A NEW METHOD FOR MICROSIMULATION MODEL CALIBRATION: A CASE STUDY OF I-710

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Abstract: As a part of the feasibility analysis of electric truck roadways for some of the major corridors near Los Angeles, California, this paper aims to introduce and investigate a new method for microsimulation model calibration. The model of I-710 southbound was developed in VISSIM software and calibrated through two sets of data: O-D demand from planning models and field data which was consist of traffic flow and speed. Due to the lack of proper count data for on-ramps/off-ramps, the O-D demand was estimated via path flow estimator. After determining the calibration parameters, in an attempt to avoid unnecessary VISSIM’s time-consuming runs, a statistical model was developed to evaluate the impacts of different values of these parameters on microsimulation results. This model was used to partially evaluate the initial population of a genetic algorithm which was used to calibrate the parameters. The results indicate that, even with a lack of proper data, the outputs of the calibrated model can mimic the field data closely in every 5-minute intervals for every station along the studied corridor.

Keywords: microsimulation, model calibration, path flow estimator, statistical model, genetic algorithm.

Introduction

Surface transportation, nowadays, is part and parcel of human civilization, working as the foundation of our social and economic life. With all its complexity and widened range, it proposes a decent challenge to investigate changes, whether in geometry or new applied to control system, using old methods and manuals [1]. The advent of advanced computational technology paved the way for the creation of software packages which made it possible to simulate surface transportation at a microscopic level. Today, microsimulation models not only is used for investigating changes that surface transportation undergoes, but also it can be used to investigate the impact of emerging technology such as intelligent transportation system, electric cars, and wireless charging lanes in a much safer, faster, and cheaper way [1].

For a microsimulation model to be representative of real-world transportation networks, proper steps of calibration and validation are to be taken, without which the model yields erroneous results that can be misleading. These steps can be divided into two categories: parameter calibration and origin-destination (O-D) flow estimation [2]. Unlike macroscopic simulation models which have parameters that their values are measurable using “existing sensor infrastructure” and thus are easier to calibrate, some of microsimulation models’ parameters are not feasible to be measured using field data, such as parameters related to divers’ behavior [3]. However, other parameters such as geometry, input vehicles, route choice decisions, and signal timings, are fairly obtainable given the proper field data.

Researchers have deployed various methods to cope with microsimulation calibration difficulties. Guidelines are proposed by Choa [4] for calibration and validation purposes. Similarly, Helinga [5] proposed a calibration process which is consists of three phases. These phases can be summarized in eight steps: (a,b) determining goals and purpose of the study and field data required, (c) indicating measures of performance, (d) establishing evaluation criteria, (e) performing initial calibration of model, (f) simulation and getting outputs, (g) evaluating the outputs, (h) re-calibrating if needed. Although these guidelines can be used as a basic instruction for approaching model calibration, they are too general to be used as a stepwise calibration guideline. As far as the initial calibration is concerned, choosing right parameters to calibrate, is a practical challenge and has been handled by various studied differently. Although it is ideal to change all the parameters and avoid the errors that default values may cause [6], handling the accompanying complexity is almost impossible.

After choosing the right parameters to calibrate, the problem of assigning proper value is of great importance. Some researchers applied the genetic algorithm (GA) as an optimization problem with the goal to minimize the differences between simulated measures of performance and observed ones [7, 8]. Another approach used is to statistically model a measure(s) of performance over parameters chosen to be calibrated, find a number of best values for them based on the statistical model, and run the simulation model to evaluate which set of values provides the lowest difference between simulated measure(s) of performance and observed one(s) [6]. Although this method is simple and easily applicable, the randomness involved in
traffic flow cannot be duly explained using a simple regression model. That is, when the simulation model runs, the impact of the values of each parameter changes over time and along the segments of roads. After calibrating the model, the result should be validated with the field data to test the accuracy of simulated data comparing with real fields data. Model validation is accompanied with 4 major difficulties: (a) providing clear and context-related meaning for validation, (b) obtaining relevant data, (c) quantifying uncertainties, (d) predicting measures of performance under new conditions and settings [9].

