

IMPUTATION OF RAMP FLOW DATA FOR FREEWAY TRAFFIC SIMULATION

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ABSTRACT

The Tools for Operations Planning (TOPL) employs the Link-Node Cell Transmission model for macroscopic freeway traffic simulations used for specifying operational strategies like ramp metering, demand and incident management. Traffic flow and occupancy data from loop detectors is used for calibrating these models and specifying the inputs to the simulation. However, flow data from ramps are often to be found missing or incorrect. This paper elaborates an imputation procedure used to determine these ramp flows. This automated imputation procedure is based on an adaptive identification technique that tries to minimize the error between the simulated and the measured densities. The simulation results using the imputed flow data indicate good conformation with loop detector measurements.

Keywords: Link Node Cell transmission model, Imputation, Traffic flow simulation.

1. INTRODUCTION

Tools for operational planning (TOPL) is a suite of tools used for (1) specifying operational improvements - ramp metering, incident management, traveler information and demand management and (2) quickly estimating the benefits such improvements are likely to provide. This is an essential component of the California Department of Transportation (Caltrans) “corridor management program” – which was introduced to reduce the congestion in 2025 by 40 percent [1].

Traditionally, transportation planning investigations favor use of microscopic models. The microscopic simulations involve extensive data collection and model calibration efforts, which are significantly time-consuming [2]. In comparison, the macroscopic models like the CTM model are based on aggregate variables such as volume (flow) and density. These data are available for California Freeways from vehicle detector stations (vds), which contain loop detectors. PeMS [3] routinely archives the flow, occupancy and speed data from these vds. Therefore, TOPL is based on the macroscopic Link-Node Cell Transmission Model (LN-CTM) [4]. In general, the CTM requires the flow and density measurements from the mainline vds (positioned along the freeway) for calibration of the fundamental diagrams [5]. The on-ramp flows and off-ramp split ratios also need to be specified as an input for the simulations. However, the data from the ramps are often found to be missing or incorrect. Hence, it becomes essential to impute the on-ramp and off-ramp flows to completely specify the simulation model.

Imputation of missing data in loop detectors has been investigated using various techniques like time series analysis [6] and Kalman filters [7]. These methods are useful for prediction of random errors, but in most cases, data is missing/ erroneous for extended periods of time (hours/days). Recently, Chen et.al [8] have used a linear regression based imputation procedures to successfully predict missing data in freeway mainline loop detector stations. This method cannot be applied to impute missing data in on-ramp or off-ramp vehicle detector stations, since we cannot guarantee a high correlation of data between neighboring ramp loop detector stations. Hence, model based imputation procedures are required to determine missing ramp flow data. Once the dynamic model of freeway traffic is specified, the unknown quantities can be estimated using adaptive identification techniques which have been used in Iterative learning control [9,10]. Repetitive identification algorithms can be used off-line to determine the flow profiles which minimize the error between the model calculated densities and the mainline loop detector measurements.

This paper illustrates an imputation procedure for determining ramp flows using the Link Node CTM. Section 2 reviews the LN-CTM used for traffic flow simulations. It also states a simple four-state switching approximation of the model for freeway-corridor simulations. Section 3 explains the imputation procedure used for determining on-ramp and off-ramp flows. Finally, section 4 illustrates an example where the imputation procedure is used to specify the on-ramp flows and off-ramp split ratios for a 26-mile long I-210E freeway in the Los Angeles area.

2. LINK NODE CELL TRANSMISSION MODEL

The Link-Node Cell transmission model (LN-CTM) is used to simulate traffic flows in traffic networks. Aurora, a simulation tool in TOPL, is based on this CTM implementation [11]. Other implementations of the CTM include the Asymmetric Cell Transmission Model (ACTM) used particularly for freeway traffic simulation [12]. The Link-Node Cell transmission model is preferred for simulation, since it has the capability to simulate traffic networks which include freeways and arterial networks, as compared to the ACTM, which has been primarily used for freeway simulations. As a result, the Link-Node CTM model has been used for imputation of on-ramp and off-ramp flows in this paper.

In the LN-CTM model, the freeway (or any traffic network) is specified by a graph of links. Links represent road segments, which carry traffic. Nodes are formed at the junction of Links, where traffic flow exchange takes place. The flow exchange is indicated by a time varying split-ratio matrix, which specifies the portion of traffic moving from a particular input link to an output link. While a normal link connects two Nodes, a “source” link is used to introduce traffic into the network whereas a “sink” is used to accept traffic moving out of the network. A source link implements a queue model.

