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Estimation of Vehicular Emissions by Capturing Traffic Variations

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Abstract

Increase in traffic volumes and changes in travel-related characteristics increase vehicular emissions significantly. It is difficult, however, to accurately estimate emissions with current practice because of the reliance on travel forecasting models that are based on steady state hourly averages and, thus, are incapable of capturing the effects of traffic variations in the transportation network. This paper proposes an intermediate model component that can provide better estimates of link speeds by considering a set of Emission Specific Characteristics (ESC) for each link. The intermediate model is developed using multiple linear regression; it is then calibrated, validated, and evaluated using a microscopic traffic simulation model. The improved link speed data can then be used to provide better estimates of emissions. The evaluation results show that the proposed emission estimation method performs better than current practice and is capable of estimating time-dependent emissions if traffic sensor data are available as model input.

Key Words: Traffic congestion, link speed, vehicle emissions, microscopic traffic simulation, travel forecasting models.

INTRODUCTION

Over the past several decades, the rapid growth in travel has increased traffic congestion, especially in the major metropolitan areas. To combat congestion, more highway capacity has been built and Intelligent Transportation Systems (ITS) have been introduced. However, current facilities have not kept pace with increased travel demands. Based on the latest mobility report by the Texas Transportation Institute, 67 percent of peak period travel in urban areas was congested in 2003 compared to only 32 percent in 1982 (Schrank and Lomax, 2005).

Transportation is the single largest source of air pollution in urban areas. Traffic congestion has caused vehicular emissions to increase significantly. The Clean Air Act Amendments (CAAA) requires Metropolitan Planning Organizations (MPO) and Department of Transportation (DOT) to study environmental impacts for major capital investments that utilize federal funds, like including the construction of new highway capacity. The current practice to estimate vehicular emissions for a regional transportation network is based on static travel forecasting models and emission models (Deakin and Harvey, 1993). Traffic assignment results from travel forecasting models (average speed and vehicle miles traveled (VMT) by facility type) serve as input to the emission model that calculates total emissions for the transportation network.

Regional travel forecasting models generally use the Bureau of Public Roads (BPR) link performance function (see figure 1) to estimate average link speed (Dowling et al., 2005).

This function specifies that speed decreases as vehicle flow increases, which yields a monotonically increasing travel time function. According to this function, low flow always corresponds to high speed. However, according to the fundamental diagram of traffic flow, a low flow may correspond to either a low speed or a high speed traffic condition. A low flow rate (with very few vehicles crossing a point per unit time) often corresponds to congestion, with a high vehicle density and stop-and-go or stopped flow conditions. Conventional travel forecasting models can not capture this condition, in part due to the limitations of the selected link performance functions, even when such performance functions have been found to be adequate for prediction of average hourly flow. Introducing proper short-period travel time performance curves (as shown in Figure 1) is not possible in conventional, static forecasting models since typical iterative assignment algorithms require a BPR-type travel time function. Since the forecasting model cannot provide accurate travel speed data, it may significantly affect estimation of emissions. At a theoretical level, the research in this paper addresses this problem and proposed a solution which may improve the performance of emission models. The intent is to adjust for possible dynamic variations in speed by focusing on a set of factors that correlate congestion. The authors are cognizant of the fact that traffic dynamics are network-wide phenomena that can properly be modeled only through dynamic assignment (DTA) schemes. However, the state of the art in DTA is perhaps not ready for application in practice 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 this issue. Using statistical modeling, an intermediate model component is developed, which can improve estimates of the link speeds by considering a set of Emission Specific Characteristics (ESC) for each link. The improved estimate of link speed is then used for emission estimation.

The remainder of this paper presents a review of relevant literature, followed by a presentation of the proposed methodology to estimate emissions. The following section utilizes a microscopic simulation method to test the proposed methodology. A summary section concludes the paper and discusses future research directions.

LITERATURE REVIEW

Relevant literature is discussed regarding emission models and emission-specific characteristics.

Emission Models

To calculate emission rates for different types of vehicles, emission factor models are used. In the U.S., two such models are commonly used for conformity analysis: MOBILE (Mobile Source Emissions Factor) and EMFAC (EMission FACtor). MOBILE was developed by EPA to estimate rates associated with criteria pollutants (HC, CO, NOx, PM, and CO_2) and toxic pollutants (benzene, formaldehyde etc). The latest MOBILE version (MOBILE6) has recent emission rates and off-cycle emissions that better reflect

real-world traffic conditions. It accounts separately for start emissions and running emissions. MOBILE6 reports emissions by roadway type (freeways, arterials, ramps, and local streets), time of day, and other characteristics (EPA, 2002). EMFAC was developed by the California Air Resource Board (CARB) to estimate emission rates (for HC, CO, NOx, PM, SO_2, Pb, and CO_2) as well as fuel consumption. The latest version of the EMFAC 2002 model includes low emission vehicle standards and EPA Tier II standards (CARB, 2000). It also assumes modest emission reductions for proper inspection and maintenance programs. EMFAC produces separate emission factors for cold starts, hot starts, and hot stabilized conditions.

An assumption in current practice is that all vehicle activity is the same regardless of variations in traffic and driving characteristics. Further, emission rates are based on average speed and assumed urban driving cycles, which may not represent real-world driving patterns. To address some of these shortcomings in current practice, the latest version of MOBILE has included driving cycles based on facility-type and level-of-service, which are more similar to real-world profiles in terms of average speed and acceleration. Modal emission models that are based on various vehicle operating modes (cruise, acceleration, deceleration, and idle) have also emerged as alternatives (Barth et al., 1996a), (Guensler et al. 1998). The accuracy of these models, however, relies on estimates of traffic network activity data from travel forecasting models, which are still based on steady state (static) analyses.