As it mentioned, effects of calibration parameters’ value can be variable along the studied corridors and during different times of the day (simulation time), this variability cannot be correctly explained and predicted using fixed effect regression which is used frequently in the literature. In this paper, we tried to, first, handle the O-D estimation using path-flow-estimator based method. Then, as a part of our GA which calibrates both parameters and vehicle input, we developed a mixed integer model with random intercepts and coefficients, to capture the effects of variable-over-time (and location) vehicle inputs and calibration parameters’ value on simulation results. This model is used to evaluate a proportion of the initial population of a GA to the end that, a good population is provided and randomness remains unaffected. Afterward, the GA, calibrating parameters such as car following and lane changing parameters, was tested on the model of I-710 Freeway (Long Beach Freeway) southbound which was modeled in VISSIM software.

PROJECT DESCRIPTION

As mentioned, this study is a part of the feasibility analysis of electric truck roadways for some of the major corridors near Los Angles, California. All these corridors are analyzed using microscopic model between 6 am to midnight in order to capture all the truck traffic fluctuations, the percentage of trucks using the corridors, their speed at any given time, and acceleration decelerations to obtain a better view of their energy consumption for further analysis.

For the purpose of this study, we chose southbound of Long Beach Freeway which is approximately 23 mi, going from Valley Boulevard to West Ocean Boulevard. The time frame for our analysis for this paper is AM peak which ranges from 6:00 to 9:00 am. Most of the congested segments are located between Christopher Columbus Transcontinental Interchange and Bandini Boulevard Interchange, and also between Artesian Freeway and San Diego Freeway. The congestion is very mild at the beginning but as the demand increases the traffic starts to build up. This process continues till after pm peak. The site has 29 on-ramps and the equal amount of off-ramps, none of which had any loop detector. There were no high occupancy vehicle (HOV) lanes. The traffic was consist of four major categories of vehicle: passenger car, light truck, medium truck, and heavy truck. I-710 considers as one of the major corridors for freight transport.

MODEL DEVELOPMENT

Microsimulation Model
The software package used in this study for microsimulation modeling was VISSIM [10], version 9-11. VISSIM is a microscopic, behavior-based, multi-modal traffic simulation software package developed by Planning Transport Verkehr (PVT) in Karlsruhe, Germany. In VISSIM, a model developed by Wiedemann is used which helps mimic drivers behavior psychologically. By using different thresholds, the Wiedemann car-following model defines regimes in car flowing [11]. Using VISSIM, I-710 southbound was modeled, Figure 1.

Traffic Data
After road geometry, the first building block of our microsimulation model was defining vehicle inputs and static route choice decisions. The foundation of VISSIM dictates to input the traffic volume for at most 15-minute intervals for the results to be representatives of reality [10]. It usually is fed to the software in a form of O-D matrices to define static road choice decisions (also it can be inputted as relative flow). In the case of freeways, Origins and destinations are define as on-ramps and off-ramps, respectively. In this project we used two sources of data:
1. Planning models data: The O-D matrices was provided to us from an existing planning model outputs. This data set was provided for each type of vehicles, passenger car, light truck, medium truck, and heavy truck, for 3-hour am-peak, midday, and pm peak. The different vehicle type O-D matrices were used to obtain vehicle composition for each on-ramp. While this data set was pretty useful, there were two problems to cope with: (a) the volume did not represent the actual count data and was on average twice higher than that and (b) the data was aggregate of 3 hours which could not reflect the changes in demand during the day. These two issues pose a significant challenge in making the O-D matrices useful for simulation studies.

2. PeMS: The Caltrans Performance Measurement System (PeMS) database gathered real-time data from over 39,000 individual detectors, distributed over 30,000 mi of freeway across California. This dataset reports various types of information such as traffic flow, speed, and percentage trucks, for different time intervals during 24 hours. There were only 6 active stations along I-710 southbound for the period of time we wanted to calibrate the data, first seven days of April 2018, Figure 1. We used 5-minute interval flow and speed data for estimating the O-D demand matrices and parameters calibration.

![Image](https://via.placeholder.com/150)

Figure 1: I-710 south bound Geometry. (a) shows the freeway and crossing roads, (b) shows the north half of the freeway between Valley Blvd. and Imperial Hwy, and (c) shows the south half of the freeway between Imperial Hwy. to West Ocean Blvd.

**O-D Estimation**

Two different sequences can be found in the literature for calibrating the O-D matrices: (a) first calibrating driving behaviors parameters and then calibrating O-D matrices [2] or (b) first calibrating O-D matrices and then calibrating driving behaviors parameters [3]. In this study, we decided to use the latter since the chosen method of O-D calibration is not dependent on driving behavior parameters, but the reverse is not true. There are several ways to estimate the O-D matrices, chief among which are GA and generalized least square (GLS) [2]. A different approach was used in this work based on the proposed model by Nie [12].