Figure 1. shows the freeway specified in the Link-Node framework. Each Node contains a maximum of one on- and one off-ramp. The boundaries of the freeway are assumed to be in freeflow. Vehicles enter through a “source” attached to the upstream cell. The on-ramps are also represented as source links, while the off-ramps are represented as sinks. It is also assumed that the off-ramps are in freeflow, i.e., the flow to the off-ramps are not restricted by their flow capacity or space restrictions. Table 1. lists the model variables and parameters. Additional parameters \bar{w}_i and \bar{v}_i are defined as

$$\bar{w}_i = \min\left(w_i, \frac{F_i}{(n_i^J - n_i(k))}\right)$$

$$\bar{v}_i = \min\left(v_i, \frac{F_i}{n_i(k)}\right)$$

The LN-CTM model can be simplified for simulation of freeway traffic networks. While the general algorithm implements separate Link and Node updates at each simulation step (as shown in [11]), the algorithm can be simplified to a four mode switching model for each link for freeway simulations. The density update equations belong to the following four modes - FF, CF, CC, and FC, for each link. Here F denotes freeflow while C denotes

Congestion. These modes are selected based on the flow conditions that exist at the input node and output node of the link. Let Node i connect Link i and Link $i+1$ (Figure 1). The input demand to Link i (from Link $i-1$ and the on-ramp) is given by $c_{i-1}(k) = n_{i-1}(k)\bar{v}_{i-1}(k)(1 - \beta_{i-1}(k)) + d_{i-1}(k)$ while the available capacity at Link i is given by $\bar{w}_i(n_i^J - n_i(k))$. Link i is in congestion (alternatively, the flow in node $i-1$ corresponds to congested conditions) if input demand exceeds the output capacity i.e. $c_{i-1}(k) > \bar{w}_i(n_i^J - n_i(k))$. In this case, the flow entering into Link i is equal the output capacity, while the output flow in Link $i-1$ equals $\left(\frac{\bar{w}_i(n_i^J - n_i(k))}{c_{i-1}(k)}\right)n_{i-1}(k)\bar{v}_{i-1}(k)$. When

Link i is in freeflow, the flow entering Link i is given by $c_{i-1}(k)$ since the input demand into Link i can be accommodated. In this case the output flow in Link $i-1$ equals $n_{i-1}(k)\bar{v}_{i-1}(k)$. Since the density update equations for Link i depend on the inflow and outflow, the update equations can be specified using the four mode switching model, depending on whether the inflows and outflows are in congestion/freeflow. Hence, Link i is updated using the CF mode equations, if Link i is in congestion (i.e the inflow into Link i corresponds to flow restricted by congestion) and Link $i+1$ is in freeflow (i.e the flow out of Link i corresponds to flow unrestricted by capacity in Link $i+1$), and other modes can be interpreted similarly.

The density update equations can be written in closed form for the four modes as,

(a) FF Mode

$$n_i(k+1) = n_i(k) + c_{i-1}(k) - n_i(k)\bar{v}_i(k)$$

(b) FC Mode

$$n_i(k+1) = n_i(k) + c_{i-1}(k) - \left(\frac{\bar{w}_{i+1}(n_{i+1}^J - n_{i+1}(k))}{c_i(k)}\right)n_i(k)\bar{v}_i(k)$$

(c) CC Mode

$$n_i(k+1) = n_i(k) + \bar{w}_i(n_i^J - n_i(k)) - \left(\frac{\bar{w}_{i+1}(n_{i+1}^J - n_{i+1}(k))}{c_i(k)}\right)n_i(k)\bar{v}_i(k)$$

(d) CF Mode

$$n_i(k+1) = n_i(k) + \bar{w}_i(n_i^J - n_i(k)) - n_i(k)\bar{v}_i(k)$$

The mainline flows can be determined by

$$f_i^{in}(k) = \min(c_{i-1}(k), \bar{w}_i(n_i^J - n_i(k)))$$

$$f_i^{out}(k) = \left(\frac{\min(\bar{w}_{i+1}(n_{i+1}^J - n_{i+1}(k)), c_i(k))}{c_i(k)} \right) n_i(k) \bar{v}_i(k)$$

while the off-ramp flows are determined by

$$s_i(k) = \beta_i(k) f_i^{out}(k)$$

The on-ramp flows and demands are given by

$$r_i(k) = \left(\frac{\min(\bar{w}_{i+1}(n_{i+1}^J - n_{i+1}(k)), c_i(k))}{c_i(k)} \right) d_i(k)$$

$$d_i(k+1) = d_i(k) + fl_i^{in}(k) - r_i(k)$$

where $fl_i^{in}(k)$ is the input flow for the on-ramp i .