Finally, Barth et al. (1996b) developed a methodology to utilize both traffic sensor data and microscopic data to estimate emissions. 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 freeways and arterials driving profiles of that were recorded using a GPS-equipped vehicle. Though the forecasting model predicts the same average speed for all these links, the driving profile changes significantly. This is due to a number of factors including geometric design characteristics, traffic characteristics, traffic delay characteristics, driver behavior, weather, and roadway environmental characteristics (LeBlanc et al., 1995; Hallmark et al., 2002; Kilpelaninen and Summala, 2004; Brundell-Freij and Ericsson, 2005). Hereafter these factors are defined as Emission Specific Characteristics (ESC).

Insert Figure 2

Figure 3 shows the relationship between link speed and ESC. Geometric design characteristics, such as sight distance, horizontal and vertical curvature, pavement quality, link type, number of lanes, facility type, and grade, can have a strong influence on speed.

Safe and efficient speed depends on available sight distance. Drivers will slow down to avoid a potential collision with another vehicle when sight distance is less than that deemed necessary. If the sight distance is greater, it provides a longer perception and reaction time for drivers. Generally, sight distance is much less at sharp horizontal curves, which can influence speed (Samuel et al., 2002). Road design and quality can have significant influence on speed and emissions (Qu et al., 2003). Another important variable that can significantly affect speed is the grade or road alignment. As grades change, drivers accelerate or decelerate to maintain a desired speed. In either case, it influences emissions (Kean et al., 2003; Andre and Hammarstrom, 2000).

Insert Figure 3

Density, flow, vehicle composition, v/c ratio, the number of traffic lights per mile, signal coordination, and the number of stops per mile are traffic-related variables. Congested traffic conditions increase emissions and reduces speed compared to free flow conditions (Andre and Hammarstrom, 2000; Vlieger et al. 2000). A study by Hallmark et al. (2002) found that driving patterns (i.e., speeds) at different intersections are significantly influenced by queue position, downstream and upstream lane volume, incidents, percent of heavy vehicles, and posted link speed. Rakha et al. (2000) concluded that proper signal coordination could reduce emissions up to 50 percent.

Emissions also vary with respect to drivers' attitude, experience, gender, physical condition, and age. Aggressive driving increases emissions compared to normal driving (Vlieger et al. 2000). Sierra Research found that most drivers spend about two percent of

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total driving time in aggressive mode, which contributes about 40 percent of total

emissions (Samuel et al. 2002).

Roadway environmental characteristics along the road can have a significant influence on

link speed. A study by Galin (1981) found that the land use adjacent to roads strongly

influences speed. The type of land use (e.g., whether the landuse is residential or

commercial) is especially influential.

Weather-related variables like temperature, humidity, and visibility influence vehicle

speed. Studies have found that bad weather reduces speed about 6-7 mph (Kilpelaninen

and Summala, 2004; Andre and Hammarstrom, 2000).

METHODOLOGY

As discussed above, link speed data from travel forecasting models is inaccurate because

of the use of the BPR-type link performance function in traffic assignment. The travel

forecasting 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 serve

as 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 (Wang and Nancy,

2000). Another potential speed data source is a probe vehicle system, which can be based

on emerging technologies such as Automatic Vehicle Identification (AVI) or Global

Positioning Systems (GPS) (Guo and Poling, 1995). Probe vehicle systems usually collect point to point travel time or speed data (GPS-based probe vehicle systems have the capability of providing more detailed vehicle trajectory data). In the San Francisco Bay area, vehicles with FasTrak transceivers have been used as probes to collect travel time data (www.511.org).

Insert Figure 4

The proposed methodology to estimate emissions for a transportation network is illustrated in Figure 4 and comprises three steps. First, refined link speed data is estimated using an intermediate model that considers ESC variables defined for all links. From the literature review, a number of variables are identified that can influence 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 roadway environmental characteristics. The model is represented as:

$$\hat{S}_i = f\left(S_i,\ G_i,\ T_i,\ D_i,\ R_i\right) \tag{1}$$

where:

$\hat{S}_i$ = refined speed for link i

S_i = travel forecasting or loop detector speed for link i

G_i = geometric design variables for link i

T_i = traffic characteristic variables for link i

D_i = traffic delay characteristic variables for link i

R_i = roadway environmental characteristic variables for link i

Multiple linear regression analysis is used to establish the relationship between link speed and the ESC variables. The model has one required ESC variable (i.e. link speed), which is obtained from available data sources. The link speed is measured by a loop on the link, or estimated with a travel forecasting model where loop links were not available. This feature of the model offers the flexibility to work with different data sources or a combination of multiple data sources. For example, if traffic sensor data is not available, the model will utilize speed from travel forecasting. The intermediate model is expected to generate better link speed estimates than current practice due to 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 travel forecasting speed data to estimate emissions. For those links with traffic sensor data, the estimated emission data are time-dependent. For those links without traffic sensor data, the estimated emission data are static.

Second, for each link in the network, the MOBILE6 model is used to calculate the emission rate using the refined link speed ($\hat{S}_i$):

$$ER_{i,t,p} = \sum^n TF * (BER * CF) \tag{2}$$

where:

ER = composite emission rate (grams/mile) for link i, time t and pollutant p

TF = travel fraction by vehicle type

$BER = f(\hat{S}, V)$ = base emission rate (grams/mile)

CF = correction Factors (temperature, speed, fuel, etc)

$\hat{S}$ = refined link speed (mph) from equation (1)

V = vehicle type

n = model year (12 years for motor cycle and 25 years for other vehicle types)

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

$$E_{t,i,p} \quad = \sum VMT_{t,i} * ER_{t,i,p} \tag{3}$$

where:

E = total emissions for time t, link i, and pollutant p

VMT = vehicle miles traveled for time t and link i

ER = composite emission rate (grams/mile) for time t, link i and pollutant p from equation (2)

MODEL CALIBRATION, VALIDATION AND EVALUATION

Study Procedure

The key to the proposed method is the introduction of the intermediate model (Equation 1). The calibration of the model requires observed link speed data, which can be

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expensive to collect. As an alternative, this paper introduces a microscopic simulation method.