Assume that $G \ (N, A)$ denote the network where $N$ and $A$ are sets of nodes and arcs, respectively. $a \in A$ is connecting $i$ and $j \in N$. Let $W$ be set of O-D pairs and $K_w$ be the set of all the routes connecting origin $r$ to destination $s$. $P_{rs}^k$ is the set of all the arcs constructing route $k$. $f_{rs}^{kt}$ is traffic flow going through route $k \in K_w$ connecting origin $r \in N$ to destination $s \in N$ in time interval $t \in T$. $\hat{X}_{at}$ is the observed flow of link
\[ a \in A \] in time interval \( t \in T \). Now, the linear time interval path flow estimator model (LTIPFE) can be formulated as follows:

\[
\min Z = \sum_{r} \sum_{s} \sum_{k} \sum_{t} \hat{c}_{r,k,t}^{rs} f_{k,t}^{rs} + \alpha \sum_{a} \sum_{t} (y_{a,t}^{a,t} + y_{a,t}^{+}) + \beta \sum_{s} \sum_{k} (Y_{s}^{rs} + Y_{s}^{rs}) \tag{1}
\]

\[
\sum_{r} \sum_{s} \sum_{k} p_{k}^{rs} f_{k,t}^{rs} + y_{a,t}^{a,t} - y_{a,t}^{+} = \bar{x}_{a,t}^{t}, \quad \forall a \in A, t \in T \tag{2}
\]

\[
\sum_{k} \sum_{t} f_{k,t}^{rs} - Y_{s}^{rs} + Y_{s}^{rs} = q_{s}^{rs}, \quad \forall r, s \in N \tag{3}
\]

\[
f_{k,t}^{rs}, y_{s}^{rs}, y_{a,t}^{rs}, y_{a,t}^{+} \geq 0, \quad \forall r, s \in N, \forall a \in A, t \in T \tag{4}
\]

Where, \( \hat{c}_{r,k,t}^{rs} \), \( \alpha \), and \( \beta \) are the observed cost of route \( k \) connecting origin \( r \) to destination \( s \) in time interval \( t \) and penalty parameters, respectively. \( y_{a,t}^{a,t} \) and \( y_{a,t}^{+} \) are non-negative artificial variables that allow positive or negative deviation in the observed link flow for each time interval. Similarly, \( Y_{s}^{rs} \) and \( Y_{s}^{rs} \) are non-negative artificial variables that allow deviations of estimated O-D matrices from original O-D matrices. Finally, \( q_{s}^{rs} \) is the original O-D demand matrix.

In the above formulation, (1) represents the model objective function which minimizes the system cost along with deviations from the observed flow and original O-D matrix. Set of equations (2) relates the path flow to the observed link flow. Set of equations (3) does the same thing for path flow and origin-destination demand. Set of equations (4) guarantees that variables are nonnegative. \( \alpha \) and \( \beta \) can be calculated according to Sherali et al. [13]. Here, we choose \( 10^{18} \) and \( 10^{16} \) for \( \alpha \) and \( \beta \) respectively. Another thing to deal with before solving the model was obtaining \( \hat{c}_{r,k,t}^{rs} \). Since there was no possible way for us to gather the travel time data for on-ramps/off-ramps for different times of day according to our intervals, we used the following formulation of Bureau of Public Roads (BRP):

\[
\bar{c}_{r,k,t}^{rs} = \sum_{a} t_{a} \left( 1 + 0.15 \left( \frac{v_{t}^{rs}}{v_{a}} \right)^{4} \right), \quad \forall a \in P_{r,k}^{rs} \tag{5}
\]

where, \( t_{a} \) is the free flow travel time of link \( a \in A \), and \( v_{t}^{rs} \) and \( v_{a} \) are link volume at time \( t \) and link capacity, respectively. The model was solved using the interior point method. Before discussing the results, we need to define a measure to compare microsimulation results before and after using LTIPFE model to estimate O-D matrices. We used mean square error (MSE) presented in equation (6) which is widely recommended in the literature [14].

