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Software Engineering: A Roadmap

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ABSTRACT:

Several hybrid regression models that predict hot stabilized vehicle fuel consumption and emission rates for light-duty vehicles and light-duty trucks are presented in this paper. Key input variables to these models are instantaneous vehicle speed and acceleration measurements. The energy and emission models described in this paper utilize data collected at the Oak Ridge National Laboratory that included 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. The fuel consumption and emission models are found to be highly accurate compared to the ORNL data with coefficients of determination ranging from 0.92 to 0.99. Given that the models utilize the vehicle's instantaneous speed and acceleration levels as independent variables, these models are capable of evaluating the environmental impacts of operational-level projects including Intelligent Transportation Systems (ITS). The models developed in this study have been incorporated within the INTEGRATION microscopic traffic simulation model to further demonstrate their application and relevance to the transportation profession. Furthermore, these models have been utilized in conjunction with Global Positioning System (GPS) speed measurements to evaluate the energy and environmental impacts of operational-level projects in the field.

Key words: A road map

INTRODUCTION

Problem Definition

Vehicle fuel consumption and emissions are two critical aspects considered in the transportation planning process of highway facilities. Recent studies indicate that as much as 45% of the pollutants released in the U.S. are a direct consequence of vehicle emissions (National Research Council, 1995). The introduction of Intelligent Transportation Systems (ITS) makes a compelling case to compare alternative ITS and non-ITS investments with emphasis on energy and emission measures of effectiveness. Until now, the benefits derived from ITS technology in terms of energy and emissions have not been systematically quantified.

Current state-of-the-art models estimate vehicle emissions based on typical urban driving cycles. Most of these models offer simplified mathematical expressions to compute fuel and emission rates based on average link speeds without regarding transient changes in a vehicle's speed and acceleration as it travels on a highway network (US EPA, 1993). Moreover, most models use an aggregate modeling approach where a 'characteristic' vehicle is used to represent dissimilar vehicle populations. While this approach has been accepted by transportation planners for the evaluation of network-wide highway impacts on the environment, it is not suited for the evaluation of energy and environmental impacts of operational-level projects. Instead, it can be argued that modeling individual vehicle fuelconsumption and emissions coupled with the modeling of vehicle kinematics on a highway network could result inmore reliable evaluations of operational-level project impacts.

Paper Objective

In an attempt to overcome the limitations of current energy and emission models, this paper develops mathematical models that predict vehicle fuel consumption and emissions using instantaneous speed and acceleration as explanatory variables. The availability of relatively powerful computers on the average desktop today makes this approach feasible even for large highway networks. The ultimate use of these models would be their integration into traffic network simulators to better understand the impacts of traffic policies, including introduction of ITS technology, on the environment. Furthermore, these models can be utilized in conjunction with Global Positioning System (GPS) measurements to evaluate, in the field, the energy and emission impacts of operational-level projects.

Paper Layout

This paper is organized in five sections. The first section describes the significance of the proposed models. The second section describes the data sources that were utilized to develop the proposed modeling approach. The third section describes several mathematical approaches for the evaluation of vehicle fuel consumption and emission impacts. Furthermore, the proposed model is compared to the alternative approaches in order to demonstrate the merit of the proposed models. The forth section describes how the model was validated against real world field data and current state-of-the-art emission models. Finally, the paper provides 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 traveled 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 engine size, the condition of the engine, whether the vehicle is equipped with a catalytic converter, whether the vehicle's air conditioning is functioning, and the soak time of the engine. The roadway-related factors account for the roadway grade and surface 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.

The state-of-the-art emission models such as MOBILE6 developed by the US 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 between 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 SOURCE DESCRIPTION

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 dynamometer within the vehicle's feasible vehicle speed and acceleration envelope. Data sets were generated that included vehicle energy consumption and emission rates as a function of the vehicle's instantaneous speed and acceleration levels. Several measurements 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 was1497 kg (3300 lbs) (West et al. 1997). Industry reports show that the average sales-weighted domestic engine sizein 1995 was 3.5 liters, with an average of 5.8 cylinders (Ward's Communications 1996; Ward's Communications 1995).