PARAMICS is a commercially-available, high-performance ITS-capable microscopic traffic simulation package (Smith et al., 1994). It has ability to simulate large networks and has been widely used to model the movement and behavior of individual vehicles on highway and arterial road networks. PARAMICS provides Application Programming Interfaces (API) through which users can access its core models and customize and extend many features of the simulation model without having to deal with the underlying proprietary source codes. In addition, PARAMICS comes with plug-in, a component that calculates link-by-link traffic emissions using second-by-second speed, acceleration, or deceleration data and the emission distribution data for all vehicle types. It relates emission levels to vehicle speed and acceleration and/or deceleration (Quadstone, 2006).

The proposed methodology is illustrated in Figure 5. Loop data from micro-simulation and real-world ESC data are employed to calibrate the intermediate model. The calibrated intermediate model is then used to estimate refined link speeds and total emissions, which are evaluated by comparison to the baseline emission estimates from the micro-simulation.

Insert Figure 5

Simulation Network

The study network is located in Orange County, California. As shown in Figure 6, 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 all major adjacent surface streets. The simulation model of the network was built in PARAMICS. The basic input data include network geometry, driver behavior, vehicle characteristics, transportation analysis zones, travel demands, traffic control systems, and traffic detection systems. The zone structure of the simulation model is based on the regional travel forecasting model, the Orange County Transportation Authority's OCTAM 2001 model (OCTA, 2001).

Insert Figure 6

A previous study (Chu et al., 2004) calibrated the simulation network for the morning peak period from 6 to 10 AM based on demand from the OCTAM travel forecasting model and loop detector data from the field. The simulation model was validated against travel time data from Caltrans field estimates (Chu et al., 2004). A calibrated simulation model is important for this study because it must represent real traffic conditions of the corresponding real-world network.

Model Calibration

By matching links in the simulation network with links in the travel forecasting model, 90 links (a link in a travel forecasting model usually comprises several links in a

PARAMICS micro simulation network) are selected for model calibration. The lengths

for each of these 90 links are less than 1 mile. In this study, it was assumed that all links

had loop detectors for collecting speed data. By simulating the study network in

PARAMICS, 30-sec loop data was collected and link speed data were estimated.

Therefore, rich data on dynamic variations across temporal and spatial dimensions for the

simulation network were collected. The quality of the collected data was verified with

extensive error checking. A MATLAB program was written that flagged any data values

outside of conventional ranges (e.g., acceleration greater than 3 m/s^2 or deceleration

greater than -5 m/s^2). Such extreme acceleration and deceleration values were generated

by PARAMICS' car-following and lane changing models under some extreme situations.

Via systematic sampling, 1400 data points were generated to develop the intermediate

model. Examination of the collected data was conducted to remove any data points whose

inclusion would have undue influence on the fitted model. These points were removed

using robust regression analysis.

Other summary statistical analyses were further conducted to generate the final data sets,

which were used to construct a multiple linear regression model for Equation 1. Table 1

defines the variables and their range of values utilized in the analysis.

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. 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 link type have significant influence on link speed. This is supported by the previous research of McLean (1981) who found that there was a strong influence of curved roads on speed. The longer the link length is, the higher the speed. Although number of lanes shows positive correlation with link speed, it is not a significant variable in the model. Pavement 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 other variables of traffic characteristics were not significant. Among traffic delay characteristics, speed limit is significant, as expected. This is supported by Fitzpatrick et al. (2001) who found that speed limit is the single most influencing factor among traffic characteristics. All other traffic delay variables such as traffic signals and stop signs were not significant, which might be due to lower variation or the use of loop detector speed data as a dominant variable. For roadway environmental characteristics, access density is significant and mixed land use is positively correlated. This is supported by Galin's (1981) research that found that the land use adjacent to roads strongly influences speed. However, neither residential nor commercial land use was significant, although each was shown to have negative correlation with link speed.

Model Validation

Model validation was conducted using links that were not used in the model calibration process. As an example, figure 7 shows the speed from arterial link. Although the travel forecasting speed for the link is 44.6 mph, the baseline speed from the simulation shows a lower speed throughout the study period. Comparing 30-second loop speed and the refined link speed estimated from the intermediate model, the latter shows better performance. The mean absolute percentage error (MAPE) over the entire period was 6.1 percent for the model's speed, 8.9 percent for the loop speed, and 31.4 percent for speed from the travel forecasting model. The validation results suggest that the travel forecasting speed is not an appropriate estimate and that the intermediate model has the potential to provide better link speed estimation.

Insert Figure 7

Emission Estimation

Based on the calibrated intermediate model, refined link speeds were estimated every 30 seconds for all links in the network. These time-dependent link speeds were used in Equation 2 to estimate emission factors, which were used to calculate the total time-dependent emission for every link using Equation 3.

Evaluation Results and Analysis

For evaluation purposes the total emissions for network links were estimated three ways:

(1) PARAMICS plug-in: Simulated link speeds are input to the plug-in, which is regarded as the baseline emission data.

(2) Current practice: Link speeds estimated from the travel forecasting model are input to MOBILE.

(3) Proposed method: Refined link speeds from equation 1 are input to MOBILE.

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 shows that current practice underestimates the emissions in the range of 3 to 24 percent. The main reason for the poor estimation from the travel forecasting method is its inaccurate prediction of average speed, which is for the entire morning peak period and thus averages out speed variation due to changing traffic conditions. The proposed method underestimates emissions within a 5% range of values from PARAMICS. A reason for this better performance of the proposed method is its capability to capture traffic variations by using 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 current practice underestimates the emissions on arterial streets

more than on freeway mainlines and ramps. This might be attributed to the presence of

traffic control devices that can increase the variation of speeds on arterial networks.

