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Abstract

The goal of this paper is to predict the fraction of time vehicles spend in different operating conditions from readily observable emission specific characteristics (ESC), which include geometric design, roadway environment, traffic characteristics, and driver behavior. We rely on a calibrated micro-simulation model to generate second-by-second vehicle trajectory data and use structural equation modeling to understand the influence of observed link ESC on vehicle operation. Our results reveal that 67 percent of link speed variance is explained by emission specific characteristics. At the aggregate level, geometric design elements exert a greater influence on link speed than traffic characteristics, the roadside environment, and driving style. Moreover, the speed limit has the strongest influence on vehicle operation, followed by facility type and driving style. This promising approach can be used to predict vehicle operation for models like MOVES, which was recently released by the Environmental Protection Agency.

Keywords: Vehicle operation; emission specific characteristics; structural equation modeling; micro-simulation.

1. Introduction

Spurred by increasing concerns about global warming, the state of California committed in 2006 to reducing its greenhouse gas emissions (GHG) to 1990 levels by 2020. To help achieve this ambitious goal, SB 375 ("Redesigning Communities to Reduce Greenhouse Gases", passed in 2008) attempts to reduce cars and light trucks GHG emissions by incorporating regional land use and housing strategies into Regional Transportation Plans (RTP). To better measure the effectiveness of emission reduction measures, guidelines for preparing an RTP require improvements in transportation models, including better methods for travel forecasting, traffic analysis, and emissions modeling.

Improving our estimates of vehicular emissions and fuel use compared to conventional methods requires a better understanding of vehicle operation (i.e., driving patterns). It is well known that vehicle operation changes significantly with traffic conditions, yet these are ignored by current emission inventory models. More generally, vehicle operation is influenced by a variety of factors, which we call emission specific characteristics (ESC). Apart from engine and vehicle characteristics, they include geometric design elements, traffic characteristics, the roadway environment, weather conditions, and driver behavior. The potential impact of ESC is not negligible. For example, recent research suggests that eco-driving (the adoption by drivers of fuel economy-maximizing behavior) alone could reduce fuel consumption and emissions by 5 to 20 percent (Johansson, 1999; CIECA, 2007).

In this context, our paper makes two contributions. First, we consider the joint impact of a large set of ESC on vehicle operation in a transportation network, including vehicle constraints, individual driver behavior, characteristics of the surrounding traffic, and physical characteristics of the roadway and its environment. Second, we use structural equation modeling (SEM) to identify the factors influencing vehicle operation and propose a model to predict the fraction of time spent in different operating conditions using ESC variables that can be readily measured by transportation analysts. This information is of direct interest for modal emission models like the Motor Vehicle Emission Simulator (MOVES) that was developed by the Environmental Protection Agency (U.S. EPA) to improve on conventional emission models (U.S. EPA, 2010). Since MOVES correlates the emission rate of various pollutants with operating conditions and vehicular technology, its accuracy depends upon correctly predicting the time vehicles spend in different operating conditions.

2. Literature Review

The relationship between vehicle operation and emission specific characteristics has attracted interest from researchers for some time but investigations have so far focused on subsets of ESC. Kent *et al*. (1978) considered average speed, the root mean square acceleration, and the percentage of idle time. Kuhler and Karstens (1978) suggested adding acceleration statistics, the mean length of a driving period, and the proportion of different operating modes. Later, Milkins and Watson (1983) and Watson (1995) established the importance of positive kinetic energy (PKE) for explaining the observed variance in fuel consumption and pollutant emissions. Matzoros and Van Vliet (1992) also added a creeping mode to account for short accelerations and decelerations when estimating time spent in different operating modes.

Ericsson (2000) broadened previous inquiries by considering different street types, driver gender, and traffic conditions. Using factorial analysis, she found that street type has the largest influence on vehicle operation. In subsequent research (Ericsson, 2001), she studied how 16 independent factors impact vehicle operation; nine of these factors turned out to be significant for fuel consumption and emissions, including four factors related to acceleration and power demand, three associated with gear changing behavior, and two describing speed bins.

Using a hierarchical tree approach, Hallmark *et al*. (2002) found that queue position, grade, downstream and upstream volume, the percentage of heavy duty vehicles, and posted speed limits affect vehicle operation at signalized intersections. More recently, Brundell-Freij *et al*. (2005) reported that junction density, speed limit, street function, and neighborhood type are all statistically significant variables for explaining vehicle operation. Lederer *et al*. (2005) studied the effect of on-ramp geometric and operational factors on vehicle operation using linear regression and hierarchical tree-based regression methods; grade had the greatest impact on vehicle operation followed by ramp curvature, length of curvature, and traffic volume.

To improve current practice, Nesamani *et al*. (2007) developed an intermediate regression model to refine the link speed obtained from travel forecasting models using ESC. This improved emission estimation but their model cannot predict vehicle operation on a link.

Our work departs from the above cited literature not only by the breadth of the ESC we are considering but also by our methodology because previous studies relied either on factor analysis (Ericsson, 2000) or on regression with or without hierarchical tree analysis (Hallmark *et al*., 2002; Lederer *et al*., 2005; Nesamani *et al.*, 2007).

3. Methodology

In this paper, we model vehicle operation as a function of average speed and specific power (SP). Average speed is the rate at which a vehicle moves from one position to another over a period of time. Several definitions of specific power have been proposed. Initially, Watson (1995) defined SP as a function of speed and distance. Then, the U.S. EPA (1993) expressed SP as a function of speed and acceleration. Here, we follow instead Jimenez-Palacios (1999) who defined SP as "the instantaneous power generated by the engine used to overcome rolling resistance and aerodynamic drag and to increase the kinetic and potential energies of the vehicle". SP is defined as follows:

$$SP = \frac{\text{Power}}{\text{Mass}} = v*\left(a*\left(1+\varepsilon_i\right)+g*s+g*C_R\right)+\frac{1}{2}*\rho_a*\frac{C_D*A}{m}*\left(v+v_w\right)^2*v, \tag{1}$$

where:

- SP = specific power (kW/metric ton = W/kg = m^2/s^3);
- v = vehicle speed (assuming no headwind) (m/s);
- a = vehicle acceleration (m/s^2);
- ε_i = mass factor accounting for rotational masses; it depends on gear, shaft etc. (~0.1);
- g = acceleration due to gravity (9.81 m/s^2);
- s = road grade (vertical rise/slope length);
- C_R = coefficient of rolling resistance (~0.0135; dimensionless);
- ρ_a = ambient air density (~ 1.207 kg/m^3 at 68◦F);
- C_D = drag coefficient (~ 0.2 for sedans and ~0.6 for vans; dimensionless)
- A = frontal area of the vehicle (m^2);
- m = vehicle mass (kg); and
- v_w = headwind (m/s^2).

The parameter values above are average values obtained from different sources. For a flat road (s=0) with no headwind (v_w =0) and $\frac{C_D*A}{m} = 0.0005$ m^2/kg, Equation (1) simplifies to:

$$\text{SP} = 1.1*a*v+0.132*v+0.000304*v^3 \tag{2}$$

To understand the influence of various ESC factors on vehicle operation, we implemented the process summarized in Figure 1:

- First, we identified a study area and collected driving patterns along different links.
- Second, from the literature we identified variables likely to influence vehicle operation on a link. To keep our approach practical, we focused on ESC variables that can easily be observed: geometric design, traffic characteristics, driver behavior, and roadway environment.
- Third, we developed a statistical model to understand the direct and indirect effects of various ESC variables on vehicle operation.