2. IMPUTATION OF RAMP FLOWS

The LN-CTM model is utilized to impute the missing on-ramp input flows as well as the off-ramp split ratios for one day (24-hour) traffic flow simulation on a large freeway (eg. 40 miles) segment. The imputation procedure involves two stages - First, the total demands $c_i(k)$ are determined and then the demands and split-ratios are extracted from the total demand.

The imputation procedure employs an adaptive iterative learning procedure described in [9,10]. It is assumed that the density and ramp flow profiles are 24 hour periodic (i.e. the initial and final densities are assumed to be equal). This is not a restrictive assumption, since the freeway is found to be in free-flow (with low densities) around midnight. The LN-CTM algorithm is run multiple times, and at each run, the algorithm adapts the unknown demand estimates to minimize the error between the density generated by the model at each link and the data from the corresponding PeMS measurement. The procedure is repeated until the density error reduces to a sufficiently small value or stops decreasing.

As detailed in [9], because of the 24 hour periodicity, the demand vector can be represented as a convolution of a kernel on a constant influence vector

$$c_i(k) = K(k)^T C_i$$

where $K(k)$ represent a 24 hour periodic time dependent kernel vector, and C_i is the influence vector. The influence vector has the same dimensions as $c_i(k)$. Some typical kernel functions ($K(k)$) include a unit-impulse or a Gaussian window centered at time k . The imputation procedure estimates the influence vectors instead of the estimating c_i .

The imputation procedure assumes initial estimates for the influence vectors \hat{C}_i . These estimates are then dynamically adapted at each time step, so that the model calculated densities, for all whole freeway, match with the density profiles obtained from PeMS. At each time step, the mode for each cell is determined, and the corresponding learning update equations are used to adapt the influence vectors. Let $n_i(k)$, $\hat{n}_i(k)$ denote the actual density measurements and the model calculated densities and $\tilde{n}_i(k) = n_i(k) - \hat{n}_i(k)$ denote the density error. Then the learning updates are specified by the following equations

(a) FF Mode

$$\tilde{n}_i^o(k+1) = n_i(k+1) - \left(\hat{n}_i(k) + K(k)^T \hat{C}_{i-1}(k) - \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k) \right)$$

$$\tilde{n}_i(k+1) = \frac{\tilde{n}_i^o(k+1)}{1 + GK(k)^T K(k)}$$

$$\hat{C}_{i-1}(k+1) = \hat{C}_{i-1}(k) + GK(k) \tilde{n}_i(k+1)$$

$$\hat{n}_i(k+1) = \hat{n}_i(k) + K(k)^T \hat{C}_{i-1}(k+1) - \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k)$$

(b) FC Mode

$$\tilde{n}_i^o(k+1) = n_i(k+1) - \left(\hat{n}_i(k) + K(k)^T \hat{C}_{i-1}(k) - \left(\frac{\hat{w}_{i+1} (n_{i+1}^J - \hat{n}_{i+1}(k))}{K(k)^T \hat{C}_i(k)} \right) \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k) \right)$$

$$\tilde{n}_i(k+1) = \frac{\tilde{n}_i^o(k+1)}{1 + (G + G')K(k)^T K(k)}$$

$$\hat{C}_{i-1}(k+1) = \hat{C}_{i-1}(k) + GK(k) \tilde{n}_i(k+1)$$

$$\hat{C}_i(k+1) = \hat{C}_i(k) - \frac{K(k)}{K(k)^T K(k)} \left(K(k)^T \hat{C}_i(k) - \frac{1}{1/K(k)^T \hat{C}_i(k) - GK(k)^T K(k) \tilde{n}_i(k+1)} \right)$$

$$\hat{n}_i(k+1) = \hat{n}_i(k) + K(k)^T \hat{C}_{i-1}(k+1) - \left(\frac{\hat{w}_{i+1} (n_{i+1}^J - \hat{n}_{i+1}(k))}{K(k)^T \hat{C}_i(k+1)} \right) \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k)$$