From another perspective, the simulation link speed can be compared to the refined link

speed estimated using the proposed method and the link speed from the travel forecasting

model. As shown in Table 3, the travel forecasting model overestimates all link speeds in

the range of 7 to 20 mph, while the proposed methodology overestimates within the range

of 5 mph. This implies that the travel forecasting model does not accurately represent the

real-world traffic condition. A possible reason for the poor travel forecasting speed

estimation could be that the travel forecasting model was not well calibrated. A reason

for the better 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 8 show that the proposed method has capabilities to estimate time-dependent

emissions. One freeway link and one arterial link were selected for the analysis. Similar

results were obtained as discussed in the previous section; again, all the pollutants were

underestimated by the proposed model compared to the baseline / PARAMICS

simulation emission data. There are several possible reasons for this underestimation:

(1) When the Monitor plug-in collects baseline emission data from the simulation, both

acceleration and deceleration of vehicles at every second are used. However, while

MOBILE6 considers higher accelerations at high speeds, it does not consider sharp

accelerations at different speeds. A previous study showed that emissions can vary 2-

3 times during significant acceleration/deceleration changes (Joumard et al., 1999).

(2) One of the limitations of MOBILE6 is that it cannot estimate emission rate for speeds greater than 65 mph, which can commonly occur in daily traffic conditions. This paper applied the same emission rates to all speeds greater than 65 mph, which may cause the underestimation of the total emissions, as was clearly depicted for all three pollutants on freeway links.

(3) Assumptions about the model and the inputs of the Monitor plug-in challenge the accuracy of the baseline emission data. For example, the model used by the plug-in was from the UK Department of Transport and was calibrated against UK data, and thus it might not fit typical situations in the US. The associated input emission distribution data for all vehicle types may not keep pace with improved performance for many vehicle types due to the rapid advance of vehicle pollution control technologies.

Insert Figure 8

DISCUSSIONS & FUTURE WORK

This paper presents a revised emission estimation method that offers improved performance in comparison to the current practice. The core of the method is an intermediate model that provides better estimates of link speed by considering a set of emission specific characteristics for each link. The intermediate model is developed using multiple linear regression analysis and was calibrated, validated, and evaluated based on a microscopic simulation method. Using the baseline emission data from a PARAMICS

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simulation as reference, the proposed emission estimation method was evaluated. It was found that it performs better than the current practice and is capable of estimating time-dependent emissions with the presence of traffic sensor data.

It is noted that micro-simulation models may not accurately model acceleration or deceleration when compared to actual on-road vehicle activities. Although this may be a restriction of the approach, it is the only standard approach that is feasible given the limitation on obtaining real-world data. Furthermore, a calibrated simulation model was applied.

While the proposed method underestimates total emissions, the model has the potential to be further improved. The model can incorporate other ESC variables, such as driver characteristics, weather and vehicle characteristics, some of which cannot be modeled and captured by micro-simulation. In addition, the relationship between speed and ESC can be further improved by using multivariate statistical analysis techniques, such as structural equation modeling, where linear relationships between a number of endogenous and exogenous variable (as well as latent variables) can be established.

Although this paper assumes the existence of good detectors in the target network for dynamic estimation of emissions, the developed intermediate model is actually flexible enough to work with different data sources, such as probe vehicle data, historical speed data, and the speed output from travel forecasting model. If the speed data from travel forecasting model are used, the proposed model will only be restricted to provide a static

emission estimate, which may still be a better estimate than from current practice due to the involvement of other ESC variables. When advanced traffic information systems are deployed, this methodology would be readily available to better estimate emissions. Two separate models could be calibrated: one for cases when sensor speed data (or other real data) are not available and another when they are available. Furthermore, this research can be developed to include the effect of different vehicle type mixes.

It is realize that, while a fundamental problem in the modeling of emissions and energy consumption in travel forecasting is examined, the most fundamentally detailed solution is not necessarily provided (such as utilizing dynamic models). The state of the art in this area is still several years away from any practical application, due primarily to the lack of route choice and other behavioral paradigms for the dynamic domain (as well as deeper questions as to what extent dynamic equilibrium exists in the real-world). Simulation-based non-equilibrium analysis to augment travel forecasting is one option, but again this is also not an option in which the planning community has sufficient level of comfort for practical use. The 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 estimates based on available data sources. The calibration of the intermediate model would be required prior to adoption 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 types of street characteristics and traffic conditions with large data sets.

ACKNOWLEDGEMENT

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LIST OF FIGURES

Travel time = FL/speed

BPR

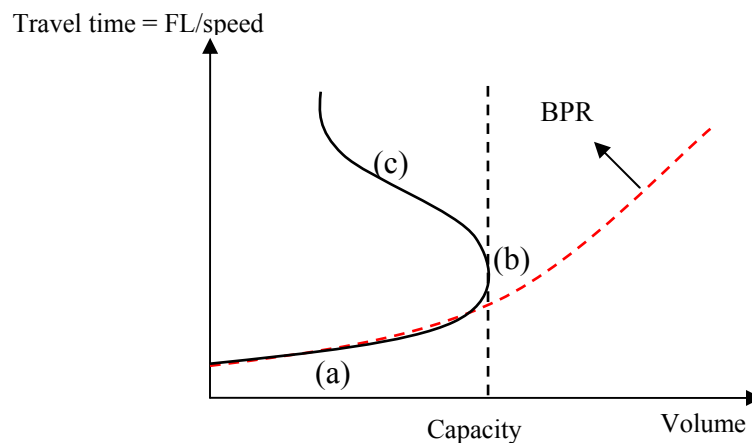(c)

(b)

(a)

Capacity

Volume

FIGURE 1 Fundamental diagram of traffic flow

Note: FL = Facility length
BPR = Bureau of Public Roads
(a) = indicates low flow, low density and low travel time
(b) = indicates curve turn back and goes to infinity
(c) = indicates low floe, high density and high travel time.
Travel time is estimated using following equation:
$$tf = t_o*(1+ \alpha*(V/C)^{\beta})$$

