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Estimation of Vehicular Emissions by Capturing Traffic Variations

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Estimation of Vehicular Emissions by Capturing Traffic Variations

Abstract

Over the past decades, the fast growth in travel has increased traffic congestion, which in turn has increased vehicular emissions significantly. It is difficult to accurately estimate and quantify emissions with current practice because of its reliance on transportation planning models that are based on steady state hourly averages and thus are incapable of capturing the effects of traffic variations in the transportation system. This paper proposes an intermediate model component that can better estimate link speed by considering a set of Emission Specific Characteristics (ESC) for each link. The improved link speed data will then be used to estimate emissions. The intermediate model component is developed using multiple linear regression; it is then calibrated, validated, and evaluated using a microscopic simulation model. The evaluation results show that the proposed emission estimation method performs better than the current practice and is capable of estimating time-dependent emissions if traffic sensor data are available as model input.

INTRODUCTION

Over the past decades, the rapid growth in travel has increased traffic congestion, especially in the major metropolitan areas. To combat congestion, more highways have been built and Intelligent Transportation Systems (ITS) have been applied. However, current facilities cannot keep pace with increased travel demands. Based on the latest mobility report by the Texas Transportation Institute (TTI), 67% of peak period travel in urban areas was congested in the year of 2003 compared to 32% only in 1982 (1).

Transportation is the single largest source of air pollution in urban areas. Traffic congestion has caused vehicular emissions to increase significantly. United States Environmental Protection Agency (USEPA) requires Metropolitan Planning Organization (MPO) to study environmental impacts for major capital investments using federal funds, such as the construction of highways. The current practice to estimate vehicular emissions for a regional transportation system is based on static transportation planning models and emission models (2). Traffic assignment results from transportation planning models (average speed, vehicle miles traveled (VMT) or vehicle hours traveled (VHT)) serve as input to the emission model that calculates total emissions for the transportation system.

The regional transportation planning models generally use the FHWA/BPR link performance function to estimate average travel speed. This function assumes that speed decreases as vehicle flow increases, which yields a monotonously increasing travel time function (as shown in Figure 1b). According to this assumption, low flow always corresponds to high speed. However, according to the fundamental traffic flow diagram, a low flow may correspond to either a low speed or a high speed traffic condition. Indeed, a low flow rate (with very few vehicles crossing a point per unit time) could correspond to congestion, with a high vehicle density and stop-and-go or stopped conditions. Conventional transportation planning models can not capture this condition due to the inadequacy of the cost functions, even when such cost functions have been found to be adequate for average hour flow prediction in planning. Introducing proper short-period travel time costs curves (as shown in Figure 1a) is not possible in conventional (static) planning models since the assignment step requires a monotonically-increasing, BPR-type travel time function. Since the planning model cannot provide accurate travel speed data, it may significantly affect emission rate estimation. At a theoretical level, the research in this paper tackles this problem and finds a solution which may help address the poor emission predictions in the planning analysis. The intent is to adjust for possible dynamic variations in speed, by focusing on a set of factors that may cause congestion, even while we are cognizant of the fact that traffic dynamics is a network-wide phenomenon that can properly be modeled only through a dynamic assignment (DTA) scheme. However, as the state of the art in DTA is perhaps not ready for planning practitioners to use and it may remain so for the near future, alternate schemes need to be developed.

Insert Figure 1

This paper proposes a practical way to reconcile the above issue, which is relatively important as far as emission estimation and prediction is concerned. Using statistical modeling, an intermediate model component is developed, which can better estimate the link speed by considering a set of Emission Specific Characteristics (ESC) for each link. The improved link speed is then used for the emission estimation.

The remainder of this paper is organized as follows. The next section presents the proposed methodology to estimate emissions. The succeeding section uses a microscopic simulation method to test the proposed methodology. The last section concludes the paper and discusses future research directions.

LITERATURE REVIEW

Emission Models

To calculate the emission rates for different types of vehicles, a number of emission factor models can be used. In the U.S., two emission rate models are commonly used for conformity analysis: MOBILE (Mobile Source Emissions Factor) and EMFAC (EMission FACtor). MOBILE was developed by USEPA to estimate criteria pollutants and toxic pollutants. The latest MOBILE version (MOBILE6) has recent emission rates and off-cycle emissions to better reflect real world traffic conditions. It accounts separately for start emissions and running emissions. MOBILE6 reports emissions by roadway type (freeways, arterial, ramp and locals), time of day, and other characteristics (3). EMFAC was developed by the California Air Resource Board (CARB) to estimate the emission rates for HC, CO, NOx, PM, SO_2, Pb, and CO_2 as well as fuel consumption. The latest version of the EMFAC model includes low emission vehicle standards and EPA Tier II standards. It also assumes modest emission reductions, due to proper inspection and maintenance programs that reduce all pollutants, particularly ROG and NOx. EMFAC produces separate emission factors for cold starts, hot starts, and hot stabilized conditions (4).

