and emission rates based on average link speeds without taking into account transient changes in a vehicle's speed and acceleration as it travels on a particular route.
. (U.S. EPA 1993). Additionally, the majority of models employ an aggregate modelling strategy in which distinct vehicle populations are represented by "characteristic" vehicles. Even though this method has been approved by transportation planners for the assessment of network-wide highway environmental impacts, it is unsuitable for the assessment of energy and environmental implications

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of operational-level initiatives. It can be argued that more accurate assessments of operational-level project impacts could be obtained by simulating individual vehicle fuel consumption and emissions along with vehicle kinematics on a highway network.

Paper Objective

This work offers mathematical models that forecast vehicle fuel consumption and emissions using instantaneous speed and acceleration as explanatory factors in an effort to get around the shortcomings of current energy and emission models. Today's relatively powerful processors are available on the typical desktop, making this method practical even for massive highway networks. These models' ultimate application would be their incorporation into traffic network simulators in order to better understand the effects of traffic policies, including the introduction of ITS technologies like signal coordination, incident management, and electronic payment systems on the environment. Additionally, these models can be used in conjunction with GPS observations to assess the energy and emission effects of operational-level projects on the ground.

There are five sections to this essay. The importance of the suggested models is discussed in the first section. The second part of the article describes the data sources that were used to create the suggested modelling strategy. The third section describes several

Table 1. ORNL Test Vehicle Characteristics

Year	Make/model	Engine and transmission	Curb weight (kg)	Rated power (hp)
(a) Light-duty cars 1988	Chevrolet Corsica	2.8L pushrod V6,PFI, M5	1,209	130
1994	Oldsmobile Cutlass Supreme	3.4L DOHC V6, PFI, L4	1,492	210
1994	Oldsmobile 88	3.8L pushrod V6, PFI, L4	1,523	170
1995	Geo Prizm	1.6L OHC I4, PFI, L4	1,116	105
1993	Subaru Legacy	2.2L DOHC flat 4, PFI, L4	1,270	130
	ORNL LDV average	2.8L, 5.2 cylinder	1,322	149
1995	LDV industry average	2.9L, 5.4 cylinder	1,315	
(b) Light-duty trucks 1994	Mercury Villager Van	3.0L pushrod V6, PFI, L4	1,823	151
1994	Jeep Grand Cherokee	4.0L pushrod I6, PFI, L4	1,732	190
1994	Chevrolet Silverado Pickup	5.7L pushrod V8, TBI, L4	1,823	200
	ORNL LDT average	4.2L, 6.7 cylinder	1,793	180
1995	LDT industry	4.6L, 6.5 cylinder		
	average8-	3.3L, 5.8 cylinder	1,497	160

	vehicle average	
1995	LDV+LDT, industry avg.	3.5L, 5.8 cylinder

ematical approaches for the evaluation of vehicle fuel consump- tion and emission impacts. Furthermore, the proposed model is compared to the alternative approaches in order to demonstrate the merit of the proposed models. The fourth section describes how the model was validated against real-world field data and current state-of-the-art emission models. Finally, the paper pro- vides a summary of the findings and recommendations for future work.

Significance of Proposed Models

Numerous variables influence vehicle energy and emission rates. These variables can be classified into six broad categories, as follows: travel-related, weather-related, vehicle-related, roadway-related, traffic-related, and driver-related factors. The travel- related factors account for the distance and number of trips trav- eled within an analysis period, while the weather-related factors account for temperature, humidity, and wind effects. Vehicle- related factors account for numerous variables including the en- gine size, the condition of the engine, whether the vehicle is equipped with a catalytic converter, whether the vehicle's air con- ditioning is functioning, and the soak time of the engine. The roadway-related factors account for the roadway grade and sur- face roughness, while the traffic-related factors account for vehicle-to-vehicle and vehicle-to-control interaction. Finally, the driver-related factors account for differences in driver behavior and aggressiveness.

State-of-the-art emission models such as MOBILE6, devel- oped by the U.S. Environmental Protection Agency (EPA), and EMFAC7F, developed by the California Air Resources Board (CARB), attempt to account for travel-related, weather-related, and vehicle-related factors on vehicle emissions. However, these models generally fail to capture roadway-, traffic-, and driver- related factors on vehicle emissions. Specifically, the models use average speed and vehicle miles traveled to estimate vehicle emissions. Implicit in each facility average speed is a driving cycle. Consequently, the current state-of-the-art emission models are unsuitable for evaluating the environmental impacts of operational-level projects where changes in traffic behavior be- tween a before-and-after scenario are critical.

The models developed in this paper attempt to overcome the shortcomings of the state-of-the-art models by quantifying traffic- and driver-related factors on vehicle emissions in addition to travel-related factors. Specifically, the models use the vehicle's instantaneous speed and acceleration levels to estimate vehicle emissions. Further refinements to the model include accounting for vehicle- and weather-related factors.