Where, tf – Final congested link traversal time
t_0 - link traversal time at free flow speed
V – Link Volume/flow in veh/hr/lane
C – Link Capacity
α – Coefficients (0.15)
β – Exponent (4.0)
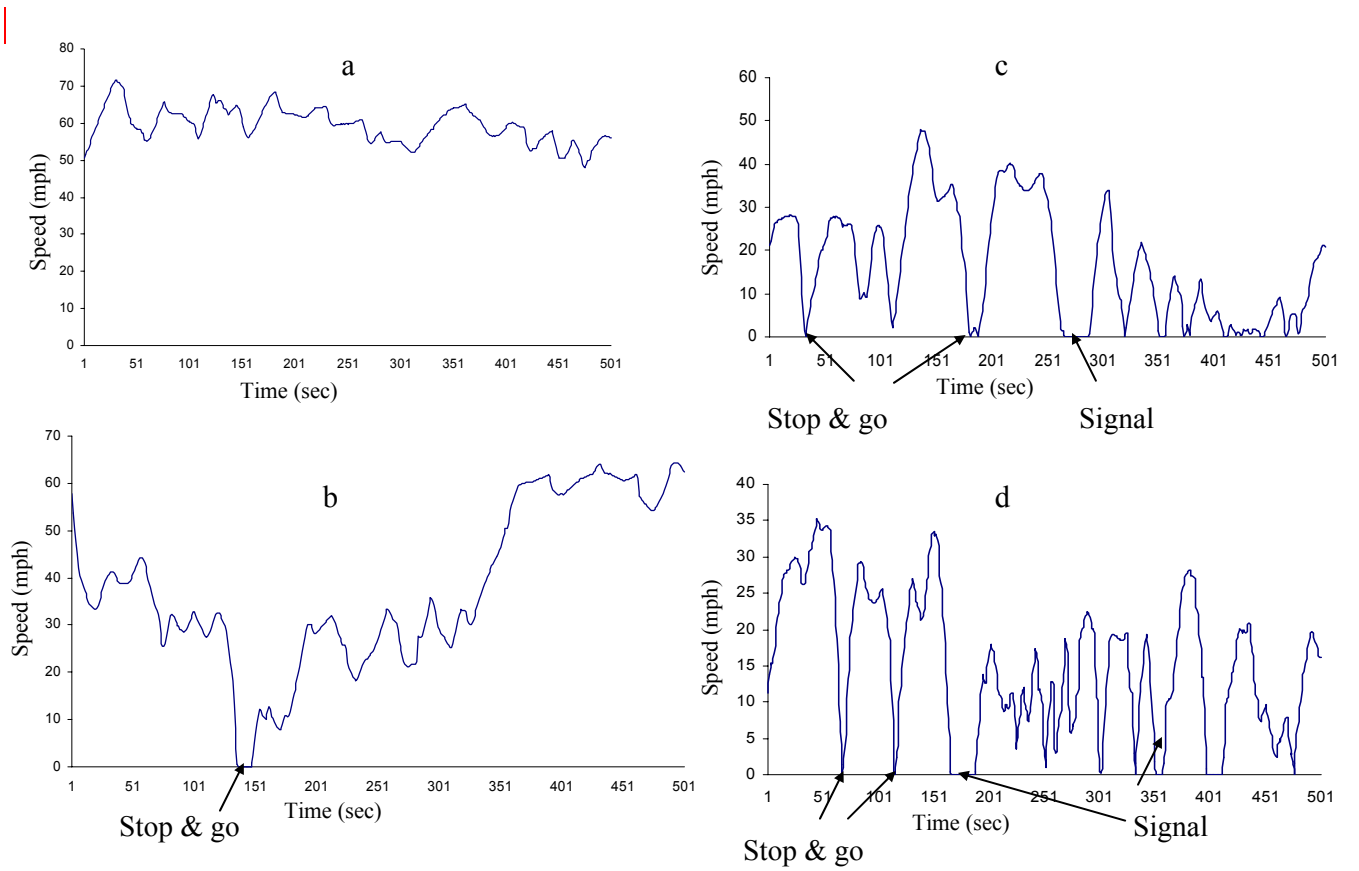
FIGURE 2 Driving profile of (a) I-405, (b) I-5, (c) Campus Dr, and (d) Culver Dr
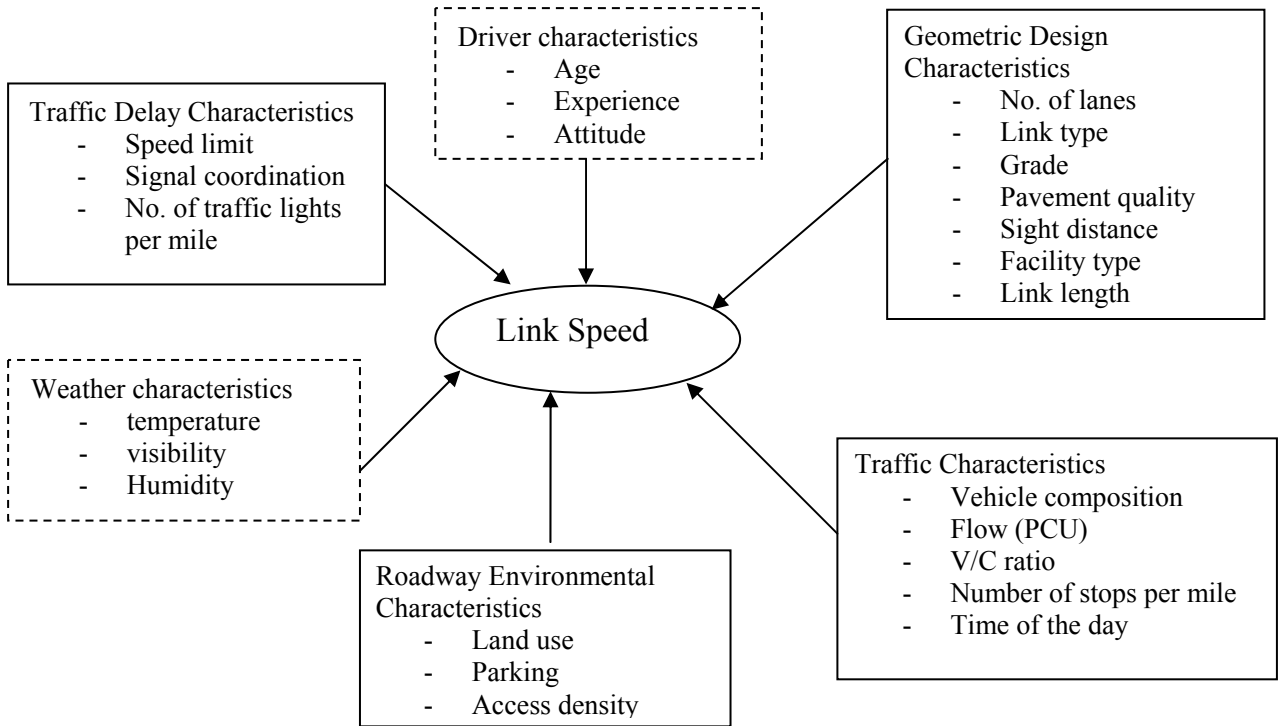
FIGURE 3 Relationship between link speed and ESC