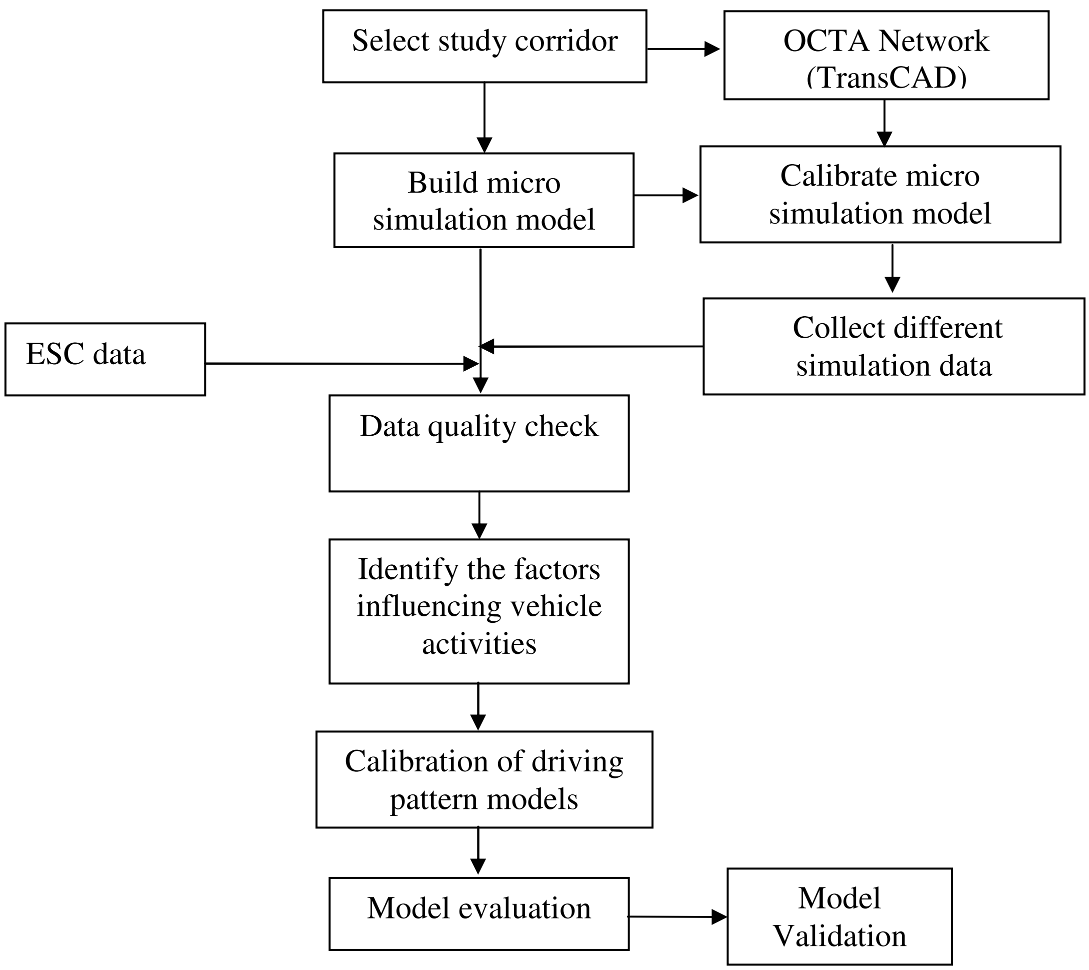


Figure 1 Methodology overview

4. Data

4.1 Network

Selecting an appropriate network is a key step for this work as the study network needs to cover a sufficiently large area to provide a wide range of geometric configurations and traffic conditions. Given these constraints, we selected the network shown in Figure 2. Located in Orange County, California, it includes 80 links, with six miles of freeway I-405, three miles each of freeways I-5 and SR-133, and all major adjacent surface streets.

Since collecting field data is expensive and also because loop detectors are not widely available, especially on arterial streets, we relied on micro-simulation to generate second-by-second vehicle trajectory data on each link. This also allowed us to monitor traffic conditions on all links, including arterial streets, by simulating loop detectors on them.

The simulation network was built in PARAMICS (parallel microscopic simulation), a commercial, high-performance, ITS-capable, microscopic traffic simulation package (Smith *et al.*, 1994). PARAMICS has been widely used to model individual vehicles on road networks, including large ones (Nesamani *et al.*, 2007). The bottom panel of Figure 2 shows the PARAMICS representation of our network. Our zone structure is based on the Orange County Transportation Authority's OCTAM 2001 regional travel forecasting model (OCTA, 2001). A well-calibrated simulation model is essential here to capture key features of actual traffic conditions. Hence in this study our simulation model underwent detailed OD demand estimation with route choice and was calibrated for driving behavior. Initial travel demand was extracted from the OCTAM travel forecasting model and fine-tuned with observed traffic counts using the PARAMICS OD estimator. To capture driving behavior, mean target headway and driver reaction time were matched to observed congestion patterns. The simulation model was then validated against travel time data from field estimates.

Source: google.com

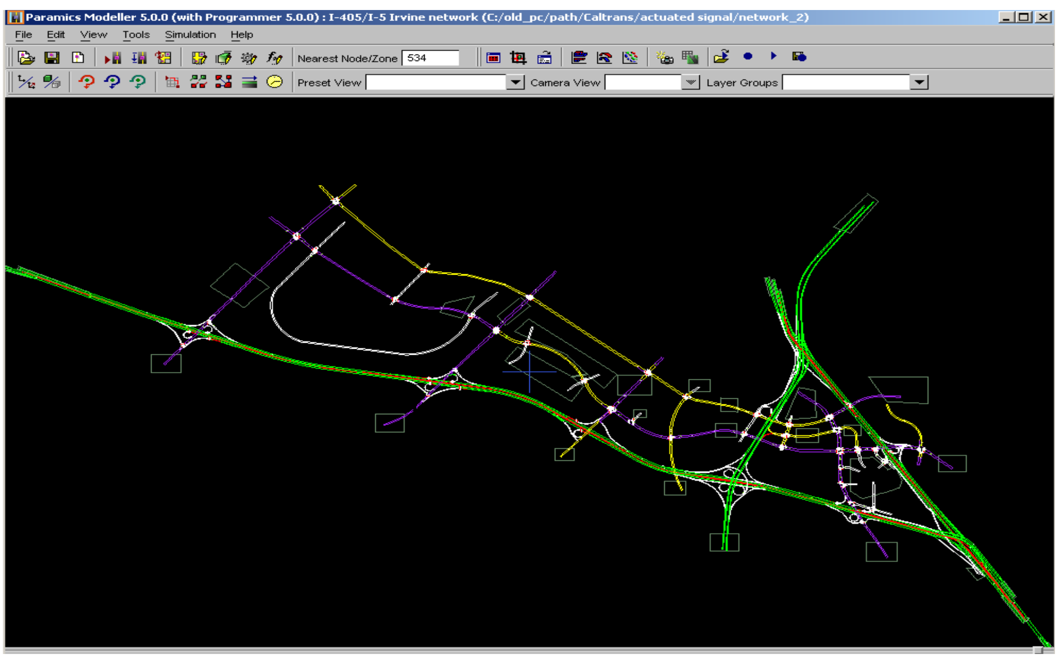


Figure 2 Study area and coding in PARAMICS.

4.2. Data Collection

Three types of data were collected to identify the factors that cause variations in vehicle operation: 1) second-by-second vehicle data from the traffic microscopic simulation; 2) loop detector data from each network link, also from our microsimulations; and 3) secondary data such as number of lanes, pavement quality, speed limit, number of intersections, presence of on-street parking, presence of bike paths, and neighboring land use.

To extract data from our simulated network, we developed two PARAMICS API plug-ins. The first one, loop aggregation, collects average link data (volume, occupancy, link type, average density, loop speed, and assigned speed limit) at 30 second intervals for each lane on a link to generate aggregate measures of link performance. It tracks all vehicles between a pair of loop detectors; vehicles that pass only one of the detectors are ignored for aggregation.

The second plug-in, vehicle aggregation, collects second-by-second vehicle statistics such as speed and acceleration. It takes a snapshot of all the vehicles on each link at each time step and aggregates this information into a single speed and acceleration.

Microscopic simulation provided us with a rich dataset that includes dynamic variations across vehicles, as well as across temporal and spatial dimensions.

4.3 Variables Description

To find factors that potentially affect vehicle operation on a link, we reviewed the literature and consulted the Highway Capacity Manual (HCM). To keep our approach practical, we ignored variables that are expensive or difficult to collect and focused on broad geometric design, traffic characteristics, the roadside environment, and driver behavior. Table 1 summarizes the variables we selected and the range of values collected.