The data collected at ORNL contained between 1,300 to 1,600 individual measurements for each vehicle and Measure of Effectiveness (MOE) combination depending on the envelope of operation of the vehicle. Typically, vehicle acceleration values 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 Figure 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 prevalent 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 inthe negative acceleration regime (-1.5 to 0 m/s^2) is generally smaller than that in the positive acceleration regime (0to 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 Figure 2 for a hypothetical composite vehicle. The composite vehicle was derived 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 tractive effort and vehicle fuel consumptionand emissions. The use of tractive effort as an independent variable for estimating vehicle fuel consumption was first proposed by Akcelik *et al*. (1983) 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 hydrocarbons and nitrogen oxides. The presumption was that the instantaneous engine tractive force was proportional to vehicle emissions 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 thoughthe 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 decelerating drive mode for 34.5percent of the time, and idling mode for 17.9 percent of the time. Consequently, these models would indicate identical vehicle emission rates for 52.9 percent 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 inexcess of 0.70 for most MOEs). These models fit the ORNL data accurately for high speed and acceleration levels, however the models are less accurate at low speed and acceleration levels, as illustrated in Figure 3.

The final model included a third degree polynomial based on Equation 1. This model produced reasonable fits to the ORNL data except in a few instances where the models produced negative dependent variable values. To solve this problem, a data transformation technique using the natural logarithm was adopted to the model that is presented in Equation 1 resulting in the model that is presented in Equation 2. The coefficient of determination of the MOE estimates using Equation 2 ranged from 0.72 to 0.99, as summarized in Table 2. The statistical results indicate agood 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, Figure 4 illustrates graphically the quality of fit between the regression models and the ORNL data. It is noted from Figure 4that the errors in the HC and CO model estimates are high in the high acceleration region (overestimates HC emissions by up to 25 percent and CO emissions by 100 percent). These errors in the regression model are causedby the significant sensitivity of the dependent variable to the independent variables at high accelerations comparedwith the marginal sensitivity of the dependent variable in the negative acceleration range. Differences in behavior for positive versus negative accelerations can be attributed to the fact that in positive accelerations the vehicle exertspower, while in the negative acceleration range the vehicle does not exert power.

Consequently, separate regression models were developed for positive and negative accelerations, as demonstratedin Equations 3 and 4. It should be noted that the intercept at zero speed and zero acceleration was estimated fromEquation 3 and fixed in Equation 4 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 all MOEs), as summarized in Table 2. Figure 5 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 comparison of Figure 4 and Figure 5 clearly demonstrates the enhancement in model predictions as a result of separating positive and negative acceleration levels. It should be noted, however that themodel estimates were less accurate than the polynomial model fits for high speed and acceleration combinations (comparing Figure 3 to Figure 5). Sample model coefficients 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 multi-colinearity between the independent variables as a result of the dependency of these variables. The Variance Inflation Factor (VIF), which is a measureof multi-colinearity, 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 multi-colinearity should be weighed against a potential reduction in model accuracy. The existence of multi-colinearity results is model estimations of the dependent 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.

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

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

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

where:

MOE_e Instantaneous fuel consumption or emission rate (l/s or mg/s)

$K^e_{i,j}$ Model regression coefficient for MOE "e" at speed power "*i*" and acceleration power "*j*"

$L^e_{i,j}$ Model regression coefficient for MOE "e" at speed power "*i*" and acceleration power "*j*" for positive accelerations $M^e_{i,j}$ Model regression coefficient for MOE "e" at speed power "*i*" and acceleration power "*j*" for negative accelerations*s* Instantaneous Speed (km/h)

a Instantaneous acceleration (m/s^2)

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 models 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 (upper limit of the testing boundary), it is impossible to establish a reliable forecasting pattern for energy and emission rates athigh speeds due to the heavy nonlinear nature of the response curves. It has been observed from the US06 cyclethat some speed and acceleration profiles exceed the speed and acceleration boundary (13 out of 596 seconds). However, in these cases, authors 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 techniques in order to ensure feasible speed measurements (Rakha *et al.*, 2001).