Vehicle Energy and Emission Data SourceDescription

The data that were utilized to develop the fuel consumption and emission models that are presented in this paper were collected at the Oak Ridge National Laboratory (ORNL). Specifically, test vehicles were driven in the field in order to verify their maximum operating boundary. Subsequently, vehicle fuel consumption and emission rates were measured in a laboratory on a chassis dyna- mometer within the vehicle's feasible vehicle speed and accelera- tion envelope. Data sets were generated that included vehicle en- ergy consumption and emission rates as a function of the vehicle's instantaneous speed and acceleration levels. Several measure- ments were made in order to obtain an average fuel consumption and emission rate (West et al. 1997). The emission data that were gathered included hydrocarbon (HC), oxides of nitrogen (NO_x), and carbon monoxide (CO) emission rates.

The eight normal emitting vehicles included five light-duty automobiles and three light-duty trucks, as summarized in Table

1. These vehicles were selected in order to produce an average vehicle that was consistent with average vehicle sales in terms of engine displacement, vehicle curb weight, and vehicle type (West et al. 1997). Specifically, the average engine size was 3.3 liters, the average number of cylinders was 5.8, and the average curb weight was 1,497 kg (3,300 lbs) (West et al. 1997). Industry re- ports show that the average sales-weighted domestic engine size in 1995 was 3.5 liters, with an average of 5.8 cylinders (Ward's Communications 1996a, b).

The data collected at ORNL contained between 1,300 and 1,600 individual measurements for each vehicle and a measure of effectiveness (MOE) combination depending on the envelope of operation of the vehicle. Typically, vehicle acceleration values

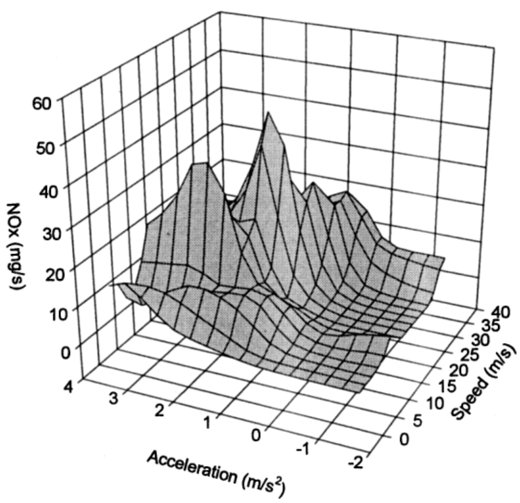

Fig. 1. ORNL NO_x emissions rates (Mercury Villager)

ranged from —1.5 to 3.7 m/s^2 at increments of 0.3 m/s^2 (—5 to 12 ft/s^2 at 1 ft/s^2 increments). Vehicle speeds varied from 0 to 33.5 m/s (0 to 121 km/h or 0 to 110 ft/s) at increments of 0.3 m/s. A sample data set for one of the test vehicles is presented in Fig. 1 for illustration purposes. The figure clearly demonstrates the large nonlinear behavior in all MOEs as a function of the vehicle speed and acceleration. Specifically, ''peaks'' and ''valleys'' are preva- lent as a result of gear shifts under various driving conditions. In addition, it is evident that as acceleration and speed increases the MOEs generally tend to increase. Furthermore, it is noted that the gradient of the MOEs in the negative acceleration regime (—1.5 to 0 m/s^2) is generally smaller than that in the positive accelera- tion regime (0 to 3.7 m/s^2).

It is interesting to note that the ORNL data represents a unique vehicle performance envelope. For example, low weight-to-power ratio vehicles have better acceleration characteristics at high speeds than their high weight-to-power ratio counterparts. This inherent performance boundary is extremely important when these models are used in conjunction with microscopic traffic flow models, as they represent a physical kinematic constraint in the car-following equations of motion. A typical speed- acceleration performance boundary is illustrated in Fig. 2 for ahypothetical composite vehicle. The composite vehicle was de- rived as an average of the eight test vehicles to reflect a typical average vehicle.

Development of Models

Background

Several regression model structures were evaluated as part of the research effort that is presented in this paper. The first of these models attempted to establish the relationship between the trac- tive effort and vehicle fuel consumption and emissions. The use of tractive effort as an independent variable for estimating vehicle fuel consumption was first proposed by Post et al. (1981) and further enhanced by Biggs and Akcelik (1986). Post et al. (1984) extended these models to develop power demand models for the estimation of vehicle fuel consumption and emissions of hydro- carbons and nitrogen oxides. The presumption was that the instan- taneous engine tractive force was proportional to vehicle emis- sions and fuel consumption rates. It should be noted that the model presented by Biggs and Akcelik (1986) assumed idling conditions for negative tractive effort conditions (deceleration mode). However, the ORNL data indicate that vehicle emissions and fuel consumption rates increase as speed increases, even though the vehicle is in a deceleration mode.

While the comparison of these models is beyond the scope of this research effort, a subsequent paper will present a detailed comparison of the various models to the models that are proposed in this paper. It is sufficient to mention at this point, however, that the Federal Test Procedure (FTP) drive cycle involves a deceler- ating drive mode for 34.5% of the time and an idling mode for 17.9% of the time. Consequently, these models would indicate identical vehicle emission rates for 52.9% of the entire cycle, which results in significant errors in estimating vehicle emissions.