One of the major assumptions in current practice is that all vehicle activities are the same irrespective of any variations in traffic and driving characteristics. Further, emission factors are based on average speed and assumed urban driving cycles, which do not represent the real-world driving patterns. To overcome some of these shortcomings in the current practice, the latest version of MOBILE has included a facility-type and level-of-service based driving cycle, which is similar to real world profiles in terms of average speed and acceleration profiles. Modal emission model also emerged as alternative, which is based on various vehicle operating modes (cruise, acceleration, deceleration, and idle) (5). However, the accuracy of these models relies on estimates of traffic network activity data from transportation planning models, which are based on a steady state (static) analysis.

Barth et.al developed a methodology to utilize both traffic sensor data and microscopic data to estimate emissions (6). However, the model does not consider road geometry data and cannot be used for links without loop detectors.

Emission Specific Characteristics

Figure 2 compares the driving profiles of freeways and arterials that were recorded driving a GPS-equipped vehicle. Though the planning model predicts the same average speed in all these links, the driving profile changes significantly, due to a number of factors including geometric design, traffic characteristics, driver behavior, weather, and roadside characteristics (7-10). Hereafter these factors are referred to as Emission Specific Characteristics (ESC).

Insert Figure 2

Road characteristics such as sight distance, horizontal and vertical curvature, road quality, number of lanes, road width, and road terrain can have a strong influence on speed. Safe and efficient speed depends on available sight distance. When driving a vehicle, if the sight distance is less than the required, drivers slow down to avoid a collision with other vehicles. If the sight distance is longer, it provides a longer perception and reaction time for drivers. Generally, sight distance is much less at sharp horizontal curves, which can influence speed (11). Road design and quality can have significant influence on speed and emissions (12). Another important variable that can significantly affect speed is the grade or topography of the road. As grade increases, drivers accelerate to maintain speed or in some cases to decrease the speed. In either case, it influences emissions (13-14).

Density, flow, vehicle compositions, number of traffic lights per mile, signal coordination, and number of stops are traffic-related variables. Congested traffic conditions increase emissions and reduce speed compared to free flow conditions (14-15). A study by Hallmark et al. at different intersections found that driving patterns (i.e., speeds) are significantly influenced by queue position, downstream and upstream per lane hourly volume, incidents (accidents, break down of vehicles), percent of heavy vehicles, and posted link speed (8). Rakha et al. concluded that proper signal coordination could reduce emissions up to 50 percent (16).

Emissions also vary with respect to drivers' attitude, experience, gender, physical condition and age. Aggressive driving increases emissions compared to normal driving (15). Sierra Research found that most of the vehicles spend about 2 percent of total time in aggressive mode, which contributes about 40 percent of emissions (11).

Environmental characteristics along the road can have a significant influence on link speed. A study by Galin found that the landuse adjacent to roads strongly influences speed (17). The type of landuse (e.g., whether the landuse is residential, commercial) is especially influential.

Weather-related variables like temperature, humidity, and visibility influence vehicle speed. One study found that bad weather reduces speed about 6-7 mph (9, 14).

METHODOLOGY

As mentioned above, link speed data from planning models is not accurate because of the use of the FHWA/BPR-type of link performance function in traffic assignment. The planning speed is applied to all times within the entire study period and thus the variations of traffic condition cannot be captured. Since loop detector systems have become more widely deployed for traffic control and surveillance, they also could be a good speed data source. Note that single loop detectors usually collect traffic volume and occupancy data, which are used in the estimation of loop speed (18). Another potential speed data source is a probe vehicle system, which can be based on the emerging technologies such as Automatic Vehicle Identification (AVI) or Global Positioning Systems (GPS) (19, 20). Probe vehicle systems usually collect point to point travel time or speed data (GPS-based probe vehicle system has the capability to provide more detailed vehicle trajectory data). In the San Francisco Bay area, vehicles with FasTrack transceivers have been used as probes to collect travel time data (21).

Insert Figure 3

The proposed methodology to estimate emissions of a transportation system is illustrated in Figure 3. It consists of three steps. First, the link speed data is refined using an intermediate model that considers ESC variables of the links. From the literature review, a number of variables are identified which can have influence on travel speed on a link. However, this paper only considered the ESC variables which can be observed in the real world without much difficulty. Those variables include geometric design characteristics, traffic characteristics, traffic delay characteristics, and roadside characteristics. The model can be represented as:

$$S_i = f\,(G_i,\ Tr_i,\ T_i,\ R_i) \qquad (1)$$

where:

S_i Refined speed for link i
G_i Geometric design of link i
Tr_i Traffic characteristics of link i
T_i Traffic delay characteristics of link i
R_i Roadside characteristics of link i

Multiple linear regression analysis can be used to establish the relationship between link speed and ESC variables. The model has one required ESC variable (i.e. a traffic characteristics variable) -- a representative link speed, which can be obtained from available data sources. The speed can be either measured by a loop on the link or from the planning model. This feature of the model offers the flexibility to work with different data sources or the combination of multiple data sources. For example, if there is no traffic sensor data, the method will work with the planning speed. The intermediate model is expected to generate a better link speed estimate than the current practice because of the consideration of ESC. If traffic sensors are available only for some links, this method has the capability to take either traffic sensor data or planning speed data (depending on their availability) to estimate emissions. For those links with traffic sensor data, the estimated emission data will be time-dependent. For those links without traffic sensor data, the estimated emission data will be static.