Table 1 List of variables collected to develop the proposed model

Emission Specific Characteristics	**Source**
Geometric Design	
Number of lanes: Ranging from 2 to 6 in each direction	Aerial photo
Link length: 0.02 – 0.9 miles	Aerial photo
Pavement quality: 0- bad quality; 1- Good quality	Observed
Link type: 0- curved; 1- straight	Observed
Facility type: Freeway, HOV, off-ramp, On-ramp Arterial	Aerial photo
Presence of median: 0-No; 1-Yes	Observed
Section type: Weaving, merging	Aerial photo
No. of 4-way intersections	Aerial photo
Presence of bike paths in arterial streets: 0-No; 1-Yes	Aerial photo
Grade: Uphill and downhill, flat (percent)	Observed
Traffic Characteristics	
V/C ratio: ranging from 0.3 to 1.1	Calculated
Travel forecasting speed: ranging from 3.4 to 60 mph	Simulation
Loop speed: ranging from 12 to 84 mph	Simulation
Volume: 0 to 11520 vehicles in each link	Simulation
Peak/off-peak: 0 – off-peak period; 1- peak period	Simulation
Speed limit: Ranging from 25 mph to 65 mph	Observed
Roadway Environmental characteristics	
Land use: Residential, commercial and mixed land use	Observed
Presence of on-street parking: 0-No; 1-Yes	Observed
Access density: ranging from 0 to 4 per mile	Observed
Driver Characteristics	
Calm: 0 – No; 1- Yes	Simulation
Aggressive: 0- No; 1-Yes	Simulation

To obtain information about geometric design, we utilized aerial photographs that provided the number of freeway and arterial lanes, as well as facilities type, link length, four-way intersections and the presence of bike paths. We considered four types of facilities: HOV lanes, freeway lanes, ramps, and arterials. Sections were classified either as weaving/merging or not. Freeway links with a ramp were classified as weaving/merging or not, and so were arterials with a left turn bay or a merging section. Aerial photographs also helped us to subjectively classify pavement quality as either good or bad because pavement index data were unavailable.

Loop speed was collected from the micro-simulation plug-in we developed. After collecting link traffic volumes from our simulations, we calculated traffic intensity (the V/C ratio) assuming a fixed capacity.

The roadside environment variables were observed by a field team who drove along the study corridor. On each link, they collected the street name, the posted speed limit, land use, and characterized on-street parking as well as the number of access points. We classified land use in three broad categories: residential, commercial, and mixed land use. On-street parking was predominately available in residential areas. Access density was defined as the number of driveways/intersection in a link; it ranged from zero to four per mile.

Finally, we characterized driver behavior based on speed and maximum acceleration rate. We considered three categories: calm, normal, and aggressive. Drivers whose speed exceeded 75 mph or whose acceleration was at least 3 m/s^2 were considered aggressive. Conversely, drivers who limited their acceleration to 1 m/s^2 and whose speed stayed under 75 mph were considered calm; others were considered normal. For more details, see Nesamani (2007).

5. Model development

Several approaches have been used to estimate the influence of ESC (exogenous variables) on vehicle operation (endogenous variables). Most previous studies relied either on regression with hierarchical tree analysis (Hallmark *et al.*, 2002; Lederer *et al.*, 2005), which is commonly known as classification and regression tree (CART), or on factor analysis (Ericsson, 2000).

CART organizes data recursively into a tree structure. It offers a number of advantages compared to traditional multivariate techniques: it requires no distributional assumption, it is easy to understand and it handles multidimensionality well. However, CART's main weakness is that it is not based on a probabilistic model and so it does not allow statistical testing of the results (Yohannes and Hoddinott, 1999).

Factor analysis primarily helps condense a large number of correlated variables into a manageable subset. However, factors may be difficult to interpret (multiple attributes can be grouped together with no straightforward interpretation) and it may be difficult to distinguish between competing models. Since we want to assess the statistical validity of our results and make sense of them, we adopted another approach, structural equation modeling (SEM), to explore the influence of observed ESC on vehicle operation.

Structural equation modeling (SEM) has become popular to analyze linear relationships. It encompasses multivariate statistical analysis techniques such as regression analysis, factor analysis, and simultaneous equations. The general objective of a SEM model is to provide a parsimonious relationship among variables and to test hypothesized interrelationships between them. SEM establishes linear relationships between endogenous and exogenous variable as well as latent (unobserved) variables. It also helps understand the estimated model by representing it graphically (Schermelleh-Engel *et al.*, 2003; Golob, 2003; Kline, 2005).

Before specifying our models, we examined the collected data to detect and remove outliers using robust statistical analysis. We also generated summary statistics to examine the variations of our variables. We then specified two models. The goal of the first model was to explain average link speed as a function of loop speed and ESC; the purpose of the second model was to predict the fraction of time spent in different SP bins as a function of ESC and loop speed.

5.1 Average link speed model

We hypothesize that average link speed can be explained by average loop detector speed and link ESC, while average loop detector speed is explained only by link ESC as shown in Equation 3, where $\hat{S}$ denotes average link speed, *SL* is the average loop detector speed, and *E* denotes emission specific characteristics:

$$\begin{cases} \hat{S} = f_1(SL, E), \\ SL = f_2(E). \end{cases} \tag{3}$$

Figure 3 shows the path diagram of the proposed average link speed model and details its variables; it corresponds to the following structural relationship

$$Y = \beta \mathrm{Y} + \gamma \mathrm{X} + \zeta, \tag{4}$$

where:

- **Y** is a 160×1 vector of endogenous variables (link speed and loop speed for each of our 80 network links);
- **β** is a 160×160 matrix linking endogenous variables;
- **X** is a 1440×1 vector of observed exogenous variables; it includes 18 exogenous variable for each of the 80 links (see Figure 3);
- **γ** is a 160×1440 matrix of unknown coefficients that relates endogenous and exogenous

variables; its structure was hypothesized based on the relevant literature and theory; and

- $\boldsymbol{\zeta}$ is a 160×1 vector of disturbance terms.