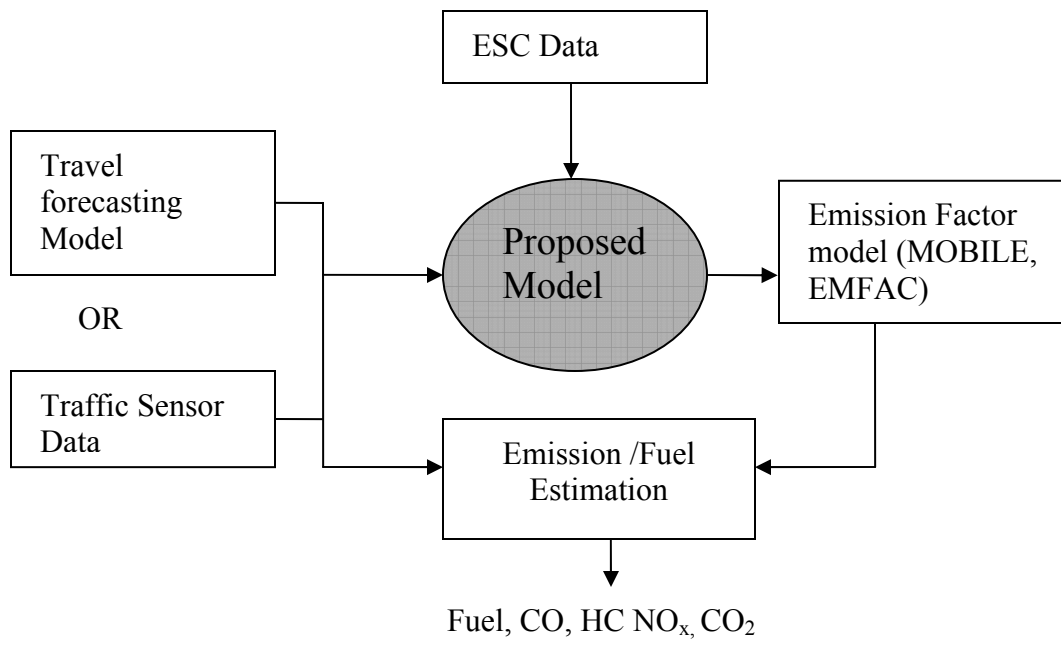Note: Variables inside the dotted boxes are not used in this study.