Then, for each link in the network, the MOBILE6 model can be used to calculate the emission factor using the refined link speed:

$$EF = \sum TF * ((BER * CF_S + offsets) + OEA_S) \qquad (2)$$

where:

TF	Mileage accumulation and registration of vehicle distribution
BER	Deterioration factor
CF	Correction factor (temperature, etc)
OEA	Off cycle emissions adjustments

Finally, total emissions for a given time period would be estimated by multiplying the corresponding link's emission rate and VMT (estimated by multiplying link length and volume):

$$E_{t,l,p} = \sum VMT_{t,l,p} * EF_{t,l,p} \quad (3)$$

where:

E	total emissions
t	Time period
l	Link length
p	Different pollutants (CO, VOC, NOx, PM)
EF	Emission factor
VMT	Vehicle miles traveled

MODEL CALIBRATION, VALIDATION AND EVALUATION

Study Procedure

The key to the proposed method is the introduction of the intermediate model, i.e. Equation 1. The model is hard to be calibrated because of the requirement of ground-truth link speed data, which are very expensive to be collected. As an alternative, this paper introduces a microscopic simulation method.

PARAMICS is a scalable, ITS-capable, high-performance microscopic traffic simulation package developed in Scotland (22). It has been widely used to model the movement and behavior of individual vehicles on urban and highway road networks. PARAMICS provides users with Application Programming Interfaces (API) through which users can access its core models, and customize and extend many features of the underlying simulation model without having to deal with the underlying proprietary source codes. In addition, PARAMICS comes with a plugin that calculates the link-by-link traffic emission pollution by relating both vehicle type and pollutants based on simulated speed and acceleration.

This paper assumes that the study network has a good loop detector data source. The study procedure is illustrated in Figure 4. The loop data from micro-simulation and ESC data from other sources are employed to calibrate the intermediate model. The calibrated intermediate model is then used to estimate link speed and the total emission, which are finally evaluated by comparing to the "ground truth" emission estimates from micro-simulation.

Insert Figure 4

Simulation Network

The study network is located in Orange County, California. As shown in Figure 5, the network includes a 6-mile section of freeway I-405, a 3-mile section of freeway I-5, a 3-mile section of freeway SR-133 and several adjacent surface streets. The simulation model of the network was built in Paramics. The basic input data include data of network geometry, driver behavior, vehicle characteristics, transportation analysis zones, travel demands, and traffic control systems and traffic detection systems. The zone structure of the simulation model is based on the regional planning model, Orange County Transportation Authority's 2001 OCTAM model (23).

Insert Figure 5

A previous study calibrated the simulation network for the morning peak period from 6 to 10 AM based on the OCTAM model and loop detector data from the field (24). A calibrated simulation model is exclusively required for the study because it is able to represent the traffic condition of the corresponding real-world network.

Model Calibration

By matching links in the Paramics network with links in the planning model, 90 planning links (a planning link is usually composed of several Paramics links) are selected for model calibration. The lengths for these 90 links are all smaller than 1 mile.

In this study, it is assumed all these links have corresponding loop detectors for collecting speed data. By simulating the study network in Paramics, 30-sec loop data and "ground-truth" link speed data are collected using the plugins we developed. Therefore, rich data on dynamic variations across temporal and spatial dimensions for the Irvine simulation network are provided. The quality of the collected data is checked both visually and temporally for errors and problems. Then by systematic sampling, 1400 samples are generated to develop the intermediate model. Initial examination of the collected data is conducted to remove any influential data points. Other summary statistical analyses are also conducted. The final data sets are employed to construct a multiple linear regression model for Equation 1. Table 1 shows the variables considered for the analysis and their range of values.

Insert Table 1

The developed model is diagnosed for homoscedasticity, multicolinearity and specification errors. Those variables that have p-values lower than 0.05 are considered as significant variables in the model. Then, the model is constructed based on the 95% significance level. The final calibrated multiple linear regression model is shown in Table 2.

Insert Table 2

The model shows that geometric design variables, such as link length and alignment, have significant influence on link speed. The longer are the link lengths, higher the speed. Although number of lanes shows positive sign of correlation with link speed, it is not a significant variable in the model. Road quality is also not significant, which might be due to less variation within the variables. Among traffic characteristics variables, loop speed is significantly correlated with link speed and all other variables are not significant. Among traffic delay characteristics, speed limit is significant, as expected. All other variables such as traffic light and stop signs are not significant, which might be due to fewer variations or the use of loop detector speed data as a dominant variable. For the roadside characteristics, access density is significant and mixed landuse is positively correlated. However, both residential and commercial landuse are not significant, although they are shown to have negative correlation with link speed.

Model Validation

An arterial link that is not in the calibration link list is selected to show the model's validation result. As illustrated in Figure 6, although the planning speed for the link is 44.6 mph, the "ground-truth" speed from simulation shows a lower speed throughout the study period. Comparing 30-sec loop speed and the link speed estimated from the intermediate model, the latter shows better performance. Regarding the mean absolute percentage error (MAPE) for the whole period, the model speed's MAPE is 6.1%; loop speed's MAPE is 8.9%; the planning speed's MAPE is 31.4%. The validation results explain that the planning speed is inaccurate and the intermediate model has the ability to provide better link speed estimation.