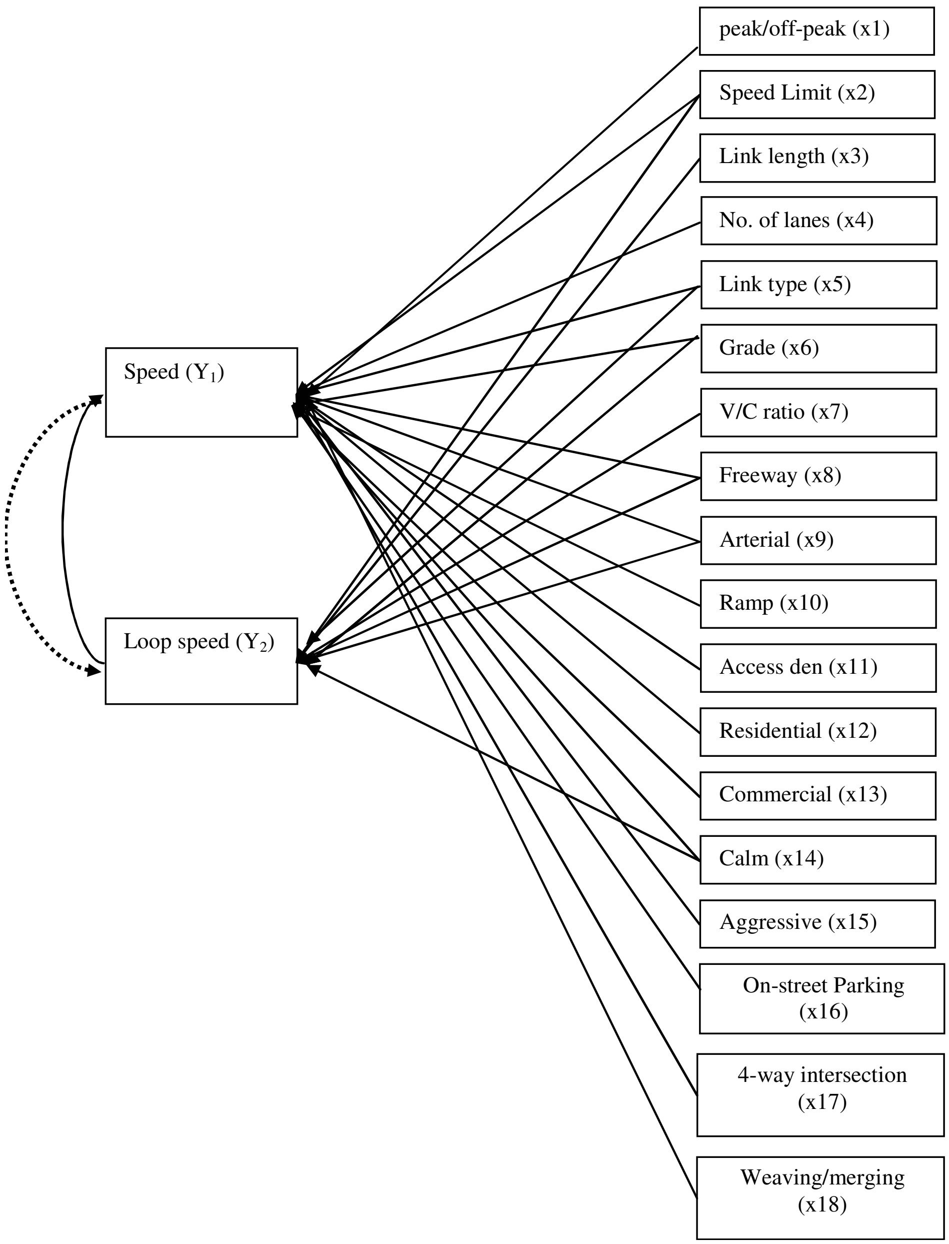


Figure 3 Path diagram of the specified average link speed model

Equation (4) comprises the equations for all network links. For a specific link, it relates link speed and loop speed, denoted by y_1 and y_2 respectively, to their link explanatory variables

($x_1,\ldots,x_{18}$) by

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} 0 & \beta_{2,1} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} + \tag{5}$$

$$\begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & 0 & \gamma_{1,4} & \gamma_{1,5} & \gamma_{1,6} & 0 & \gamma_{1,8} & \gamma_{1,9} & \gamma_{1,10} & \gamma_{1,11} & \gamma_{1,12} & \gamma_{1,13} & \gamma_{1,14} & \gamma_{1,15} & \gamma_{1,16} & \gamma_{1,17} & \gamma_{1,18} \\ 0 & \gamma_{2,2} & \gamma_{2,3} & 0 & \gamma_{2,5} & \gamma_{2,6} & \gamma_{2,7} & \gamma_{2,8} & \gamma_{2,9} & 0 & 0 & 0 & 0 & \gamma_{2,14} & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_{18} \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix}$$

β_{21} and the γ coefficients in Equation (5) are common to all links; they are estimated jointly in Equation (4).

5.2 SP bin model

For the U.S.EPA (2010) Motor Vehicle Emission Simulator (MOVES) model, vehicle operation is broadly classified into six bins (see Table 2). Second-by-second speed and acceleration data were collected and applied in Equation (1) to calculate specific power for each link. Then, the fraction of time spent in each bin was estimated. In this study, we focused on the last four bins since they influence emissions significantly; hereafter these bins are referred to as SP bins. We assume that loop speed inter-correlates different SP bins and that there was no interaction between SP bins. We assume that the fraction of time spent in each SP bin can be explained by average loop speed and link ESC, while average loop detector speed is again explained only by link ESC. Moreover, there are no interactions between SP bins, so error terms are independent of each other. Figure 4 illustrates the path diagram of the SP bin model, which is

$$\begin{cases} SP_i = g_i(SL, E), \ i = 3,\ldots,6 \\ SL = h(E), \end{cases} \tag{6}$$

where SP_i ($i \in \{3,4,5,6\}$) is the fraction of time spent in SP bin "*i*"; *SL* is the average loop detector speed; and *E* denotes emission specific characteristics. The structural relation for the path model can be described by

$$Y = \mathrm{B}\,\mathrm{Y} + \Gamma\,\mathrm{X} + \mathrm{E}, \tag{7}$$

where now:

- **Y** is a 400×1vector of endogenous variables (the last four SP bins and one loop speed value for each of the 80 network links);
- **B** is a 400×400 matrix of unknown coefficients that links endogenous variables. It reflects our assumption that loop speed correlates with SP bins, but that there is no interaction between SP bins;
- **X** is a 1440×1 vector of observed exogenous variables; it includes 18 exogenous variable for each of the 80 links (see Figure 4 for details);
- **Γ** is a 400×1440 matrix of unknown coefficients that relates endogenous and exogenous variables; its structure was hypothesized based on the literature and on theory; and
- **E** is a 400×1vector of disturbance terms.

Table 2 SP distribution and corresponding bins

SP Bin	SP (kw/ton)
1	SP<6
2	6≤SP<12
3	12≤SP<18
4	18≤SP<24
5	24≤SP<30
6	30≤SP

Equation 7 comprises equations for all network links. As in Equation (8), the fraction of time spent in each of the last four SP bin and the loop speed for each specific link, denoted by y_1 to y_5 respectively, are related to their link explanatory variables ($x_1,\ldots,x_{18}$) by

$$
\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ Y_5 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & \beta_{1,5} \\ 0 & 0 & 0 & 0 & \beta_{2,5} \\ 0 & 0 & 0 & 0 & \beta_{3,5} \\ 0 & 0 & 0 & 0 & \beta_{4,5} \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ Y_5 \end{bmatrix} + \tag{8}
$$

$$
\begin{bmatrix}
0 & 0 & \gamma_{1,3} & 0 & \gamma_{1,5} & \gamma_{1,6} & \gamma_{1,7} & \gamma_{1,8} & \gamma_{1,9} & \gamma_{1,10} & \gamma_{1,11} & \gamma_{1,12} & \gamma_{1,13} & \gamma_{1,14} & 0 & \gamma_{1,16} & 0 & \gamma_{1,18} \\
0 & 0 & \gamma_{2,3} & 0 & \gamma_{2,5} & \gamma_{2,6} & \gamma_{2,7} & \gamma_{2,8} & \gamma_{2,9} & \gamma_{2,10} & \gamma_{2,11} & \gamma_{2,12} & \gamma_{2,13} & \gamma_{2,14} & 0 & \gamma_{2,16} & 0 & \gamma_{2,18} \\
\gamma_{3,1} & \gamma_{3,2} & \gamma_{3,3} & 0 & \gamma_{3,5} & \gamma_{3,6} & \gamma_{3,7} & \gamma_{3,8} & \gamma_{3,9} & \gamma_{3,10} & \gamma_{3,11} & \gamma_{3,12} & \gamma_{3,13} & 0 & \gamma_{3,15} & \gamma_{3,16} & 0 & \gamma_{1,18} \\
\gamma_{4,1} & \gamma_{4,2} & \gamma_{4,3} & 0 & \gamma_{4,5} & \gamma_{4,6} & \gamma_{4,7} & \gamma_{4,8} & \gamma_{4,9} & \gamma_{4,10} & \gamma_{4,11} & \gamma_{4,12} & \gamma_{4,13} & \gamma_{4,14} & \gamma_{4,15} & \gamma_{4,16} & \gamma_{4,17} & \gamma_{1,18} \\
\gamma_{5,1} & \gamma_{5,2} & \gamma_{5,3} & \gamma_{5,4} & \gamma_{5,5} & \gamma_{5,6} & \gamma_{5,7} & \gamma_{5,8} & \gamma_{5,9} & 0 & 0 & 0 & 0 & \gamma_{5,14} & \gamma_{5,15} & \gamma_{5,16} & \gamma_{5,17} & \gamma_{5,18}
\end{bmatrix}
\begin{bmatrix} x_1 \\ \vdots \\ x_{18} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \end{bmatrix}
$$

β_{15} to β_{45} and the γ coefficients in Equation (8) are common to all links; they are estimated jointly in Equation (7).