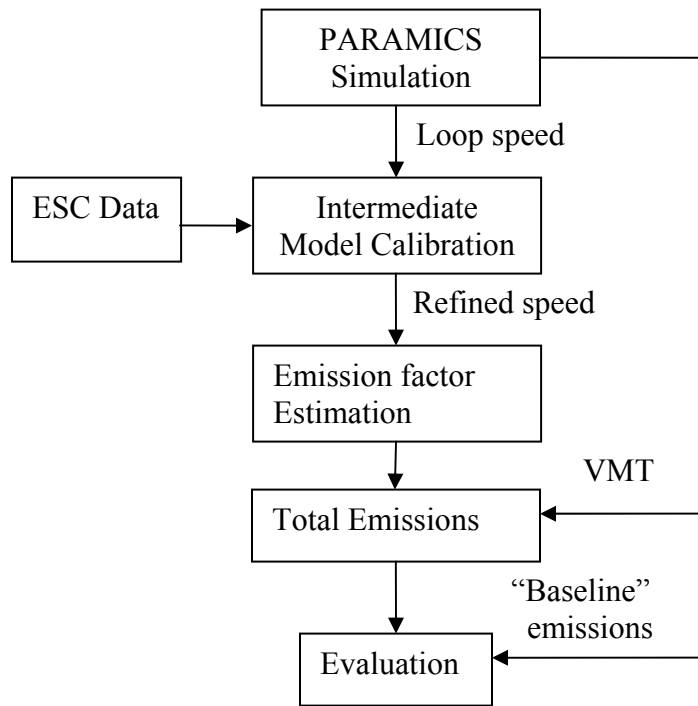**FIGURE 4** Proposed method to estimate emissions
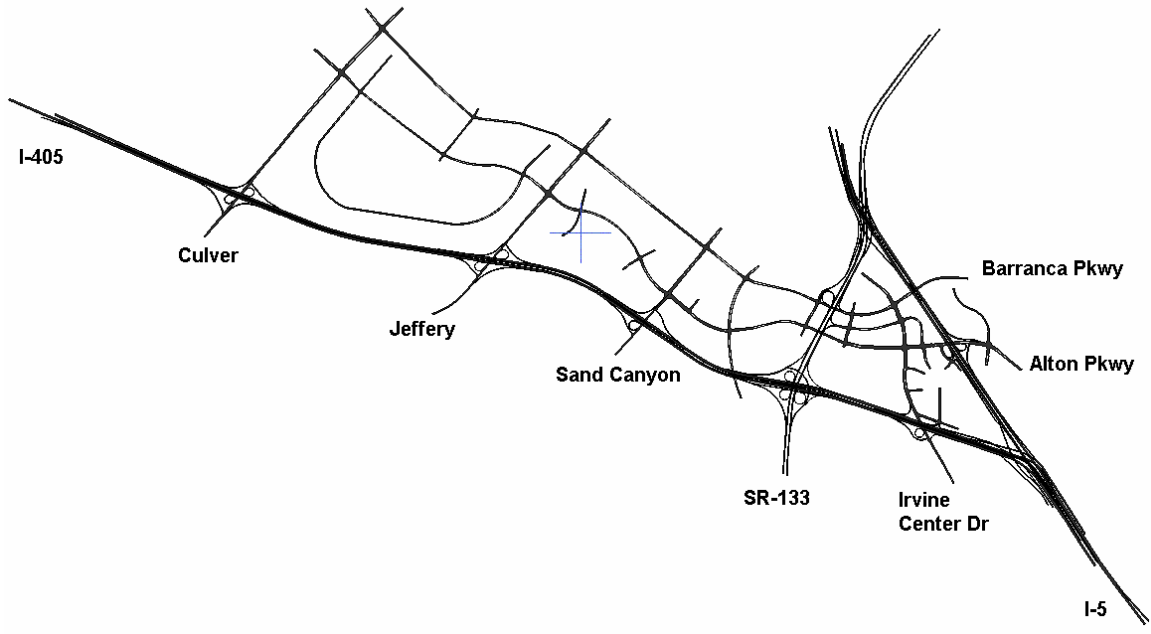
FIGURE 5 Schematic diagram of evaluation procedure

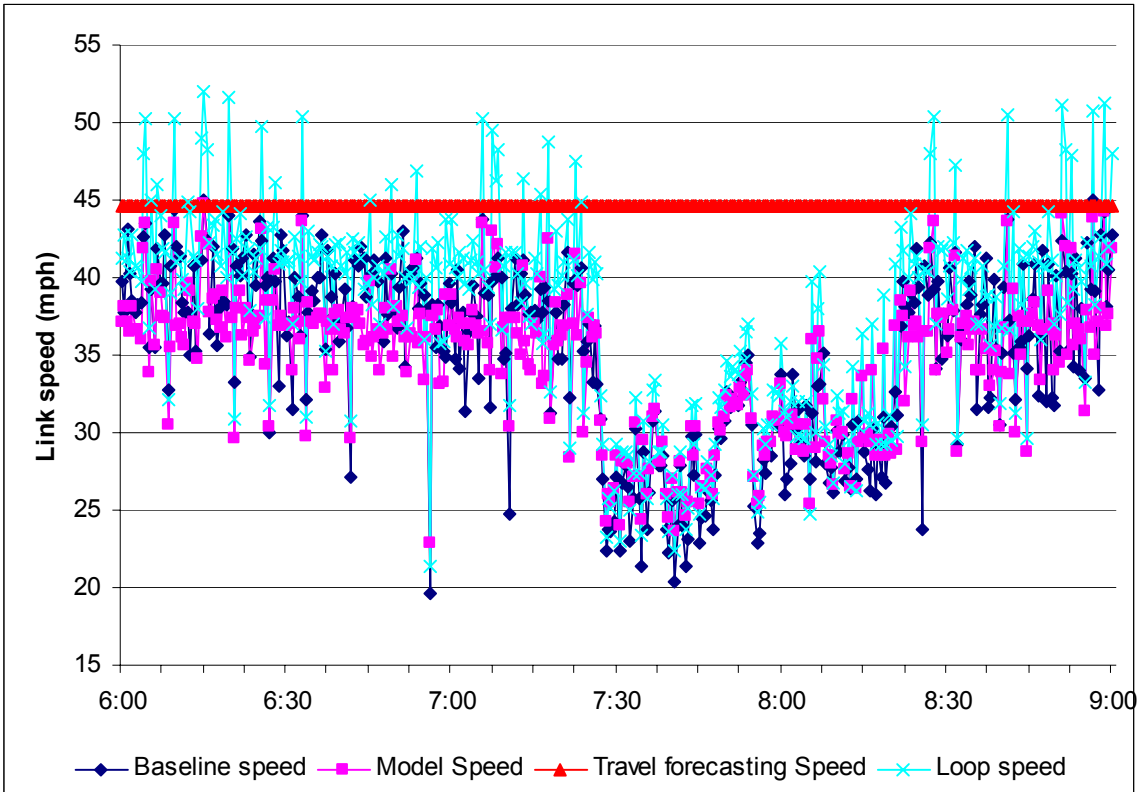**FIGURE 6** Overview of the study network