Insert Figure 6

Emission Estimation

Based on the calibrated intermediate model, link speeds are estimated every 30 seconds for all links in the network. The time-dependent link speed will be input to Equation 2 to estimate emission factors, which will then be used to estimate the time-dependent emission for every link using Equation 3.

Evaluation Results and Analysis

In the Paramics simulation, the total emissions from these links are estimated using the following three ways:

(1) Current practice, which is based on traffic assignment results using the planning model (i.e. link's average speed and VMT);
(2) Proposed method, which is based on Paramics simulation;
(3) Paramics Monitor plugin, which is regarded as a "ground truth" emission data.

Table 3 compares the emission estimation using the proposed method and the current practice. Nine links are selected from the study network, including three freeway mainline links, two ramp links, and four arterial links. Table 3 clearly shows that the current practice underestimates the emissions in the range of 3 to 24%. The main reason for the poor estimation from the planning method is due to its inaccurate average speed, which is for the whole morning peak period and thus averages out the traffic variation (such as congestion or stop and go traffic). Meanwhile, the proposed method also underestimates emissions within 5% range. The reason for the better performance from the proposed method is due to its capability to capture traffic variations by using 30-sec loop detector data.

Insert Table 3

In addition, based on the emission estimates for arterial link (233:121) and freeway link (8:10), it is found that the current practice underestimates the emissions of arterial streets more than freeway mainlines and ramps. This might be due to the existence of more fixed (e.g. traffic lights, stop sign) and variable delays (e.g. stop and go) in arterial streets.

From another point of view, let's compare "ground truth" average link speed, average estimated link speed and the link speed from the planning model. As shown in Table 3, the planning model overestimates all links' speeds in the range of 7 to 20 mph, while the proposed methodology overestimates within the range of 5 mph. This implies that the planning model does not accurately represent the real-world traffic condition. A possible reason for the poor planning speed estimation is that the planning model was not well calibrated and traffic was not properly assigned to the study network. The reason for the good performance of the proposed method is that more ESC variables, especially loop detector speed data, are considered in the intermediate model to estimate link speed.

Figure 7 shows that the proposed method has capabilities to estimate time-dependent emissions. One freeway link and one arterial link are selected for the analysis. Same as the results obtained from the previous analysis, all the pollutants are underestimated by the proposed model compared to the "ground truth" emission data. There are many reasons for the underestimation:

(1) Paramics considers both acceleration and deceleration of vehicles at every second. However, MOBILE6 does consider higher accelerations at high speed but it does not consider sharp accelerations at different speeds. A previous study shows that emissions can vary 2-3 times during significant acceleration/deceleration changes (25).
(2) One of the limitations of MOBILE6 is that it cannot estimate emission rate for speed greater than 65 mph, which is common in day-to-day traffic condition. This paper applied the same emission rates to all speed greater than 65 mph, which causes the underestimation of the total emissions, which clearly depicted in all three pollutants of freeway link.
(3) Paramics might overestimate emissions, since its car-following and lane changing model considers the acceleration and deceleration rate beyond feasible range.
(4) The inputs to the Paramics Monitor plugin, i.e. pollution emission distribution data which are different for each type of vehicles, are not accurate.

Insert Figure 7

DISCUSSIONS & FUTURE WORK

This paper presents an improved emission estimation method. The core of the method is an intermediate model that better estimates the link speed by considering a set of ESC variables of the link. The intermediate model is developed using multiple linear regression analysis. Using a microscopic simulation method, the intermediate model is calibrated, validated, and evaluated. Results show that the proposed emission estimation method performs better than the current practice and is capable of estimating time-dependent emissions if traffic sensor data are available as model input.

Although simulation results show that the method still underestimates the total emissions compared to the "ground truth" emission data, the model has the potential to be further improved by considering other ESC variables, such as driver characteristics, weather and vehicle characteristics. Moreover, the relationship between speed and ESC can be further improved by using multivariate statistical analysis technique, such as structural equation modeling (SEM), which can establish the linear relationship between number of endogenous and exogenous variable as well as latent variables.

In this paper, it is assumed that there exist good loop detectors in the target network in order to provide a dynamic emission estimate. However, the developed intermediate model is flexible enough to work with different data sources, such as probe vehicle data, historical speed data, and the speed output from planning model. If the speed data from planning model are used, the proposed model will only be restricted to provide a static emission estimate, which could be a better estimate than the current practice due to the involvement of other ESC variables. In the future, when advanced traffic information systems are deployed, this methodology would be readily available to better estimate emissions.

We realize that, while we do examine a fundamental problem in the modeling of emissions and energy consumption in transportation planning, we are not necessarily providing the most fundamentally detailed solution to it, which would be to use dynamic models themselves in planning. The state of the art in this area is still several years away from any practical application, and the primary reason is the lack of route choice and other behavioral paradigms for the dynamic domain (as well as deeper questions on to what extent dynamic equilibrium exists in the real world). Simulation-based non-equilibrium analysis to augment transportation planning is one option, but again this is also not an option that the planning community has sufficient level of comfort for practical use. Our proposed scheme however attempts to bridge the gap in a practical way, with a good understanding of the underlying theoretical problems which point to network and traffic dynamics.