(c) CC Mode

$$\begin{aligned} \tilde{n}_i^o(k+1) &= n_i(k+1) - \left(\hat{n}_i(k) + \hat{w}_i(n_i^J - \hat{n}_i(k)) - \left(\frac{\hat{w}_{i+1}(n_{i+1}^J - \hat{n}_{i+1}(k))}{K(k)^T \hat{C}_i(k)} \right) \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k) \right) \\ \tilde{n}_i(k+1) &= \frac{\tilde{n}_i^o(k+1)}{1 + G' K(k)^T K(k)} \\ \hat{C}_i(k+1) &= \hat{C}_i(k) - \frac{K(k)}{K(k)^T K(k)} \left(K(k)^T \hat{C}_i(k) - \frac{1}{1/K(k)^T \hat{C}_i(k) - G' K(k)^T K(k) \tilde{n}_i(k+1)} \right) \\ \hat{n}_i(k+1) &= \hat{n}_i(k) + \hat{w}_i(n_i^J - \hat{n}_i(k)) - \left(\frac{\hat{w}_{i+1}(n_{i+1}^J - \hat{n}_{i+1}(k))}{K(k)^T \hat{C}_i(k+1)} \right) \hat{n}_i(k) \hat{v}_i(k) - a \tilde{n}_i(k) \end{aligned}$$

(d) CF Mode

$$\hat{n}_i(k+1) = \hat{n}_i(k) + \hat{w}_i(n_i^J - \hat{n}_i(k)) - \hat{n}_i(k) \hat{v}_i(k)$$

G and G' are positive gains. The parameter a is chosen so that the error equation is asymptotically stable. In the update equations for each mode, the first equation calculates the a-priori density error at the next time step ($k+1$), while the second equation calculates the a-posteriori error from the a-priori error. Following equations reflect the parameter updates, which are effected using the a-posteriori error. Note that these updates are vector updates, i.e, the whole influence vector (all its entries) is updated and the vector $K(k)$ specifies the weighting function with which different entries are updated. The final equation uses the new parameters to calculate the model estimates of densities at the next iterations.

The adaptation procedure is carried out through the entire density profile multiple times, so as to reduce the 'error' $\sum |\tilde{n}_i(k)|$. Since the densities are represented as number of cars in a segment, the error takes into account the difference in link lengths. Since the CF mode does not involve adaptation equations, the error may converge to a non-zero value in regions where this mode is in effect, while other modes show negligible error. This occurs due to incorrect mode identification at that time instant. In this case, the corresponding estimates are "triggered" automatically so that the correct modes are identified. After the trigger, the adaptation procedure is continued, till the error becomes negligible or stops decreasing.

Thus the first part of the imputation procedure can be summarized in the following scheme

1. Initialize \hat{C}_i for all Links.
2. Do until Total error < Threshold or the Total error stops decreasing
 - For k from 1 to k_{end}
 - For all links
 - Determine the mode of the link using the a-priori estimates.
 - Use the appropriate mode update equations to calculate the new updated parameters, and use these parameters to calculate the model calculated densities at time $k+1$.

Here k_{end} denotes the period index corresponding to the last element. After the above procedure stops, we must search for wrong mode identifications and trigger the parameter values around this particular time instant and rerun all the above steps (except the initialization). Wrong mode identifications are identified by searching for large density estimate errors errors in time instants where the CF mode has been identified at a particular link. Typical stopping criteria for total error $\sum_1^{k_{end}} |\tilde{n}_i(k)|$ can be expressed as a percentage of total number of cars $\sum_1^{k_{end}} n_i(k)$. However, it was found that more often, the iterations were stopped as the error stopped decreasing. This is because of the slight errors that usually exist in the data.

After determining the Total demand vector, the on-ramp demand and off-ramp split ratios are decoupled using a linear program. Figure 2 illustrates the position of the mainline detector, from which flow data is available. Depending on the congestion state of the node, the following LP's are solved

(a) Node in Freeflow

$$\begin{aligned}
 & \min \left| \left(f_{i+1}^{in}(k) - f_{i+1}^{meas}(k) \right) - r_{i+1}(k) \right| + \left| \left(f_{i+1}^{out}(k) - f_{i+1}^{meas}(k) \right) - s_{i+1}(k) \right| \\
 & \text{s.t} \quad \hat{c}_i(k) = \hat{n}_i(k) \hat{v}_i(k) - s_{i+1}(k) + r_{i+1}(k) \\
 & \quad \quad s_{i+1}(k), r_{i+1}(k) \geq 0
 \end{aligned}$$

In this case, $\beta_{i+1}(k) = \frac{s_{i+1}(k)}{\hat{n}_i(k) \hat{v}_i(k)}$ and $d_{i+1}(k) = r_{i+1}(k)$.