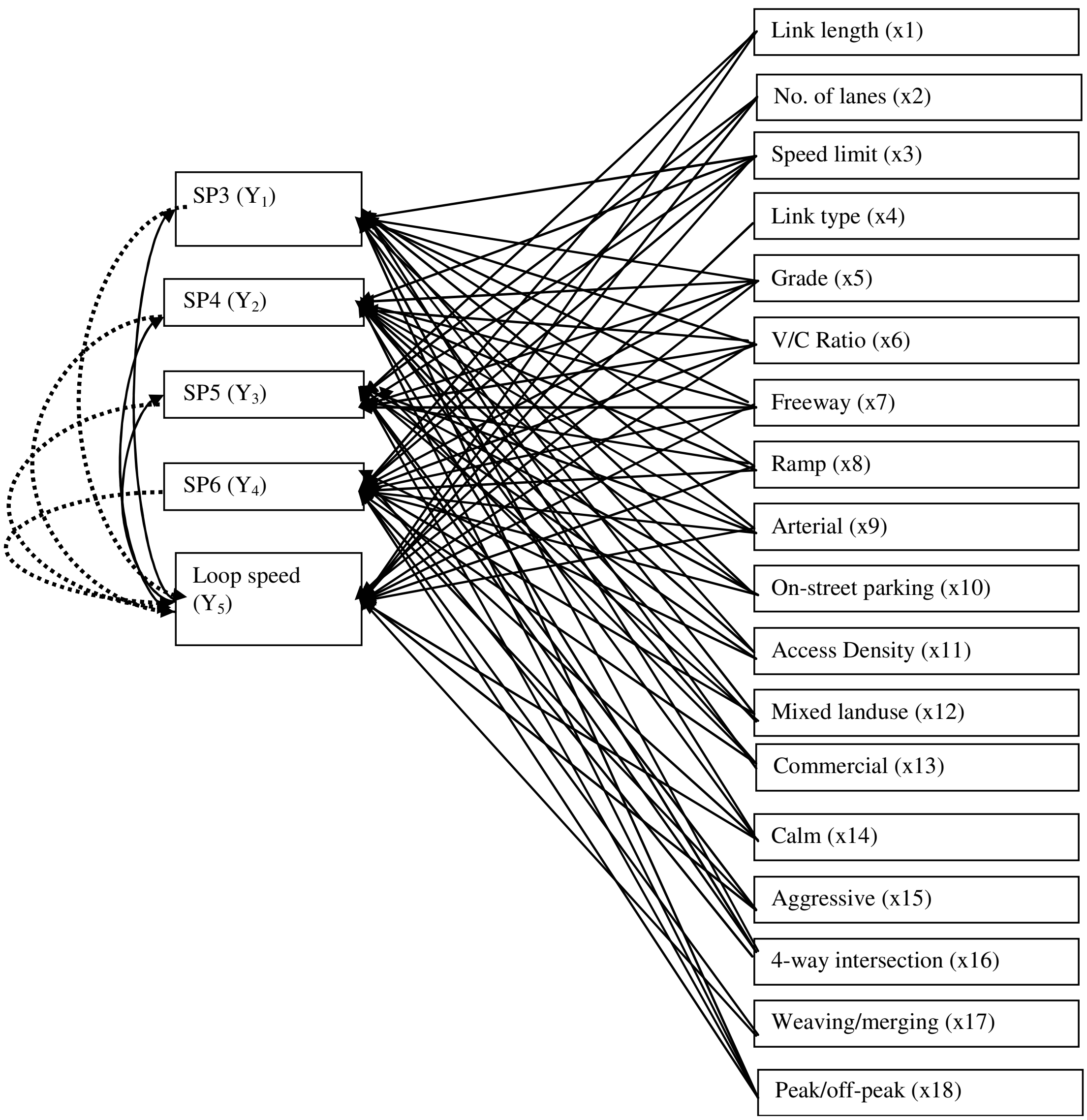


Figure 4 Path diagram of specified SP bin model

6. Results

The structural equation modeling package LISREL (SSI, 2009) was used to estimate our model parameters ($\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\mathbf{B}$, and $\boldsymbol{\Gamma}$) using maximum likelihood (ML). The goal of model evaluation is to assess whether a model was correctly specified. Kline (2005), for example, suggests that structural equation models should be evaluated in terms of (a) significance and strength of estimated parameters; (b) overall fit of the model; and (c) endogenous variables variance explained. Furthermore, results should be supported by the theory researchers are relying on.

Goodness of fit indices for the average speed and SP bin models are shown in Table 3. They suggest that our models fit the data well. The model chi-square (χ^2), which assesses the difference between the sample and fitted covariances matrices, indicates that this difference is small. The RMSEA (root mean square error of approximation) tells us how well a model with unknown but optimally chosen parameter estimates fits the population covariance matrix; it is under 0.03 for both models, which suggests very good fit. The most commonly reported fit indices (GFI, AGFI, NFI, NNFI) all have high values (>0.95) for both models, as required; GFI and AGFI calculate the proportion of variance accounted for by the estimated population variance, while NFI and NNFI measure relative fit compared to a baseline model. Finally, the CAIC statistics (which are based on Akaike's Information Criteria; see Table 3 notes) indicates that our models are parsimonious.

Table 3 Goodness of Fit Indices

Fit Index	Average Speed Model	SP bin Model	Acceptable Range
χ^2(df)[1]	31.19(23)	29.13(25)	
p-value	0.12	0.26	> 0.05
χ^2/df[1]	1.36	1.17	< 2
RMSEA[2]	0.018	0.010	< 0.05
p-value for test of close fit (RMSEA<0.05)	>0.999	>0.999	>0.05
SRMR[2]	0.0083	0.0036	< 0.08
GFI[3]	~1	~1	>0.95
AGFI[3]	0.98	0.99	>0.95
NFI[4]	~1	~1	>0.95
NNFI[4]	~1	~1	>0.95
Model CAIC[5] ($CAIC_m$)	1212.11	1704.61	$CAIC_m$<$CAIC_s$
Saturated CAIC[5] ($CAIC_s$)	1229.13	1710.82	

Notes:
1. The chi-square (χ^2) statistic is also called the discrepancy function or chi-square goodness of fit; it measures whether the observed covariance matrix is similar to the covariance matrix predicted by the model: if it is not significant, the model is regarded as acceptable. With small samples, the chi-square statistic lacks power (it may not discriminate between good models and poor fitting models) so some researchers have proposed the relative chi-square (χ^2 divided by the number of degrees of freedom, denoted here by χ^2/df).
2. The root mean square error of approximation (RMSEA) calculates the error of approximation per degree of freedom; values less than 0.03 suggest very good fit. The standardized root mean square residual (SRMR) is based on the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model; it assesses badness-of-fit based on covariance residuals.
3. The goodness-of-fit index (GFI) calculates the proportion of variance that is accounted for by the estimated population covariance; it ranges from 0 to 1 and tends to increase as the number of parameters increases. The adjusted goodness-of-fit index (AGFI) adjusts the GFI to account for degrees of freedom.
4. The normed fit index (NFI) measures the relative fit of a model compared to a baseline model which assumes no covariances between the observed variables; it has a tendency to overestimate fit in small samples. The non-normed fit index (NNFI) is similar to GFI, but it avoids the bias of complex models by considering degrees of freedom.
5. The consistent Akaike information criterion (CAIC) measure the parsimonious fit of a model; lower values are better. Like the chi-square statistic, it measures the extent to which the observed covariance matrix differs from the predicted covariance matrix, but it include a penalty if the model is complex (i.e., if it has many parameters) or if the sample size is small. A saturated model is a unrestricted model.
(Sources: Schermelleh-Engel *et al.*, 2003; Golob, 2003; Kline, 2005).

Table 4 Squared multiple correlations for the SEM model

Model	R^2 SEM[a]	R^2 for ESC[b]
Average link speed model		
Link Speed	0.74	0.67
Loop speed	0.83	0.83
SP bin model		
SP bin 3	0.10	0.05
SP bin 4	0.15	0.09
SP bin 5	0.21	0.20
SP bin 6	0.27	0.23
Loop speed	0.56	0.56

Notes:
a. This R^2 measures variance explained by both endogenous and exogenous variables.
b. This R^2 measures variance explained by exogenous variables only. The difference between 'a' and 'b' is explained by endogenous variables.

Table 4 reports the goodness of fit of our models based on the squared multiple correlation (R^2) coefficients. We see that the average speed model explains 74 percent of the variance in link speed and 83 percent of the variance in loop speed. Using only exogenous variables, the model does not perform quite as well: it explains 67 percent of the variance in link speed and 83 percent of the variance in loop speed. Moreover, 10 to 27 percent of the variance in different SP bins is explained by the SP bin model and the influence of loop speed on different SP bins ranged from 1 percent to 6 percent.

6.1 Average speed Model

Let us now discuss the direct and indirect effects of endogenous and exogenous variables on link speed as shown in Table 5. The direct effect of a variable on an endogenous variable is given by its standardized coefficient. Indirect effects are estimated as a product of direct effects.