The proposed method provides traffic agencies and practitioners with a way to improve emission estimate based on available data sources. The calibration of the intermediate model is required to adopt it in other areas. In the future, the intermediate model can be developed as a corrective model by collecting real world data sets, for more varied type of street characteristics and traffic conditions with large sets of data. Furthermore, this research can be developed to include the effect of different vehicle mixes in terms of trucks, buses, autos, etc.

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LIST OF TABLES

TABLE 1 Summary of variables considered for analysis

Geometric Design • Number of lanes: Ranging from 2 to 6 in each direction • Road quality: 0- bad quality; 1- Good quality • Alignment: 1- curved; 0- straight • Link type: Freeway, HOV, off-ramp, On-ramp Arterial • Presence of bike paths in arterial streets: 0-No; 1-Yes
Traffic Characteristics • V/C ratio: ranging from 0.3 to 1.1 • Loop Speed: ranging from 12 to 84 mph • Planning speed: ranging from 3.4 to 60 mph • Loop Volume: 0 to 11520 in each link
Traffic delay characteristics • Time of the day: 0 – off-peak period; 1- peak period • Presence of stop sign in the link: 0 – No; 1-Yes • Presence of traffic signal: 0-No; 1-Yes • Speed limit: Ranging from 25 mph to 65 mph
Roadside characteristics • Landuse: Residential, commercial and mixed landuse • Access density: ranging from 0 to 11 per km

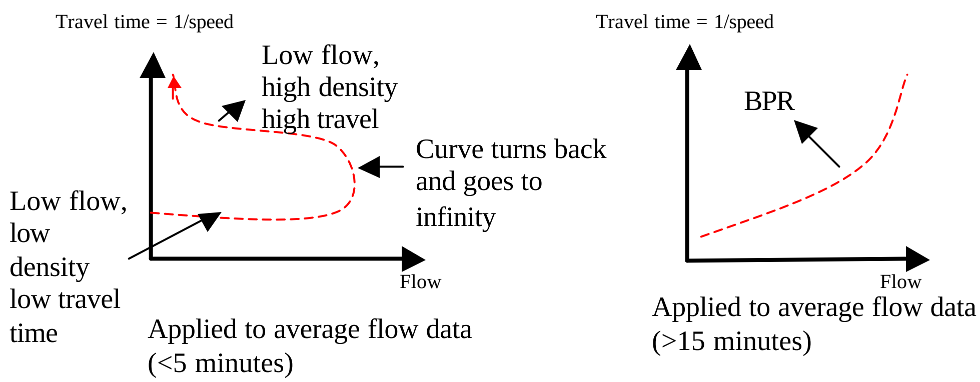
TABLE 2 Model Specifications

Variables	Coefficient	P-values
Travel speed	0.714	0.000
Road speed limit	0.51	0.000
Mixed landuse	2.46	0.032
Alignment	3.84	0.006
Link length	12.83	0.002
Access density	-1.34	0.003
Constant	-21.62	0.000
N – 1400; R^2 – 69.96%; Adj. R^2 – 69.5%		

TABLE 3 Comparison of total emissions and average link speeds of selected links

Link	Link Type	Actual Speed (mph)	Planning Speed (mph)	Model Speed (mph)	Actual Total Emissions (10^3 g)			Planning Total Emissions (10^3 g)			Model Total Emissions (10^3 g)		
					VOC	CO	Nox	VOC	CO	Nox	VOC	CO	Nox
144:138	Arterial	22.4	41.5	23.2	89	764	79	85	743	77	89	757	79
264:20	Ramp	34.4	45.0	37.7	22	178	19	21	174	16	22	170	18
149:121	Arterial	27.5	44.9	29.2	3	27	3	2	26	2	3	27	3
318:320	Ramp	29.3	41.1	29.5	6	50	5	5	47	5	6	50	5
8:10	Freeway	53.0	60.0	54.8	439	3920	401	423	3910	401	426	3924	402
62:138	Arterial	23.8	40.4	25.6	30	326	34	24	325	34	29	323	33
10:12	Freeway	35.3	60.0	36.2	2	19	2	2	18	2	2	20	2
188:222	Freeway	44.7	60.0	48.7	2	23	3	2	23	2	2	23	3
233:121	Arterial	26.1	44.1	28.4	15	139	14	12	126	13	15	137	15