(b) Node in Congestion

$$\begin{aligned}
& \min \left| \left(f_{i+1}^{in}(k) - f_{i+1}^{meas}(k) \right) - r_{i+1}(k) \right| + \left| \left(f_{i+1}^{out}(k) - f_{i+1}^{meas}(k) \right) - s_{i+1}(k) \right| \\
& \text{s.t.} \quad \hat{c}_i(k) = \hat{n}_i(k) \hat{v}_i(k) - fr_{i+1}(k) + d_{i+1}(k) \\
& \quad \quad s_{i+1}(k) = \left(\frac{\hat{w}_{i+1} \left(n_{i+1}^J - \hat{n}_{i+1}(k) \right)}{\hat{c}_i(k)} \right) fr_{i+1}(k) \\
& \quad \quad r_{i+1}(k) = \left(\frac{\hat{w}_{i+1} \left(n_{i+1}^J - \hat{n}_{i+1}(k) \right)}{\hat{c}_i(k)} \right) d_{i+1}(k) \\
& \quad \quad s_{i+1}(k), r_{i+1}(k), fr_{i+1}(k), d_{i+1}(k) \geq 0
\end{aligned}$$

$$\text{where } \beta_{i+1}(k) = \frac{fr_{i+1}(k)}{\hat{n}_i(k) \hat{v}_i(k)}.$$

The above LP's are solved for every time instant. After the values are obtained, on-ramp input flow can be decoupled from the on-ramp demands using the equations given in Section 2.

4. APPLICATION

This section illustrates the application of the imputation algorithm to determine the on-ramp and off-ramp flow measurements in a 26-mile long section of I-210 E freeway in Pasadena. In this case, the freeway was divided into 26 links. Out of a total of 30 on-ramps and 21 off-ramps, 7 on-ramps and 5 off-ramps had missing data for the whole day. In addition 2 on-ramps were identified to have incorrect data. Presently incorrect ramp detector data is identified with ad hoc rules - like flow conservation along the node connecting the ramp detector stations/flow conservation along the mainline (for the measured data). The imputation procedure was carried out for these ramps. The fundamental diagram parameters for the links were obtained from an automated calibration procedure described in [5]. The final density error in the imputation was reduced to 2.63%. Figure 3 shows that the density estimates have converged to their true values without appreciable error.

A simulation was performed with the imputed data. For this purpose, calibrated fundamental diagram parameters and on-ramp flows and off-ramp split ratios were specified for the freeway model. The simulation was performed using the Matlab implementation of the general LN-CTM model used in Aurora [11]. The simulation computes the flow, density and velocity profiles at each link for the given inputs. Figure 4 shows the simulated and the measured velocity contours and Figure 5 shows flow

contours, both of which show good agreement. The simulated contour plots clearly reproduce the locations of the major bottlenecks. The simulated and measured performance measures are compared in Figure 6, which also show good agreement. The simulated data had 2.63% and 3.58% density and flow errors respectively. The flow error has been represented as a percentage of the total flow observed in the freeway. Finally, Figure 7 lists the performance of the simulation as compared to the specifications provided in [13]. The simulation satisfies most of the requirements, while narrowly missing some of the criteria.

5. CONCLUSION

In California, while data is archived for mainline detectors routinely, ramp detector data is often found to be entirely missing. Only few freeways provide reliable on-ramp flows, and even these report at least a few ramps with missing data. Since these ramp data form necessary inputs for freeway simulations, it is imperative to reliably estimate the ramp flows. This paper has elaborated a novel imputation technique to determine missing ramp flow data. The imputation procedure is based on adaptive identification of missing ramp flow data using the Link Node Cell Transmission model. The LN CTM reduces to a four mode model for the links of a freeway, and parameter update equations were designed for each of the four modes. The imputation procedure was successfully employed to determine the missing/incorrect on-ramp and off-ramp flows in a 26 mile portion of I210E freeway. The parameter equations were applied until the error of model calculated densities stopped decreasing. Simulations were performed using the general LN-CTM model (implemented in Matlab) by specifying the on-ramp flows and off-ramp split ratios. The model generated density, flow and velocity profiles agree closely with the measured densities, and the performance measure plots and calibration specifications also indicate good conformation.

The imputation procedure finished in 20 mins. on an Intel 2.4Ghz Quad core with 3GB RAM, for the 24 link I210E freeway. This algorithm scales linearly with the number of links of the freeway (and hence the size of the freeway). The calibrating and imputing process to specify the freeway model took 2 days, with the main bulk of the time spent on detecting erroneous ramp detector data. While the current ramp overrides are based on ad-hoc rules, the authors are working towards a reliable fault detection model to determine erroneous detector data to complement the imputation algorithm.