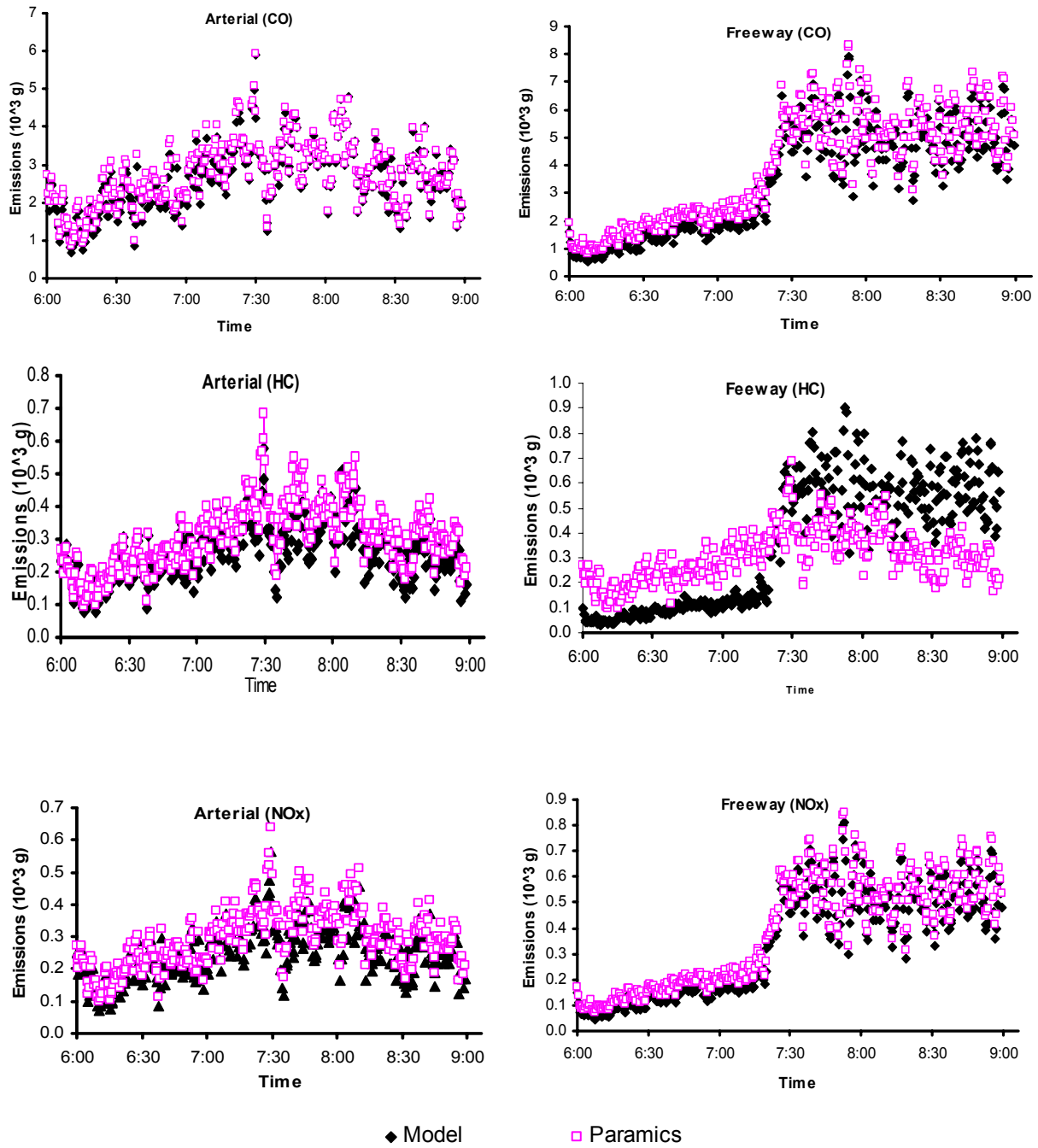**FIGURE 7** Model validation

FIGURE 8 Time-dependent emission pollutants during the morning peak period

LIST OF TABLES

TABLE 1 Summary of variables considered for analysis

Geometric Design
• Number of lanes: Ranging from 2 to 6 in each direction
• Pavement quality: 0- bad quality; 1- Good quality
• Link type: 1- curved; 0- straight
• Facility type: 1 – freeway, 0 – otherwise
1 – arterial, 0 – otherwise
1 – ramp; 0 - otherwise
• 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
• Travel forecasting speed: ranging from 3.4 to 60 mph
• Loop Volume: 0 to 11520 vph per direction
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
Roadway Environmental Characteristics
• Landuse:
1 – residential, 0 - otherwise
1 - commercial, 0 - otherwise
1 - mixed landuse, 0 – otherwise.
• Access density: ranging from 0 to 11 intersections per mile

TABLE 2 Regression model to estimate refined link speed

Variables	Coefficient	P-values
Loop speed	0.714	0.000
Speed limit	0.51	0.000
Mixed landuse	2.46	0.032
Link type	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	Loop Speed[1] (mph)	Travel forecasting Speed[2] (mph)	Model Speed[3] (mph)	Paramics Total Emissions[4] (10^3 g)			Travel forecasting Total Emissions[5] (10^3 g)			Model Total Emissions[6] (10^3 g)		
					VOC	CO	NO_x	VOC	CO	NO_x	VOC	CO	NO_x
8:10	Freeway	53.0	60.0	54.8	439	3920	401	423	3910	401	426	3924	402
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
144:138	Arterial	22.4	41.5	23.2	89	764	79	85	743	77	89	757	79
233:121	Arterial	26.1	44.1	28.4	15	139	14	12	126	13	15	137	15
149:121	Arterial	27.5	41.9	29.2	3	27	3	2	26	2	3	27	3
62:138	Arterial	23.8	41.4	25.6	30	326	34	24	325	34	29	323	33
264:20	Ramp	34.4	41.1	37.7	22	178	19	21	174	16	22	170	18
318:320	Ramp	29.3	41.1	29.5	6	50	5	5	47	5	6	50	5

Note:
[1] Estimated from a PARAMICS simulation
[2] Estimated from OCTAM 2001 travel forecasting model
[3] Refined speed from intermediate model
[4] Calculated using PARAMICS plug-in with simulated link speed as inputs
[5] Calculated using MOBILE with link speed from travel forecasting model
[6] Calculated using MOBILE with refined speed from intermediate model