LIST OF FIGURES



(a) **(b)**

FIGURE 1 Fundamental diagram of traffic flow

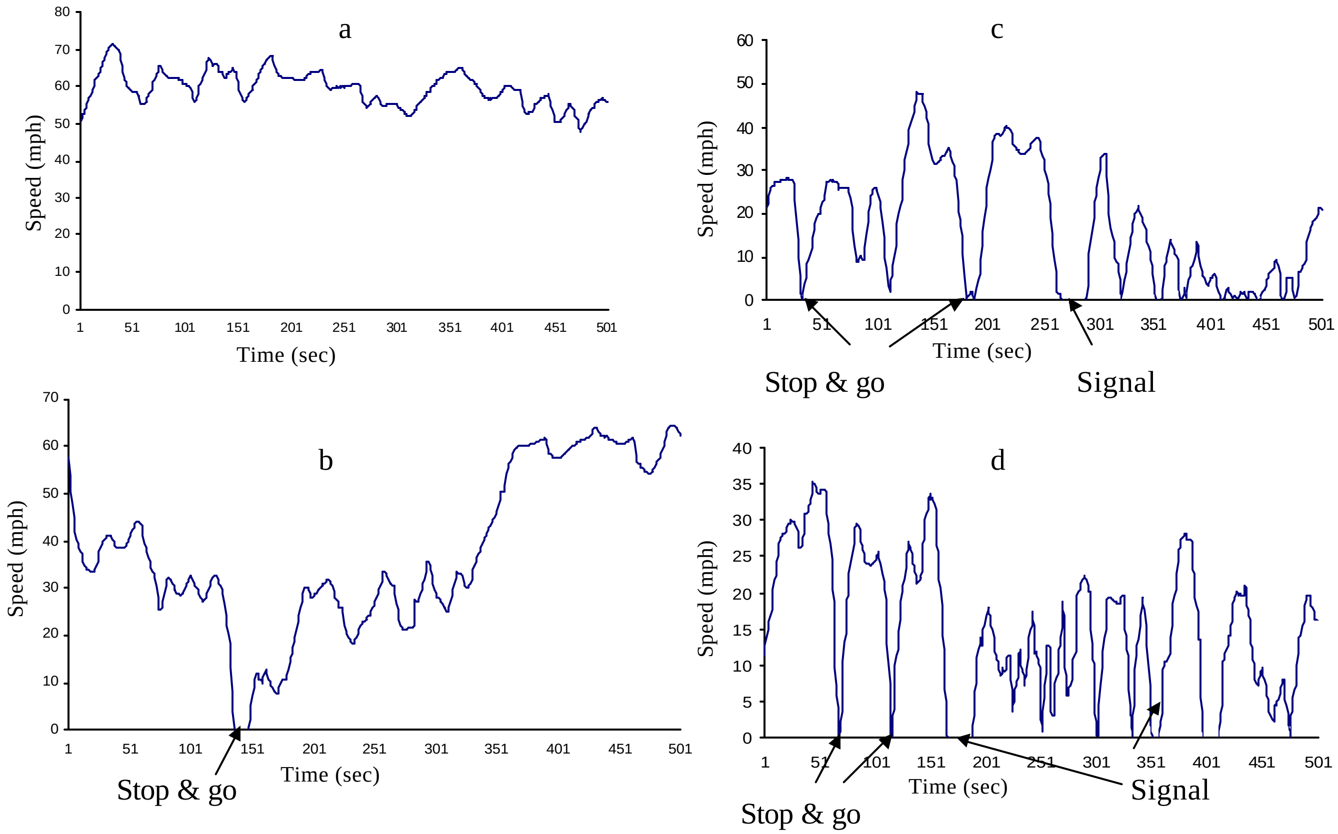


FIGURE 2 Driving profile of (a) I-405, (b) I-5, (c) Campus Dr, and (d) Culver Dr