Model Development

The derivation of the final models involved experimentation with numerous polynomial combinations of speed and acceleration levels. Specifically, linear, quadratic, cubic, and quartic terms of speed and acceleration were investigated. The final regression models included a combination of linear, quadratic, and cubic speed and acceleration terms because it provided the least number of terms with a relatively good fit to the ORNL data (R^2 in excess of 0.70 for most MOEs). These models fit the ORNL data accu- rately for high speed and acceleration levels; however, the modelsare less accurate at low speed and acceleration levels.

The final model included a third degree polynomial based on Eq. (1). This model produced reasonable fits to the ORNL data except in a few instances where the models produced negative

Table 2. Regression Model Comparison

	Correlation of determination			
Model	Fuel	HC	CO	NO_x
Force model with log transformation	0.870	0.319	0.870	0.667
Polynomial regression model	0.996	0.716	0.748	0.805

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Fig. 2. Maximum acceleration as function of vehicle speed (compos- ite vehicle)

with log transformation				
Hybrid regression model with log transformation	0.998	0.974	0.918	0.982

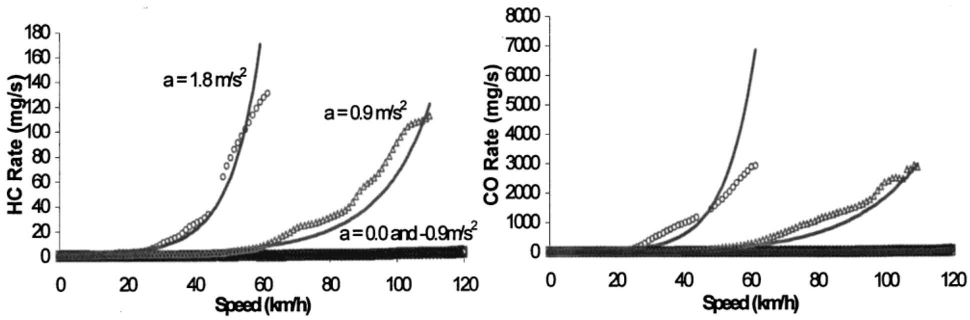

Fig. 3. Regression model predictions (composite vehicle, log-transformed polynomial model)

dependent variable values. To solve this problem, a data transfor- mation technique was adopted to the model that is presented in Eq. (1), resulting in the model that is presented in Eq. (2). First, independent variables were transformed using the natural loga- rithm. Second, regression models were fitted to the transformed data. Finally, the predicted values were then transformed back by utilizing an exponential function. The coefficient of determination of the MOE estimates using Eq. (2) ranged from 0.72 to 0.99, as summarized in Table 2. The statistical results indicate a good fit for fuel consumption estimates (R^2=0.996), an average fit for NO_x estimates (R^2=0.805), and a relatively poor fit for HC and CO emission estimates (R^2=0.72 and 0.75, respectively). In order to isolate and identify the shortcomings of the log- transformed polynomial regression models, Fig. 3 illustrates graphically the quality of fit between the regression models and the ORNL data. It is noted from Fig. 3 that the errors in the HC and CO model estimates are high in the high acceleration region (it overestimates HC emissions by up to 25% and CO emissions by 100%). These errors in the regression model are caused by the significant sensitivity of the dependent variable to the indepen- dent variables at high accelerations as compared with the mar- ginal sensitivity of the dependent variable in the negative accel- eration range. Differences in behavior for positive versus negative accelerations can be attributed to the fact that in positive accel- erations the vehicle exerts power, while in the negative accelera- tion range the vehicle does not exert power. Consequently, sepa- rate regression models were developed for positive and negative

all MOEs), as summarized in Table 2. Fig. 4 further illustrates the effectiveness of the hybrid log-transformed models in predicting vehicle fuel consumption and emission rates as a function of a vehicle’s instantaneous speed and acceleration levels. A compari- son of Figs. 3 and 4 clearly demonstrates the enhancement in model predictions as a result of separating positive and negative acceleration levels. It should be noted, however, that the model estimates were less accurate than the polynomial model fits for high speed and acceleration combinations. Sample model coeffi- cients for estimating HC emission rates for an average composite vehicle are summarized in Table 3.