MODEL VALIDATION

Description of EPA Data Sets

In order to evaluate the accuracy of the proposed hybrid emission models, "real world" emission data were comparedto regression model estimates. The field measurements were gathered by the Environmental Protection Agency (EPA) at the Automotive Testing Laboratories, Inc. (ATL), in Ohio and EPA's National Vehicle and Fuels EmissionLaboratory (NVREL), in Ann Arbor, Michigan, 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 totalof 62 vehicles in East Liberty, Ohio and 39 vehicles in Ann Arbor, Michigan were recruited and tested. The sample of 101 vehicles included 3 heavy-duty trucks, 34 light-duty trucks, 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 certification 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.

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 regardless 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 emission 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 effortinvolved an aggregate level comparison between EPA's aggregate emission measurements over 15 drive cycles using vehicles that were classified as clean with the proposed model estimates of vehicle emissions. In identifyingclean vehicles, manufacture'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.

Figure 6 illustrates the variation in the 95th percentile, 5th percentile, and mean EPA field measurements for the 15 drive cycles that were considered. The bar plots represent the proposed model emission estimates using an average composite vehicle. The emissions are computed as the sum of instantaneous vehicle emissions for each of the 15drive cycles. Figure 6 clearly illustrates a good fit between the model estimates and the field measurements. Specifically, the predictions lie within the 95th percentile and the 5th percentile confidence limits. Furthermore, 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 compared to 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 perfectly.

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 consistency 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 a1993 model and the EPA data included a 1992 model.

Figure 7 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 theARTA drive cycle involves a more aggressive and realistic driver behavior compared to the FTP City cycle. In addition, Figure 7 illustrates the variation in the instantaneous vehicle emissions of HC as measured 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 vehicle speed and acceleration levels.

The total vehicle emissions of HC as measured in the laboratory was 0.86 grams, while the estimated HC emissions based on the proposed hybrid model was 1.06 grams, which corresponds to a 19 percent difference in overall emissions for the entire cycle. The figure illustrates that in general the model prediction almost perfectly follows the EPA vehicle emission measurements, demonstrating the uniqueness of the model for assessing traffic improvement projects, including ITS technology, on the environment.

Figure 7 demonstrates that the EPA emission rates are slightly shifted to 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 emissionstypically range between 5 and 10 seconds.

Comparison with MOBILE5a

The hybrid log-transformed polynomial models were validated against MOBILE5a (EPA, 1996) because MOBILE6 was not commercially available at the time the models were developed. The comparison is made for the FTP Citycycle, 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 parmameters. First, vehicle compositions were set to be consistent with the ORNL vehicle 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 ORNLvehicle 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 modeled without the inclusion of high emitters.

The results of the model comparisons are summarized in Table 5 and illustrated in Figure 8. The composite vehicle emissions are represented by the rectangles in Figure 8 while the minimum and maximum vehicle emissions are represented by the extents of the vertical lines. The MOBILE5a results reflect different vehicle year compositions with the rectangles reflecting the year composition that is consistent with the ORNL data. Figure 8 clearly demonstrates consistency in the vehicle emissions between the instantaneous emission models and MOBILE5a for both the LA4 and Highway Economy drive cycles. Furthermore, 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 speedand acceleration levels as input variables. The models, that were developed using the ORNL data, estimate hot stabilized vehicle emissions for normal light duty vehicles. The models are found to produce vehicle emissions thatare consistent with the ORNL data (coefficient of determination is excess of 90 percent).

The development of these models attempts to bridge the existing gap between traffic simulation models, traditional transportation planning models, and environmental impact models. The models presented in this paper are general enough to be incorporated within microscopic traffic simulation models. It is believed that given the current power of desktop computers, the implementation 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. Currently, 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 engineering studies(Rakha *et al*., 2000a).

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

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 emissions are currently being developed

that account for the ambient 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 microscopic models. Third, models are currently being developed to account for high emitting vehicles. Finally, models are being developed to account for other important pollutants including, particulate matters and CO_2.

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