Table 5 Decomposition of different effects for the average speed model

Exogenous variable	Effect on Loop Speed	Effects on Link speed		
	Direct effect	Direct Effect[1]	Indirect effect through (Y_2)	Total effect[2]
Peak/off-peak	--	-0.24 (0.09)		-0.24 [8.5%]
Speed limit	0.90 (0.03) *	0.26 (0.03) *	0.333	0.59 [20.9%]
Link length	0.12 (0.03)*	--	0.044	0.04 [1.4%]
No. of lanes	--	0.09 (0.01) *	--	0.09 [3.2%]
Link type	-0.13 (0.02) *	-0.07 (0.02) *	-0.048	-0.12 [4.3%]
Grade	-0.11 (0.14)	-0.19 (0.07)	-0.041	-0.23 [8.2%]
V/C ratio	-0.27 (0.02) *	--	-0.100	-0.10 [3.5%]
Freeway lanes	-0.08 (0.03) *	-0.03 (0.01) *	-0.030	-0.06 [2.1%]
Arterial streets	-0.23 (0.03) *	-0.39 (0.03) *	-0.085	-0.48 [17.0%]
Ramp	--	-0.29 (0.03) *	--	-0.29 [10.3%]
Access density	--	-0.06 (0.02) *	--	-0.06 [2.1%]
Residential	--	0.09 (0.02) *	--	0.09 [3.2%]
Commercial	--	-0.04 (0.02) *	--	-0.04 [1.4%]
Calm	0.17 (0.02) *	0.19 (0.02) *	0.063	0.25 [8.9%]
Aggressive	--	-0.04 (0.02) *	--	-0.04 [1.4%]
On-street parking	--	-0.02 (0.11)		-0.02 [0.7%]
4-way intersection	--	-0.06 (0.09)		-0.06 [2.1%]
Weaving/merging	--	-0.02 (0.01) *	--	-0.02 [0.7%]

Notes.

1. Values in parentheses indicate standard errors.

2. Values in brackets represent the percentage effect of each ESC variable on link speed. It is calculated based on the absolute value of each variable.

*: values are significant at the 0.05 level.

The total effect is the sum of all direct and indirect effects of one variable on another. For example, according to our model, being an aggressive driver reduces speed by 0.04 mph.

A study by Fitzpatrick *et al.* (2001) reported that speed limit is the single most influential factor among traffic characteristics. Our findings confirm this result: speed limit is one of the most important variables for predicting link and loop speeds ($\gamma_{1,2}$=0.59). Although most drivers may drive at the speed they perceive to be safe rather than at the posted speed limit, the posted limit in practice indirectly reflects the geometric characteristics of a corridor. This observation is corroborated by Garber and Gadiraju (1989) who found that drivers increased speed based on geometric characteristics regardless of the posted speed limit. Moreover, in their study of the effects of changing posted speed limits on driver behavior, Parker and Associates (1997) report that drivers respond to posted speed limits although their adjustments tend to be small. The total effect of speed limit on link speed is approximately 21 percent. Link length has an indirect effect on link speed: speed tends to be higher on longer links as drivers encounter less interference.

An increase in the number of lanes increases both loop speed and link speed ($\gamma_{1,4}$= 0.09); it may also influence driving patterns. Moreover, the number of lanes influences link capacity, as expected.

Link type has a negative association with both loop speed and link speed ($\gamma_{1,5}$= -0.12), so if a link is curved, it has lower loop and link speeds compared to straight sections (the latter is reduced by 0.12 mph.) Generally, drivers tend to slow down slightly in curved sections due to reduced visibility. McLean (1989) also found that curvature reduces speed.

As expected, link grade has a negative impact on both loop and link speeds, as steeper grades make engines work harder ($\gamma_{1,6}$= -0.23).

The V/C ratio has a negative sign for the loop speed model and indirect effects on link speed ($\gamma_{1,7}$= -0.100). A higher V/C ratio reduces speed because of more frequent stop-and-go conditions. Indeed, research in Europe found that in higher density conditions, speed varied from 10 to 16 km/h and stop frequencies averaged three to four stops per km (André and Hammarstrom, 2000). The V/C ratio has a 3.5 percent total effect on link speed.

Facility type (HOV lanes, freeway lanes, ramps, and arterials) is significant for both loop and link speeds. Arterial streets have a significant influence on both loop speed and link speed ($\gamma_{1,9}$ = -0.48), possibly because of fixed and variable delays. This confirms Rosqvist's (1998) result that residential street design has a strong influence on fuel consumption and emissions. The negative correlation of freeway lanes with link and loop speeds may be due to congestion ($\gamma_{1,8}$= -0.06). It has a smaller effect for the average speed mode than other facility types since there are no fixed delays on freeways.

We also see that access density has a negative influence on link speed ($\gamma_{1,11}$=-0.06). This is not surprising since a higher access density reduces speed mainly due to increased interactions with vehicles from driveways and intersections; it confirms results from Tignor and Warren (1990) and Fitzpatrick *et al.* (2005). By contrast, the presence of on-street parking was not found to be significant. This might be due to insufficient variations in our data set.

Among land-use variables both residential and commercial land-use are significant. This result is in agreement with Wang *et al.* (2006), who found that drivers tend to drive faster on low volume residential streets than on higher volume commercial streets. Residential land use has a positive influence ($\gamma_{1,12}$= 0.09) on link speed, unlike commercial land use ($\gamma_{1,13}$= -0.04), mainly due to interference from pedestrians, median areas, and parking.

Driver behavior is also significant but the influence of calm driving is more substantial. Interestingly, aggressive driving reduces overall speed ($\gamma_{1,15}$= -0.04). In our study, some aggressive driving took place at intersections. Weaving/merging also has a negative sign ($\gamma_{1,18}$ = -0.02). It does not have any statistically significant effect on loop speed, but it has a direct effect on link speed, which is mainly caused by lane changing behavior.

6.2 SP Bin Model

Our second model tries to capture the fraction of time spent in different SP bins. Results are summarized in Table 6.

Link length is positively correlated with all four bins. This factor didn't have any direct effect on link speed in the average speed model. The influence of link length was statistically significant in bins 5 and 6 but not in bins 3 and 4. Standardized estimates indicate that vehicles spend less time in bin 3 and more time in bin 6 as vehicles travel faster on longer links.

Likewise, the number of lanes is positively correlated with all bins. The total effect of the number of lanes on bins 5 and 6 is 0.248 ($\gamma_{3,2}$) and 0.334 ($\gamma_{4,2}$) respectively. This indicates that a higher number of lanes increases the fraction of time spent in bins 5 and 6.

Table 6 Decomposition of different effects for the micro-scale (SP bins) path model