The use of polynomial speed and acceleration terms may result in multicolinearity between the independent variables as a result of the dependency of these variables. The variance inflation factor (VIF), which is a measure of multicolinearity, can be reduced by removing some of the regression terms with, however, a reduction in the accuracy of the model predictions. Consequently, a trade- off between reducing the model multicolinearity should be weighed against a potential reduction in model accuracy. The ex- istence of multicolinearity results in model estimations of the de- pendent

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variable that are unreliable for dependent variable values outside the bounds of the original data. Consequently, the model was maintained with the caveat that the model should not be utilized for data outside the feasible envelope of a typical vehicle:

accelerations, as demonstrated in Eq. (3). It should be noted that the intercept at zero speed and zero acceleration was estimated for positive accelerations and fixed in the negative acceleration formulation in order to ensure a continuous function between the two regression regimes. The final models that were developed resulted in good fits to the ORNL data (R^2 in excess of 0.92 for

$$MOE_e = \sum_{i=0}^{3} \sum_{j=0}^{3} (K^e_{i,j} \times s^i \times a^j) \quad (1)$$

$$\ln(MOE_e) = \sum_{i=0}^{3} \sum_{j=0}^{3} (K^e_{i,j} \times s^i \times a^j) \quad (2)$$

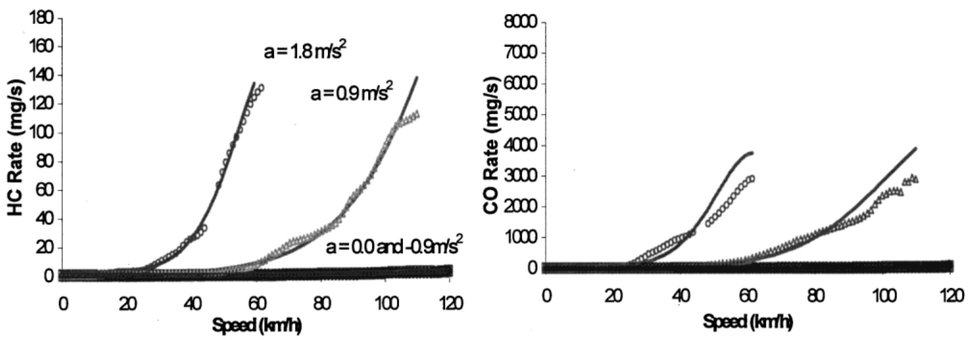

Fig. 4. Regression model predictions (composite vehicle, log-transformed hybrid polynomial model)

Table 3. Sample Coefficients of Hybrid Regression Model (HC Emissions for Composite Vehicle)

Coefficients	Constant	Speed	$Speed^2$	$Speed^3$
Positive acceleration				
Constant	—0.87605	0.03627	—0.00045	2.55E—06
Acceleration	0.081221	0.009246	—0.00046	4.00E—06
$Acceleration^2$	0.037039	—0.00618	2.96E—04	—1.86E—06
$Acceleration^3$	—0.00255	0.000468	—1.79E—05	3.86E—08
Negative acceleration				
Constant	—0.75584	0.021283	—0.00013	7.39E—07
Acceleration	—0.00921	0.011364	—0.0002	8.45E—07
$Acceleration^2$	0.036223	0.000226	4.03E—08	—3.5E—08

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Acceleration[3]	0.003968	—9E—05	2.42E—06	—1.6E—08

Note: Speed: km/h; acceleration: km/h/s; HC emission rate: mg/s.

$$\ln(\mathrm{MOE}_e) = \sum_{i=0}^{3}\sum_{j=0}^{3} (L^e_{i,j} \times s^i \times a^j) \quad \text{for } a \geq 0 \qquad (3)$$

els presented here. Third, the models are confined to speed and acceleration levels within the envelope of the ORNL data.

The third limitation results from the inherent limitation of any model to extrapolate response values beyond the boundaries used in the model calibration procedure. While most vehicles can travel faster than 121 km/h (the upper limit of the testing bound- ary), it is impossible to establish a reliable forecasting pattern for energy and emission rates at high speeds due to the heavy non- linear nature of the response curves. It has been observed from the US06 cycle that some speed and acceleration profiles exceed the speed and acceleration boundary (13 out of 596 seconds). However, in these cases, the writers recommend using boundary speed and acceleration levels in order to ensure realistic vehicle MOE estimates. Furthermore, it should be noted that these models have been successfully applied to global positioning system (GPS) speed measurements after applying robust smoothing tech-niques in order to ensure feasible speed measurements (Rakhaet al. 2000a).

Model Validation

$$\sum_{i=0}^{3}\sum_{j=0}^{3} (M^e_{i,j} \times s^i \times a^j) \quad \text{for } a < 0$$

Description of EPA Data Sets

Model Domain of Application

As is the case with any mathematical model, the proposed models are applicable for a specified domain of application. First, the models are developed to estimate vehicle fuel consumption and emission rates for light duty vehicles and trucks. Second, the models estimate vehicle emissions for hot stabilized conditions and do not consider the effect of vehicle start effects. It should be noted, however, that second-by-second data obtained from the EPA have proven valuable in determining the differences between hot-running and cold-start engines. A model is being developed to add this contribution as an external additive function to the mod-

In order to evaluate the accuracy of the proposed hybrid emission models, ‘‘real-world’’ emission data were compared with regres- sion model estimates. The field measurements were gathered by the Environmental Protection Agency (EPA) at Automotive Test- ing Laboratories, Inc. (ATL), in Ohio and EPA’s National Vehicle and Fuels Emission Laboratory (NVREL), in Ann Arbor, Michi- gan, in the spring of 1997. All the vehicles at ATL were drafted at Inspection and Maintenance lanes utilized by the State of Ohio and tested under as-received condition (without repairs). A total of 62 vehicles in East Liberty, Ohio, and 39 vehicles in Ann Arbor, Michigan, were recruited and tested. The sample of 101 vehicles included three heavy-duty trucks, 34 light-duty trucks,