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FIGURE. 5 - Flow Contours obtained from the I-210E simulation using imputed parameters.

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FIGURE. 7 - Calibration criteria for freeway simulations.

Symbol	Name	Unit
	section length	miles
	period	hours
F_i	capacity	veh/period
v_i	free flow speed	section/period
w_i	congestion wave speed	veh/section
n_i	jam density	veh/section
β_i	split ratio	dimensionless
k	period number	dimensionless
$f_i^{in}(k)$	flow into section i at period k	veh/period
$f_i^{out}(k)$	flow out of section i at period k	veh/period
$s_i(k), r_i(k)$	off-ramp, on-ramp flow in node i at period k	veh/period
$d_i(k)$	on-ramp demand for Link $i+1$ at period k	veh/period
$c_i(k)$	total demand for Link $i+1$ at period k	veh/period

TABLE. 1 – Model variables and parameters

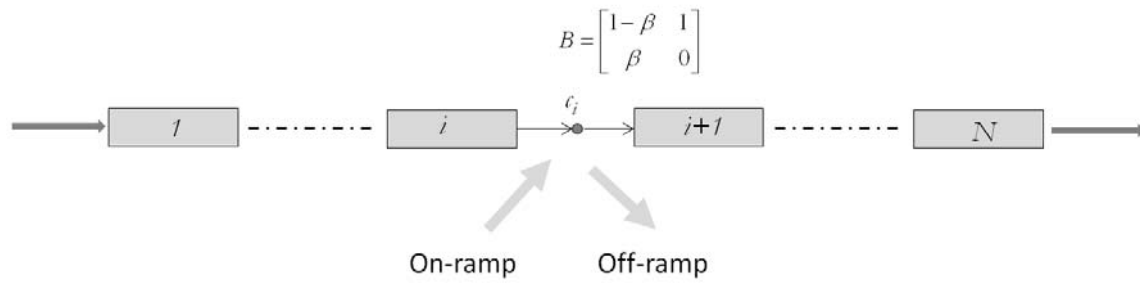


FIGURE. 1 -Freeway with N links. Each Node contains a maximum of one on- and one off-ramp.

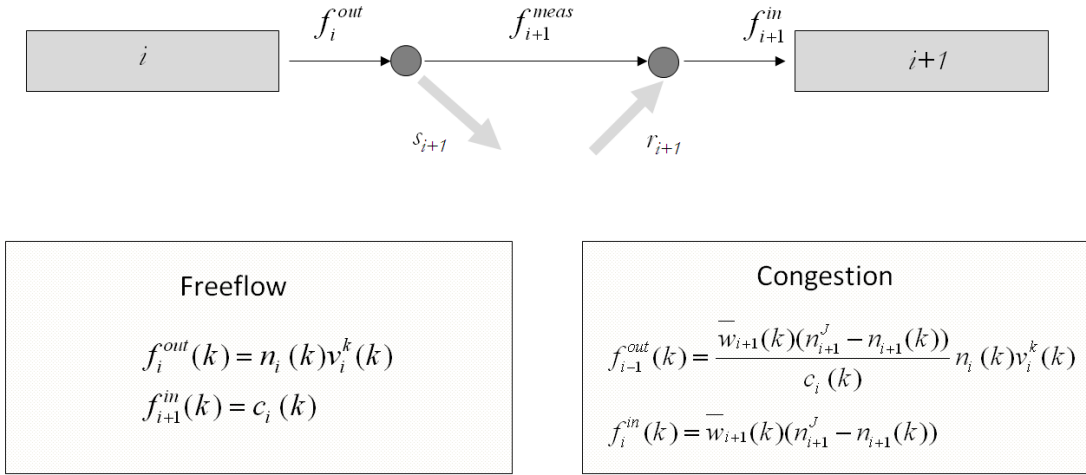


FIGURE. 2 - Decouple on-ramp and off-ramp flows.