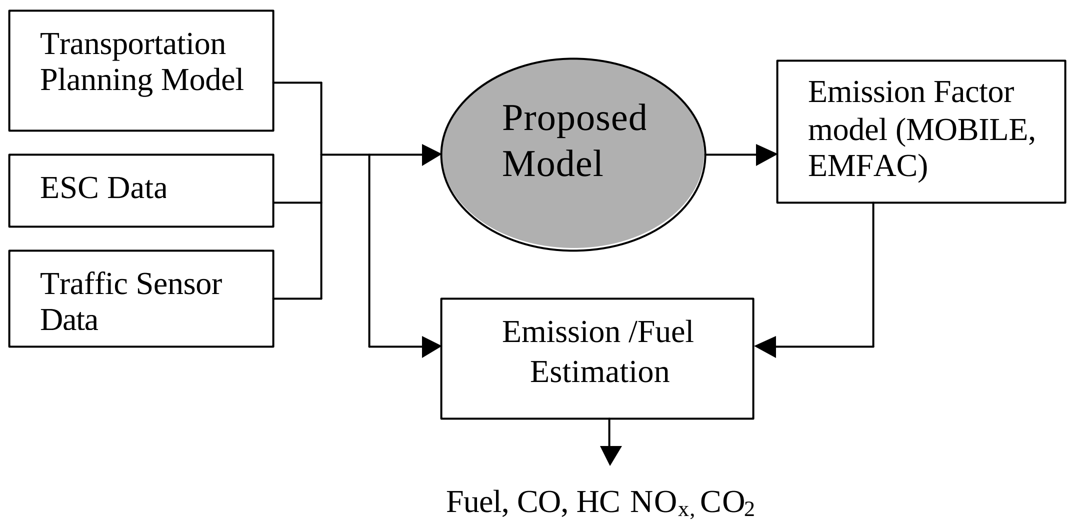


FIGURE 3 Proposed method to estimate emissions

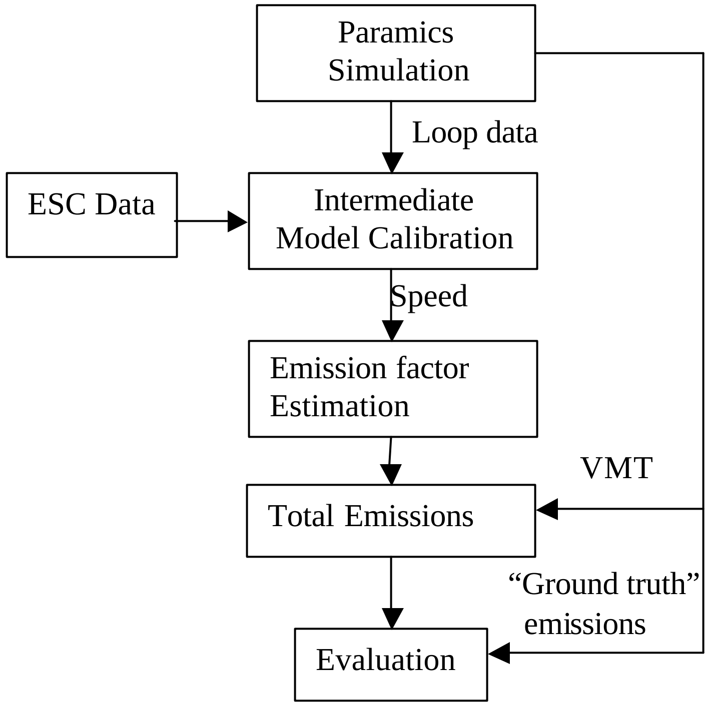


FIGURE 4 Schematic diagram of evaluation procedure

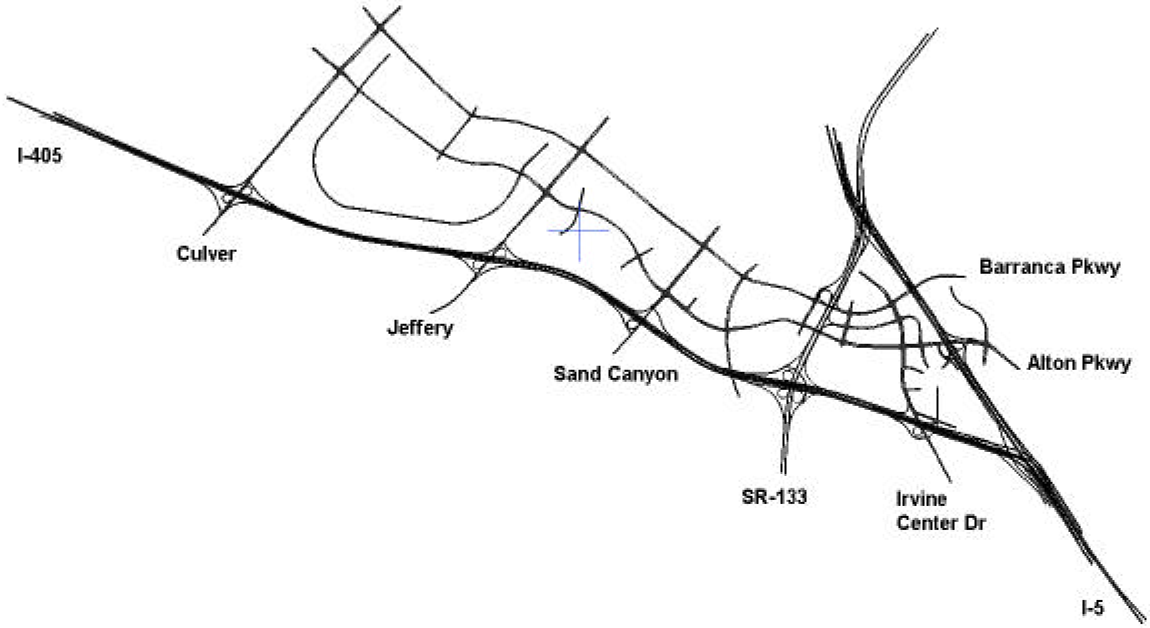