Table 4. EPA's New Facility-Specific Drive Cycle Characteristics

Cycle	Average speed (km/h)	Maximum speed (km/h)	Maximum acceleration (km/h /s)	Duration (s)	Length (km)
Freeway, high speed	101.12	119.52	4.32	610	17.15
Freeway, LOS A-C	95.52	116.96	5.44	516	13.68
Freeway, LOS D	84.64	112.96	3.68	406	9.54
Freeway, LOS E	48.8	100.8	8.48	456	6.18
Freeway, LOS F	29.76	79.84	11.04	442	3.66
Freeway, LOS G	20.96	57.12	6.08	390	2.27
Freeway ramps	55.36	96.32	9.12	266	4.10
Arterial/collectors LOS A-B	39.68	94.24	8	737	8.11
Arterial/collectors LOS C-D	30.72	79.2	9.12	629	5.38
Arterial/collectors LOS E-F	18.56	63.84	9.28	504	2.59
Local roadways	20.64	61.28	5.92	525	2.99
Nonfreeway area-wide urban travel	31.04	83.68	10.24	1,348	11.60
LA04	31.36	90.72	5.28	1,368	11.92
Running 505	40.96	90.72	5.28	505	5.744
LA 94	39.36	107.52	11.04	1,435	15.696
ST01	32.32	65.6	8.16	248	2.224
New York Cycle	11.36	44.32	9.6	600	1.888

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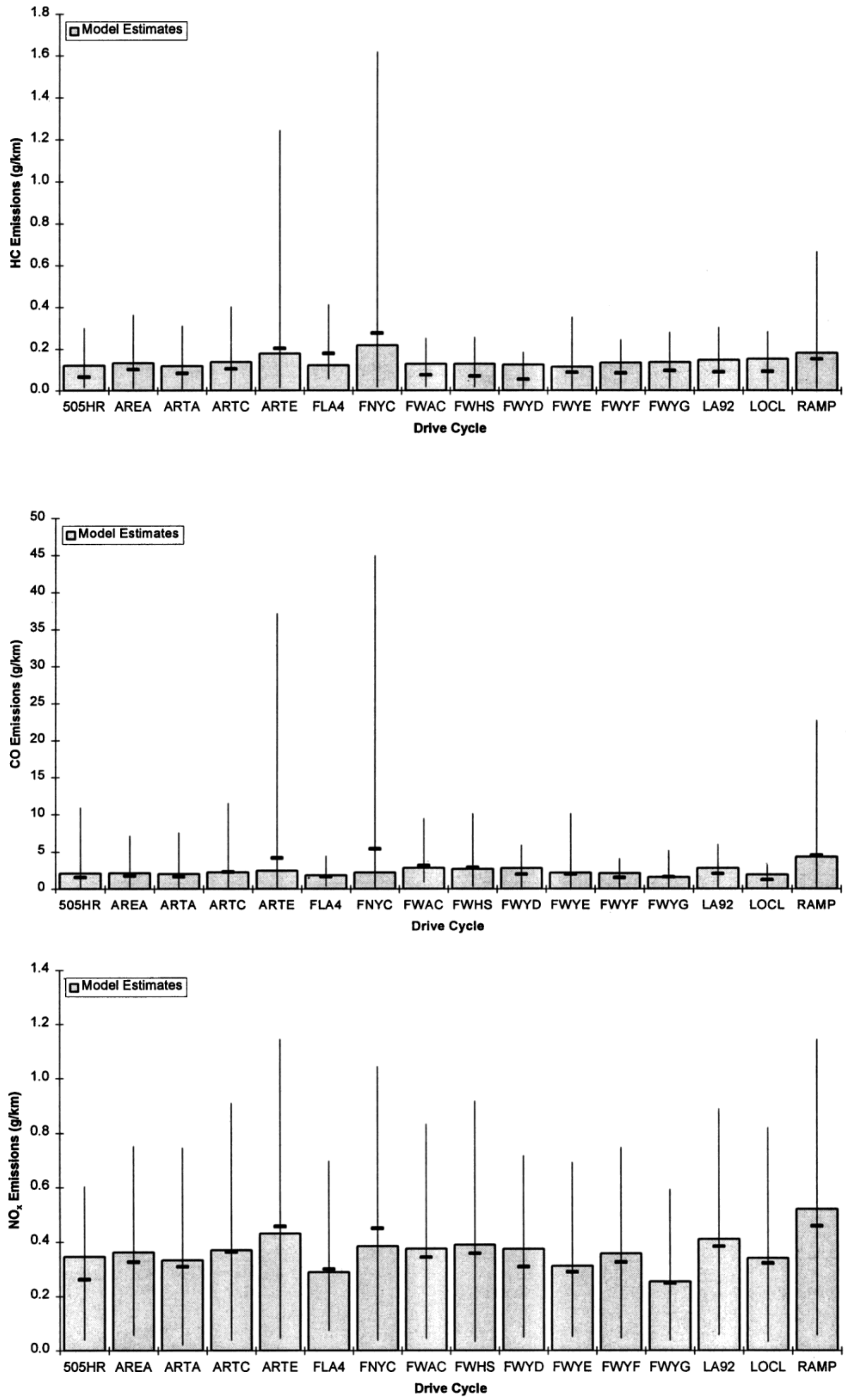