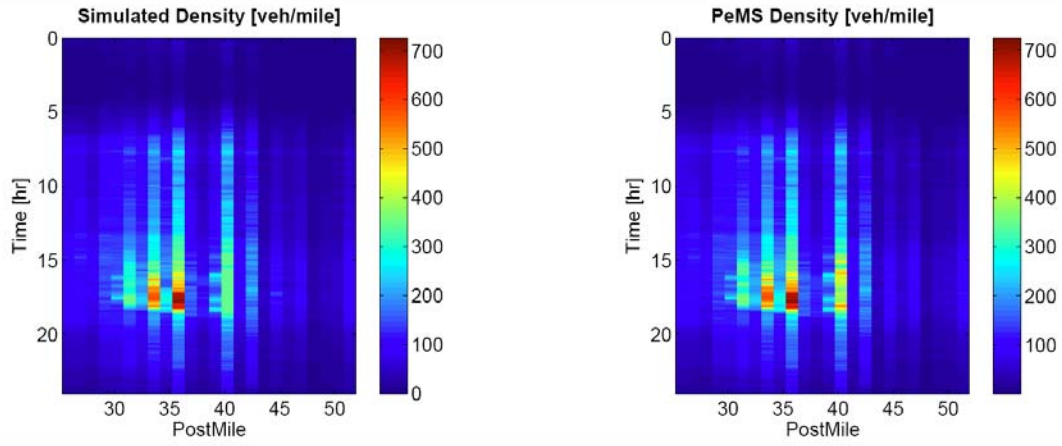


FIGURE. 3 - Final density contours obtained after imputation.

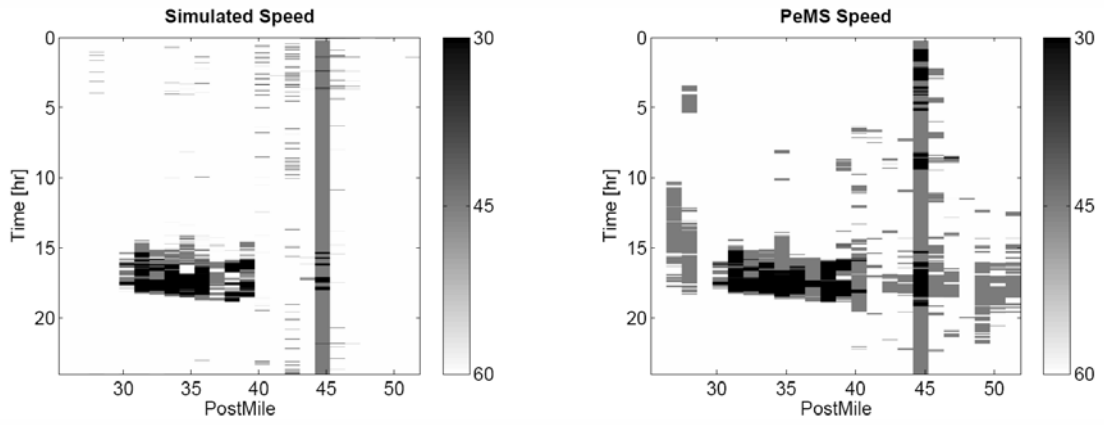


FIGURE. 4 - Velocity Contours [in mph] obtained from the I-210E simulation using imputed parameters.

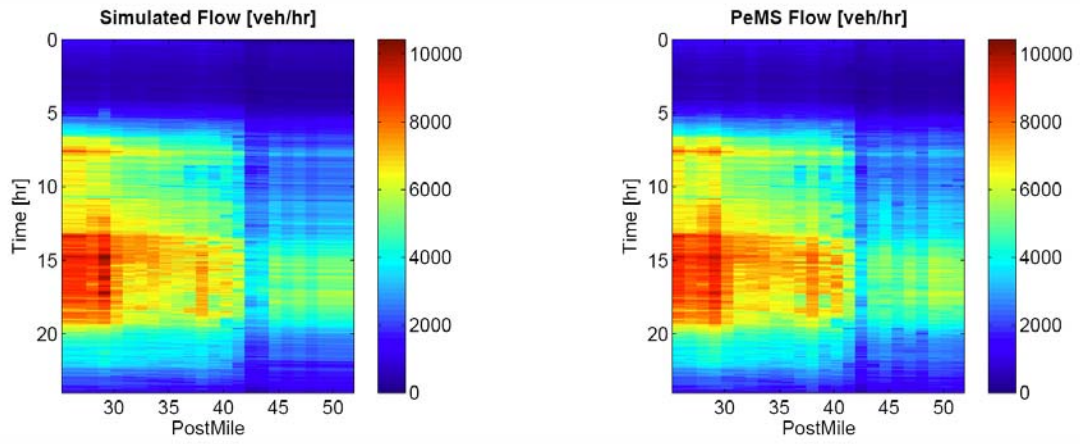


FIGURE. 5 - Flow Contours obtained from the I-210E simulation using imputed parameters.