Exogenous Variables	Effect on loop speed	Effect on SP bin 3 (12 kw/ton≤SP<18 kw/ton)			Effect on SP bin 4 (18 kw/ton≤SP<24 kw/ton)			Effect on SP bin 5 (24 kw/ton≤SP<30 kw/ton)			Effect on SP bin 6 (30 kw/ton≤SP)		
	Direct Effects	Direct Effects[1]	Indirect Effects	Total Effects[2]	Direct Effects[1]	Indirect Effects	Total Effects[2]	Direct Effects[1]	Indirect Effects	Total Effects[2]	Direct Effects[1]	Indirect Effects	Total Effects[2]
Link length	-0.100 (0.02)*	--	0.040	0.035 [1.5%]	--	0.036	0.036 [2.0%]	0.160 (0.03)*	0.010	0.170 [9.4%]	0.170 (0.03)*	0.030	0.200 [7.2%]
No. of Lanes	-0.280 (0.05)*	--	0.1	0.098 [4.2%]	--	0.101	0.101 [5.7%]	0.220 (0.04)*	0.028	0.248 [13.7%]	0.25 (0.04)*	0.084	0.334 [12.1%]
Speed limit	0.570 (0.05)*	-0.230 (0.04)*	-0.20	-0.43 [18.5%]	-0.150 (0.03)*	-0.205	-0.355 [20.1%]	-0.140 (0.03)*	-0.057	-0.197 [10.9%]	0.27 ((0.05)*	-0.171	0.099 [3.6%]
Link type	-0.090 (0.08)	--	0.031	0.031 [1.3%]	--	0.032	0.032 [1.8%]	--	0.009	0.009 [0.5%]	--	0.027	0.027 [1.0%]
Grade	-0.040 (0.06)	0.001 (0.08)	0.014	0.015 [0.6%]	0.003 (0.11)	0.014	0.017 [0.8%]	0.000 (0.09)	0.004	0.004 [0.2%]	0.000 (0.08)	0.012	0.012 [0.4%]
V/C ratio	-0.180 (0.03)*	0.003 (0.06)	0.06	0.063 [2.7%]	0.190 (0.03)*	0.065	0.255 [14.4%]	0.290 (0.03)*	0.018	0.308 [17.1%]	0.34 (0.05)*	0.054	0.394 [14.3%]
Freeway	-0.010 (0.06)	-0.320 (0.05)*	0.004	-0.316 [13.6%]	-0.100 (0.03)*	0.004	-0.096 [5.4%]	0.150 (0.03)*	0.001	0.151 [8.4%]	0.500 (0.04)*	0.003	0.503 [18.2%]
Ramp	-0.350 (0.05)*	-0.280 (0.04)*	0.123	-0.158 [6.8%]	0.031 (0.08)	0.126	0.157 [8.9%]	0.170 (0.03)*	0.035	0.205 [11.4%]	0.200 (0.05)*	0.105	0.305 [11.0%]
Arterial street	-0.650 (0.05)*	0.320 (0.04)*	0.23	0.55 [23.7%]	0.021 (0.06)	0.255	0.255 [14.4%]	-0.248 (0.06)	0.065	-0.183 [10.1%]	-0.520 (0.05)*	0.195	-0.325 [11.8%]
On-street parking	--	0.003 (0.09)	--	0.003 [0.1%]	0.009 (0.10)	--	0.009 [0.5%]	-0.016 (0.08)	--	-0.016 [0.9%]	-0.054 (0.12)	--	-0.054 [2.0%]
Access density	--	0.200 (0.03)*	--	0.200 [8.6%]	0.110 (0.03)*	--	0.110 [6.2%]	-0.030 (0.01)*	--	-0.030 [1.7%]	-0.020 (0.01)*	--	-0.020 [0.7%]
Mixed	--	-0.080 (0.02)*	--	-0.080 [3.4%]	-0.080 (0.02)*	--	-0.080 [4.5%]	-0.180 (0.03)*	--	-0.18 [10.0%]	-0.230 (0.03)*	--	-0.230 [8.3%]
Commercial	--	0.080 (0.02)*		0.080 [3.4%]	0.060 (0.02)	--	0.060 [3.4%]	0.020 (0.06)	0.005	0.025 [1.4%]	-0.040 (0.02)	--	-0.004 [0.1%]
Calm	-0.080 (0.03)*	0.080 (0.02)*	0.03	0.130 [5.6%]	0.050 (0.02)*	0.029	0.079 [4.5%]	--	0.008	0.008 [0.4%]	-0.120 (0.02)*	0.024	-0.096 [3.5%]
Aggressive	--	--	--	--	--	--	--	-0.030 (0.01)*	--	-0.030 [1.7%]	-0.140 (0.03)*	--	-0.140 [5.1%]
4-way intersections	--	0.021 (0.06)	--	0.021 [0.9%]	0.016 (0.08)	--	0.016 [0.9%]	-0.009 (0.10)	--	-0.009 [0.5%]	0.014 (0.12)	--	-0.014 [0.5%]
Weaving /Merging	-0.320 (0.05)*	--	0.112	0.112 [4.8%]	--	0.115	0.115 [6.5%]	--	0.032	0.032 [1.8%]	-0.09 (0.02)	0.096	0.006 [0.2%]
Peak/off-peak	--	0.003 (0..09)	--	0.003 [0.1%]	0.005 (0.11)	--	0.005 [0.3%]	-0.004 (0.07)	--	-0.004 [0.2%]	-0.007 (0.08)	--	-0.007 [0.3%]

Notes.

1. For direct effects, values in parentheses indicate standard errors.

2. For total effects, values in brackets represent the percentage effect of each ESC variable on different SP bin. It is calculated based on the absolute value of each variable. The total effect is the sum of all direct and indirect effects of one variable on another.

* indicates significance at the 0.05 level.

The speed limit has a negative influence on all bins except bin 6; this means that a higher speed limit allows vehicles to spend less time in lower bins, especially in bin 3. Link type and grade influence different bins through loop speed. The total effect column shows that vehicles spend a higher fraction of time in lower bins when grade is present.

As expected, the V/C ratio has a positive influence on all bins: when the V/C ratio increases, vehicles spend more time in lower bins due to vehicle-to-vehicle interactions. This typically corresponds to peak hour traffic conditions. Table 6 shows that the influence of the V/C ratio ranges from 2.7 to 17.1 percent.

Interestingly, different facility types have a different influence on SP bins. On freeways and ramps, vehicles spend less time in lower bins (5.4 to 13.6 percent) and more in higher bins (8.4 to 18.2 percent); the reverse is true for arterial streets because vehicles are affected by fixed delays (traffic lights, stop sign). Likewise, a higher access density increases the time spent in lower bins and decreases time spent in higher bins, again because traffic from different intersections reduces the average speed in a link.

Among land use variables, both mixed and commercial land uses are statistically significant. Mixed land use (schools and commercial activities) has a negative sign for all bins, which may be due to interactions between vehicles and pedestrian traffic. Commercial land use has a positive sign for lower bins and negative for higher bins, as vehicles move more slowly because of traffic entering and leaving parking lots at shopping centers. This indicates that stop-and-go conditions are more prevalent in commercial land-use.

Results for driver characteristics show that variables for “calm” and “aggressive” drivers were both statistically significant. As expected, a calm driving style leads to spending more time in lower bins and less in higher bins.

Finally, section type has a negative sign because a section with weaving or merging is conducive to a lower speed than a straight section as discussed above. The total effects of weaving/merging are felt more in lower bins than in higher bins (Table 6). Link type, on-street parking, 4-way intersections, peak/off-peak are not statistically significant.

6.3 Model Validation

To validate our model, average link speed was predicted using the proposed model on different links. Figure 5 depicts predicted average speed, loop speed, and observed speed (micro-simulation); it shows that the average speed model over-predicts speed compared to the observed speed. This might be due to missing ESC variables such as trip conditions and vehicle characteristics that were not considered in this analysis. Nevertheless, the average speed model has the capability of capturing traffic variations using loop detector data. It could also use travel forecasting data in the absence of loop detector data; however, whether this will capture traffic variations accurately needs to be tested.

The mean absolute percentage error (MAPE) was estimated for a freeway link to further understand the accuracy of the proposed average speed model (see Figure 6). The MAPE for the one-hour peak period was 7.1 percent for the average speed model and 14.7 percent for the loop speed. This indicates that the average speed model predicts link speed better than loop speed.

The fractions of time spent in different bins were estimated using second-by-second data for a freeway link and for an arterial link to validate the SP bin model. Vehicle operation was estimated for the same links using the proposed SP bin model at 30-second intervals and they were compared against the baseline. We found that more time was spent in higher bins on freeways, whereas more time was spent in lower bins on arterial streets, again probably because of fixed delays or stop-and-go traffic conditions on arterial streets. However, our SP bin model does not capture the fraction of time spent in different bins very accurately. This might again be due to omitted ESC factors.