Fig. 5. Simulated emissions for different driving cycles

and 64 light-duty cars. The vehicle model years ranged from 1986 through 1996 (Brzezinski et al. 1999).

All vehicles were tested using the standard vehicle certifica-tion test fuel. Vehicle emission tests were performed in random

order to offset any possible order bias that could result in different ambient conditions for the tested cycles. The emission results were measured as composite ''bags'' and in grams on a second- by-second basis for HC, CO, NO_x, and CO_2 emissions.

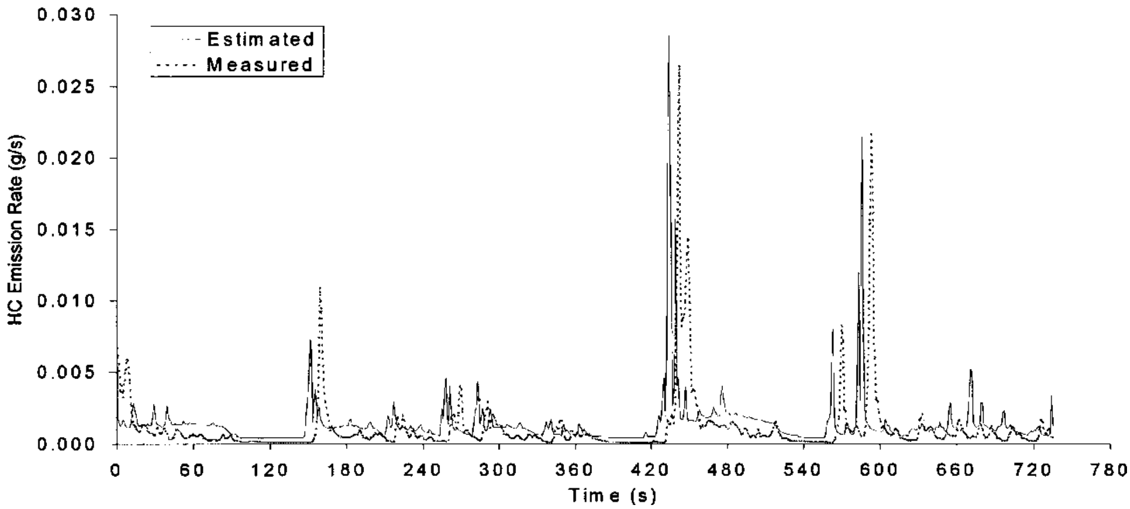

Fig. 6. HC emission comparison for ARTA driving cycle

Description of EPA Drive Cycles

The MOBILE5a model was developed based on vehicle emission testing using the Federal Test Procedure (FTP) drive cycle. If the estimated average speed is different from the average speed of the FTP drive cycle (31.4 km/h or 19.6 mph), speed correction factors are used to adjust the emissions measured using the FTP drive cycle. However, these speed correction factors are utilized regard- less of the roadway type or traffic conditions. For example, the MOBILE5 model cannot compare a highly congested freeway and a normal density arterial with the same average speed, though each may involve a significant different distribution for speeds and accelerations causing distinct emission levels.

In order to address these problems, EPA has developed new facility-specific and area-wide driving cycles based on real-world driving studies to incorporate within EPA's new MOBILE6 model (Brzezinski et al. 1999). Table 4 provides a brief description of the new cycles and additional emission test cycles used for emis- sion testing. It should be noted that the ST01 drive cycle was not utilized for the model validation because the cycle involves cold starts.

Aggregate Emission Model Validation

The EPA data that were described earlier were utilized to validate the proposed models. The initial validation effort involved an aggregate level comparison between EPA's aggregate emission

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measurements over 15 drive cycles using vehicles that were clas- sified as clean with the proposed model estimates of vehicle emis- sions. In identifying clean vehicles, manufacturers's standard emission rates were applied, which are 0.41 grams/mile for HC,
3.4 grams/mile for CO, and 1.0 gram/mile for NO_x for Bag 2 of the FTP city cycle. Based on these criteria, a total of 51 vehicles of the 101 vehicles were classified as clean for HC emissions, 47 vehicles for CO emissions, and 60 vehicles for NO_x emissions.