FIGURE 5 Overview of the study network

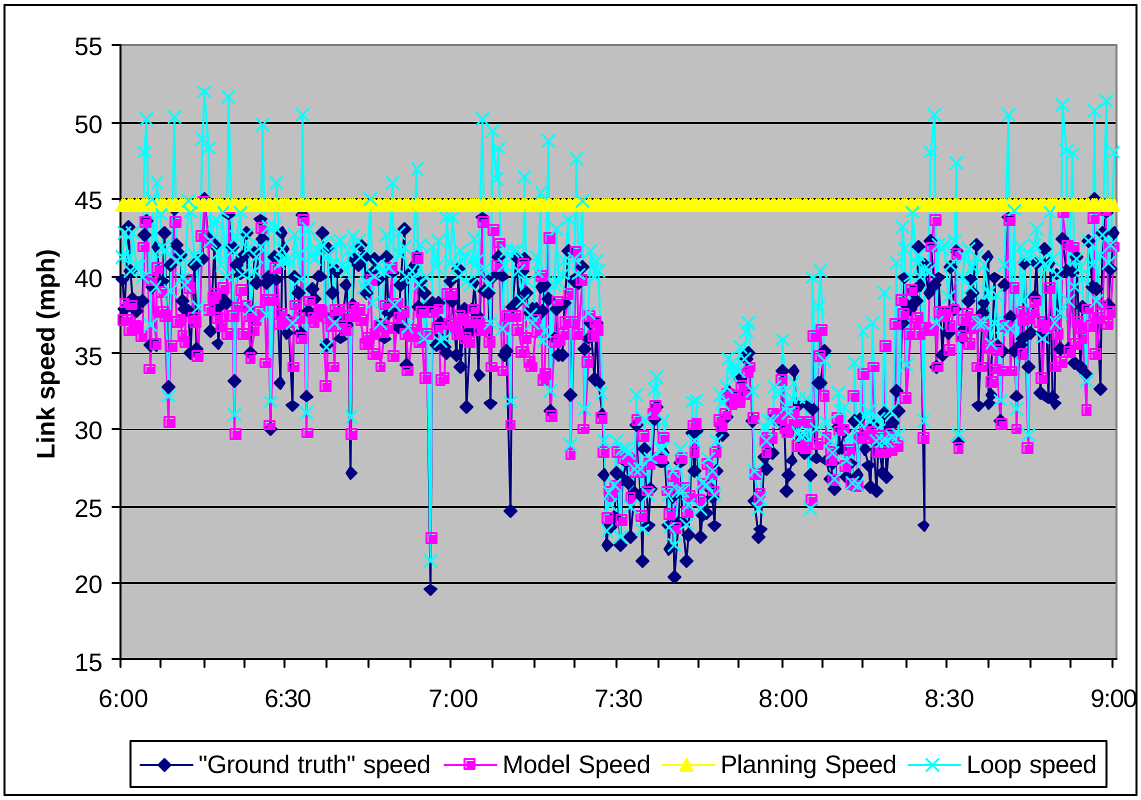


FIGURE 6 Model validation

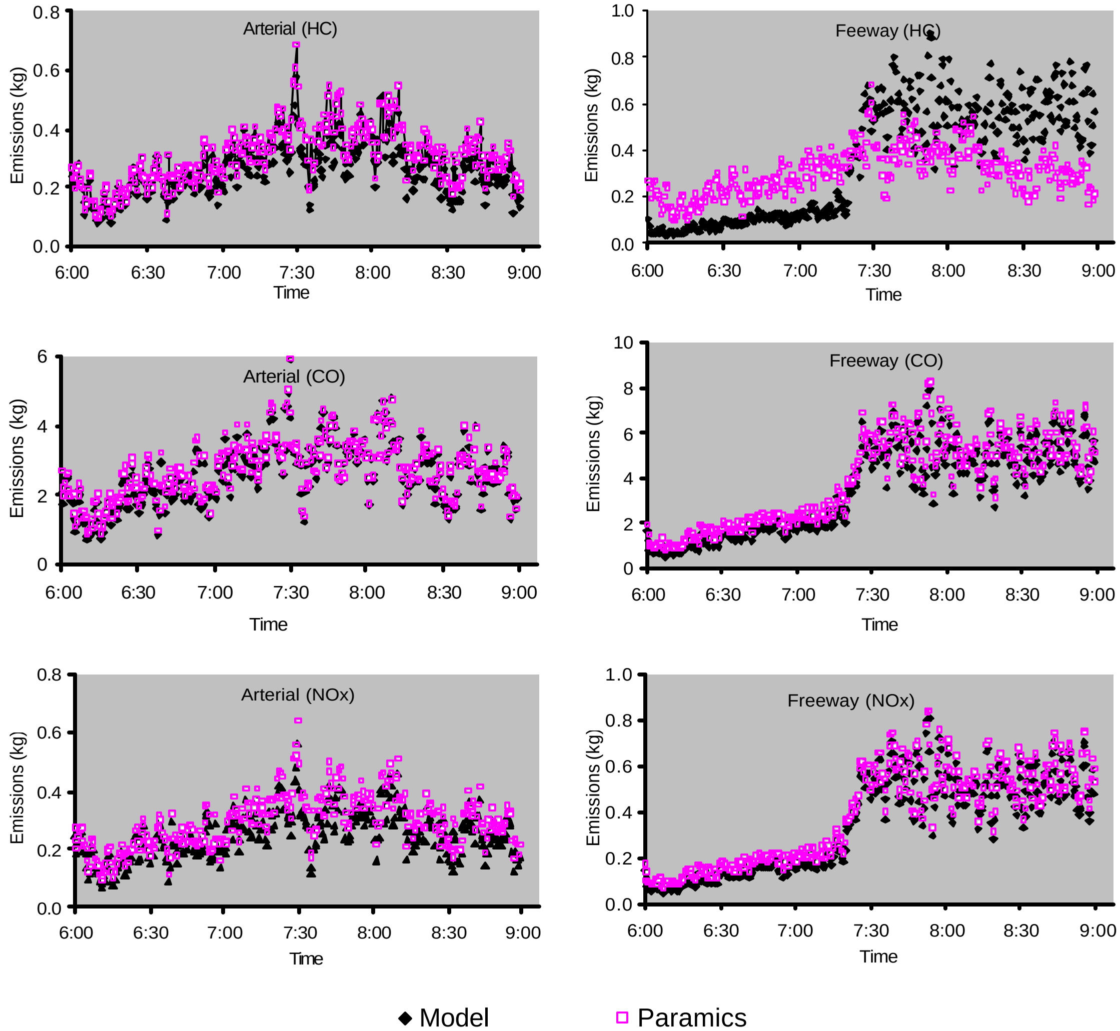


FIGURE 7 Time-dependent emission pollutants during the morning peak period