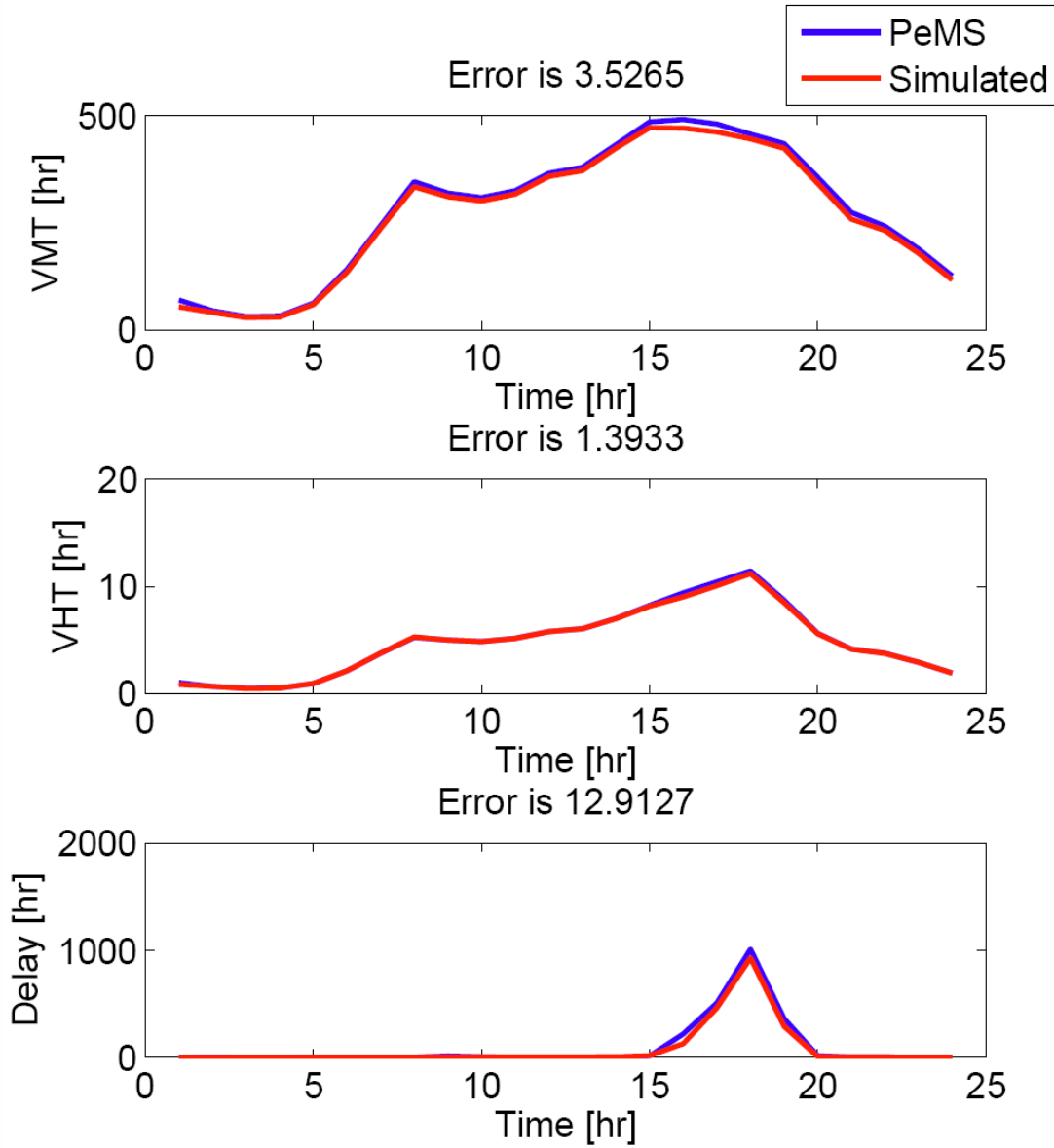


FIGURE. 6 - Performance measures - Vehicle Hours Traveled (VHT), Vehicle Miles Traveled (VMT) and Delay.

Test : for individual flows < 700	
total number of data points	80
number within 100 vph of data	70
85% of total number of data points	68
Test : for individual flows > 700 , < 2700	
total number of data points	141
number within 15% of data	116
85% of total number of data points	119
Test : for individual flows > 2700	
total number of data points	355
number within 400 vph of data	305
85% of total number of data points	301
Test : for sum of all link flows	
measured	2.13E+06
simulated	2.06E+06
Error	3.07%
Test : GEH for individual link flows	
total number of data points	576
number < 5	473
85% of total number of data points	489

FIGURE. 7 - Calibration criteria for freeway simulations.