Fig. 5 shows the comparisons between simulated regression model results and EPA's real-world data for different driving cycles. Fig. 5 illustrates the variation in the 95th and 5th percen- tiles using vertical lines and mean values of EPA field measure- ments using a small bar for the 16 drive cycles. The bar plots represent the proposed regression model emission estimates using an average composite vehicle. The emissions are computed as the sum of instantaneous vehicle emissions for each of the 15 drive

cycles. Fig. 5 clearly illustrates a good fit between the model estimates and the field measurements. Specifically, the predictions lie within the 95th and 5th percentile confidence limits. Further- more, the model estimates generally follow the average field emission values of the clean vehicle fleet. Also, it is noted that the average HC and CO values of the ARTE and FNYC cycle are high as compared with the model estimates as a result of a few emission measurements that are extremely high. The simulation results for NO_x appear to follow the average values almost per- fectly.

Instantaneous Emission Model Validation

The next step in validating the proposed models was to compare second-by-second field HC, CO, and NO_x measurements against instantaneous model estimates with the objective of identifying any shortcomings in the proposed models. In order to ensure con- sistency in the comparison, the Subaru Legacy was selected for comparison purposes, because both the ORNL data set and the EPA data set included a Subaru Legacy vehicle. Specifically, the ORNL included a 1993 model and the EPA data included a 1992 model.

Fig. 6 illustrates the speed and acceleration profiles of the ARTA drive cycle, which involves several full and partial stops in addition to travel at a fairly high speed (in the range of 100 km/h). The figure clearly demonstrates that the ARTA drive cycle in- volves a more aggressive and realistic driver behavior as com- pared with the FTP city cycle. In addition, Fig. 6 illustrates the variation in the instantaneous vehicle emissions of HC as mea- sured on a dynamometer as it travels through the drive cycle. Superimposed on the figure are the hybrid log-transformed model estimates of vehicle emissions based on instantaneous vehiclespeed and acceleration levels.

The total vehicle emissions of HC as measured in the labora- tory was 0.86 grams, while the estimated HC emissions based on the proposed hybrid model was 1.06 grams, which corresponds to a 19% difference in overall emissions for the entire cycle. The figure illustrates that in general the model prediction almost per- fectly follows the EPA vehicle emission measurements, demon- strating the uniqueness of the model for assessing traffic improve- ment projects, including ITS technology, on the environment. Fig. 6 demonstrates that the EPA emission rates are slightly shifted

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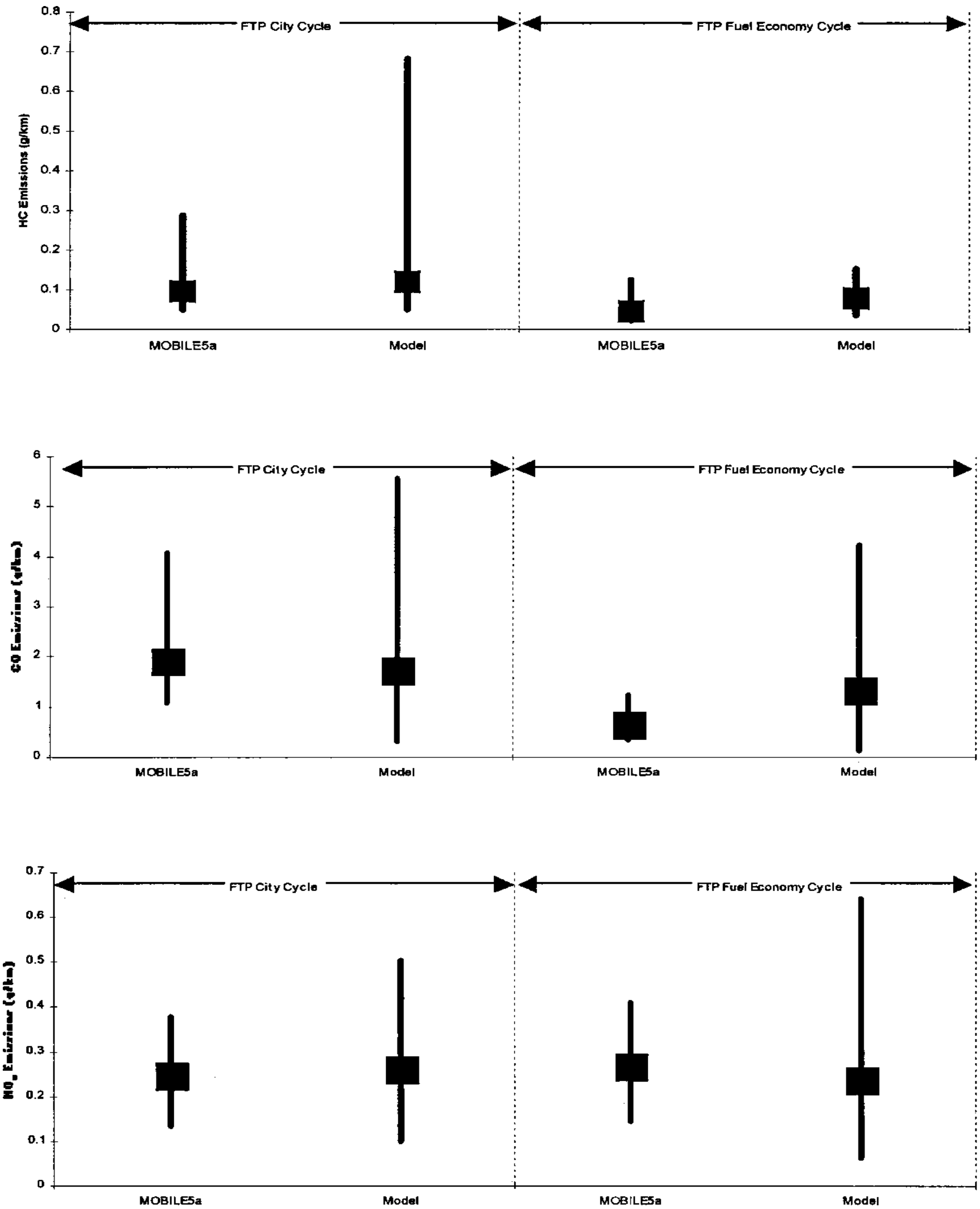