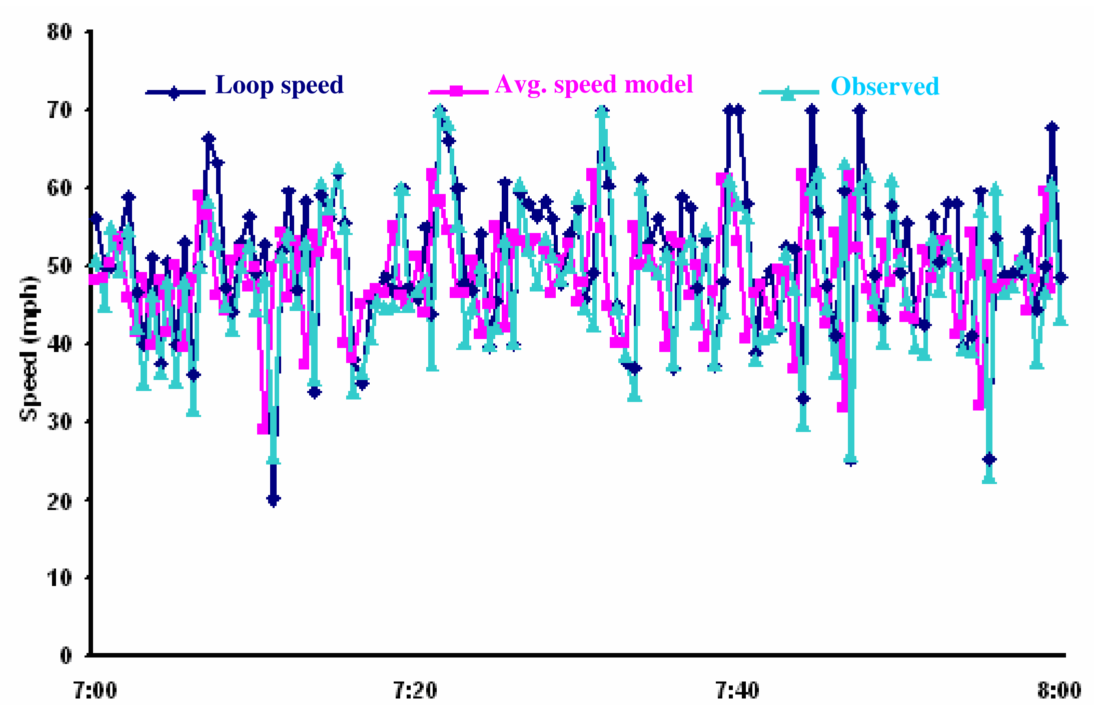
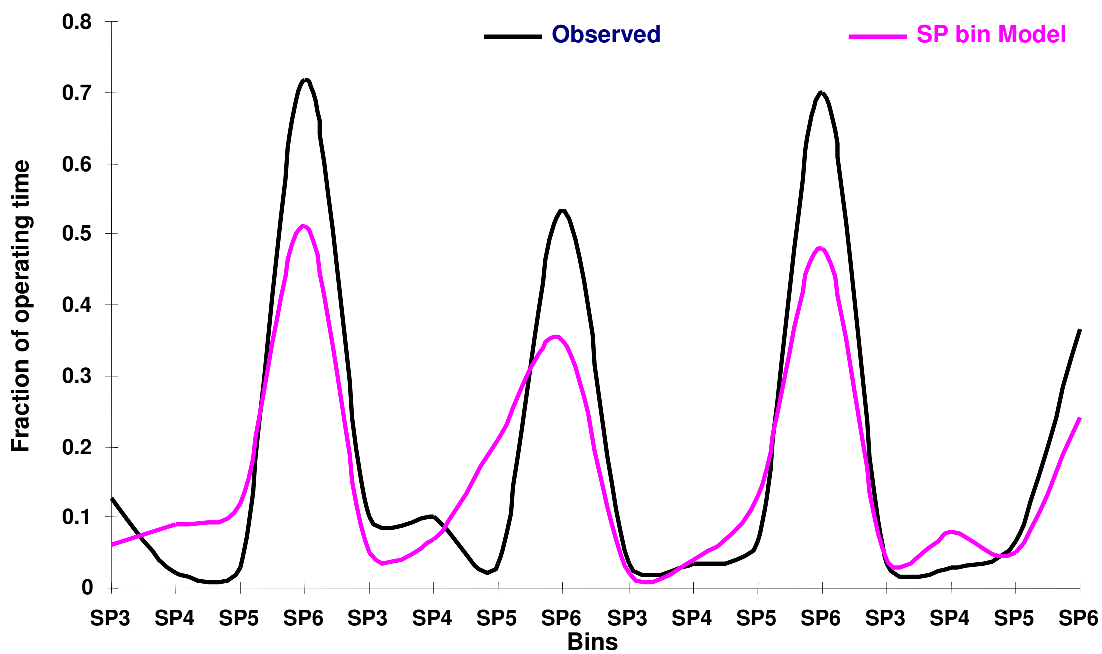
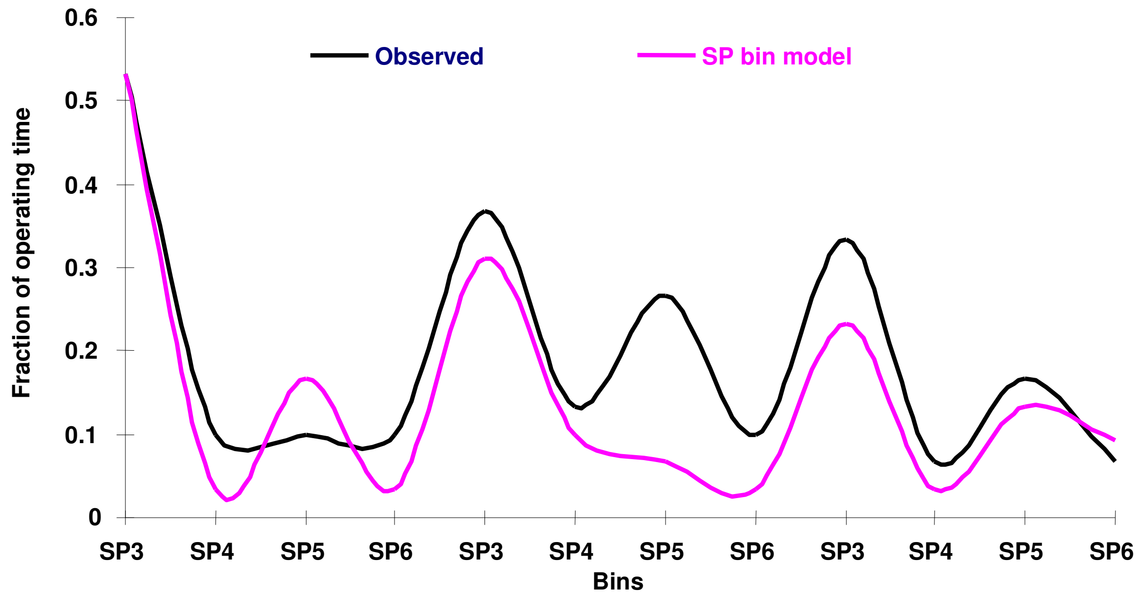


Figure 5 Mean absolute percentage error for loop speed and average speed model



(a) Freeway link



(b) Arterial link

Figure 6 Distribution of operating time predicted by SP bin model

7. Conclusions

The main goal of this paper was to explain link level vehicle operation data generated via microsimulation using readily observable emission specific characteristics (ESC) in a structural equation framework. Our microsimulation model was calibrated and validated to obtain reliable second-by-second vehicle trajectories; it enabled us to generate a large dataset, with high quality data and substantial variation in our ESC explanatory variables. At the aggregate level, we found that geometric design elements exert a greater influence on vehicle operation than traffic characteristics, the roadside environment, and driving style. Speed limit has the strongest influence on vehicle operation, probably because of the strong correlation between speed limit and geometric design. Facility type is the next highest impacting factor on vehicle operation: speed on arterial streets is significantly impacted by stop-and-go traffic caused by traffic lights and traffic-calming measures; and ramps may increases the temptation to drive aggressively since they connect a freeway to an arterial street over a short distance. Driving style is the third most significant variable influencing vehicle operation.

Although our approach allows us to tease out the relative importance of various factors on vehicle operation, it has a number of limitations. First, we relied on micro-simulation and not on real-world data, primarily because we could not find a network with enough loop detectors on arterial streets. We are aware that micro-simulation models may not accurately reflect acceleration or deceleration compared to actual on-road vehicle activities. However, micro-simulation allows us to easily generate data with enough variability in our potential explanatory variables. We also note that our micro-simulation model was calibrated, which reinforces the validity of our results. Another limitation is that our data are from a relatively small network in Southern California, which may not be representative of other parts of the country, where geometric characteristics may differ. For example, Northern California HOV lanes are not buffered but they are buffered in Southern California.

Future research could use real-world data to assess to the validity of our results. Furthermore, it could incorporate other ESC variables such as weather characteristics, road surface characteristics, vertical gradients, radius of curvature, trip characteristics and incidents. Another promising avenue would be to analyze the impact on vehicle operation of different vehicle type mixes, especially those that include heavy-duty trucks.

With formal calls, such as in California's SB375, for improvements in modeling practice, the need to better understand the relationships between traffic operations and vehicle emissions has never been greater. This paper represents one step in that direction.

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