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Fig. 7. Model comparison to MOBILE5a

right side relative to the model estimates. The offset in vehicle emissions results from a time lag between vehicle accelerations and their corresponding emissions through the tailpipe. It is noted that the time lags between vehicle accelerations and vehicle emis- sions typically range between 5 and 10 s.

Comparison with MOBILE5a

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The hybrid log-transformed polynomial models were validated against MOBILE5a (U.S. EPA 1996) because MOBILE6 was not commercially available at the time the models were developed. The comparison is made for the FTP city cycle, also known as

LA4, and the highway economy cycle, because these cycles are reflected in the MOBILE5a.

In conducting the comparison, the following constraints were implemented within the MOBILE5a input parameters. First, ve- hicle compositions were set to be consistent with the ORNL ve- hicle composition (i.e., 5/8 were light-duty vehicles and 3/8 were light-duty trucks). Second, the model year distribution was made consistent with the ORNL vehicle sample. Third, the vehicle mileage was set to be less than 50,000 miles, to be consistent with the ORNL data. Finally, only hot stabilized conditions were mod-eled without the inclusion of high emitters.

The results of the model comparisons are illustrated in Fig. 7. The composite vehicle emission estimates are represented by the rectangles in Fig. 7 while the 95th and 5th percentile emission

ent temperature. Second, the environmental impact of heavy duty vehicles cannot be ignored in the modeling process. Data on heavy-duty vehicle emissions are required to develop similar mi- croscopic models. Third, models are currently being developed to account for high emitting vehicles. Finally, models are being de- veloped to account for other important pollutants, including par- ticulate matters and CO_2 .

Notation

The following symbols are used in this paper: a = instantaneous acceleration (m/s^2);

K^e = model regression coefficient for MOE *e* at speed

estimates for individual ORNL eight vehicles are represented by

, *j*

power *i* and acceleration power *j*;

the extents of the vertical lines. The MOBILE5a results reflect

L^e = model regression coefficient for MOE *e* at speed

different annual vehicle mileage compositions, with the rectangles reflecting the composition that is consistent with the ORNL data.

i, *j*

power *i* and acceleration power *j* for positive ac-celerations;

Fig. 7 clearly demonstrates consistency in the vehicle emissions

M^e = model regression coefficient for MOE *e* at speed

between the instantaneous emission models and MOBILE5a for both the LA4 and the highway economy drive cycles. Further-

i, *j*

power *i* and acceleration power *j* for negative ac-celerations;

more, the results indicate similar relative differences across the different drive cycles.

Conclusions

The paper presents microscopic fuel consumption and emission models that require instantaneous vehicle speed and acceleration levels as input variables. The models, which were developed using the ORNL data, estimate hot stabilized vehicle emissions for normal light-duty vehicles. The models are found to produce vehicle emissions that are consistent with the ORNL data (coef- ficient of determination in excess of 90%).

The development of these models attempts to bridge the exist- ing gap between traffic simulation models, traditional transporta- tion planning models, and environmental impact models. The models presented in this paper are general enough to be incorpo- rated within microscopic traffic simulation models. It is believed that, given the current power of desktop computers, the imple- mentation of any of the models presented in this paper adds an acceptable computational overhead to a microscopic simulation model. The benefit of this integration would be substantial if one considers that current environmental models are quite insensitive to traffic- and driver-related factors on vehicle emissions. Cur- rently, the models developed in this study have been incorporated within the microscopic traffic simulation tool INTEGRATION to further demonstrate their application and relevance to traffic en- gineering studies (Rakha et al. 2000b).

The models can also be applied directly to estimate vehicle fuel consumption and emissions using instantaneous GPS speed measurements (Rakha et al. 2000a).

Recommendations for Further Research

A number of areas of research are currently being pursued to expand the applicability of the models that were presented. First, microscopic emission models that account for engine start emis- sions are currently being developed which account for the ambi-

MOE = instantaneous fuel consumption or emission rate (L/s or mg/s); and

s = instantaneous speed (km/h).

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