\[
MSE = \frac{1}{n} \sum_{s} \sum_{r} MSE_{s} = \frac{1}{n} \sum_{r} \sum_{s} \left( \left( \sum_{t} f_{sim}^{ts} - f_{obs}^{ts} \right)^{2} + \left( \theta \sum_{t} s_{sim}^{ts} - s_{obs}^{ts} \right)^{2} \right) \tag{6}
\]

where, \( f_{sim}^{ts} \) and \( f_{obs}^{ts} \) are simulated and observed flow at time interval \( t \) at station \( s \). \( s_{sim}^{ts} \) and \( s_{obs}^{ts} \) are similarly defined for speed. \( \theta \) is a scaler, assumed to be 10 here. The result revealed that after using this method, the average MSE function for 10 runs decreased by \( 217910 \) (17%). Although it’s a significant change in MSE, the estimated flow pattern is an underestimation of what real vehicle inputs should be. To handle the issue, a method to obtain the true vehicle input value will be introduced in the following section.

**CALIBRATION PROCEDURE**

Before delving into the calibration of parameters several things need to be highlighted. First of all, the nature of the problem needs to be investigated. Afterward, parameters that need to be calibrated must be determined. Then, a surface function must be introduced and optimized to help facilitate the pre-evaluation
of different settings (different sets of parameters’ value). Then a GA is introduced to find the parameters’ optimum value. Following subsections would draw these highlights.

**Measure of Effectiveness**

As mentioned, this paper is part of a feasibility analysis of electric truck roadways for some of the major corridors near Los Angles, California. Using charging lanes is an empirical solution to problems that held back electric vehicles’ (EV) adoption. It extends the range of EVs, making it compatible with the conventional vehicle and also undermines the limited capacity of energy storage units (onboard batteries) which solves the range anxiety issues of drivers to some extent [15]. To determine traffic-related parameters that affect the energy consumption of each coil, i.e., embedded panels that charge EVs wirelessly, assume a coil with an average charging rate of $\omega$ and length of $l$ (m). Also, assume that one average, $n$ vehicles pass over it every hour with the speed of $v \left( \frac{km}{h} \right)$. Approximately, the average energy consumption of this coil can be easily calculated using:

$$EC = \frac{l}{1000v} \omega n$$

(7)

According to (7), two parameters are important in EC: traffic flow and speed of a vehicle. Here, we choose these parameters as our measure of effectiveness. Aside from that, average flow and speed are widely used for calibration and validation of microsimulation models in the literature [2, 3, 16].

**Development of Surface Function**

There are numerous parameters that can effect VISSIM results. However, by increasing the number of parameters the number of simulation runs for finding the best value would increase multiplicatively. Thus, similar to literature, we chose 6 calibration parameters as our main calibration parameters to develop our surface function based on: (a) emergency stopping distance, (b) lane-change distance, (c) number of observed preceding vehicles, (d) average standstill distance, (e) waiting time before diffusion, and (f) minimum headway.

Emergency stopping distance (ESD) is the last possible position behind connectors that a vehicle can change lane to stay on his desirable route. Failure to find an acceptable gap necessary for a lane change, force vehicles to stop at this distance and wait for a proper gap to change lane. The default value for this parameter is 5.0 meter which causes unrealistic bottlenecks along the I-710 south bound. Thus, values less than this 5m only aggravate the situation. Additionally, values more than 20m seems unreasonable since it forces cars to stop long before connectors. Consequently, we chose the range between 5 and 20 m, i.e., $5 \leq ESD \leq 20$.

Lane-change distance (LCD) is used alongside ESD to model drivers’ behavior to stay on their desired routes. LCD marks the start of drivers’ attempts to change lane; that is, the distance that drivers start making an attempt to change their lane to stay on their desirable routes. The default value of LCD is 200 m which causes unrealistic bottlenecks along the entire length of I-710. Since values lower than this number worsen the situation, 200 m was chosen as the lower bound of this variable. After 96 runs of the microsimulation model with different parameters value, we observed that after 2000 m flow and speed starts deviating from observed value severely, starting to become much higher than observed values. Thus, we chose 2000 m as the upper bound. So, for this variable, the range is $200 \leq LCD \leq 2000$.

The number of observed preceding vehicles (NOPV) shows the number of vehicles (network objects) that a vehicle can predict their movements and react accordingly. Higher values result in better react to multiple cars in the network. The default value here is 2 for freeways and 4 for arterials. Here, the range for this variable was chosen between 2 and 4, i.e. $2 \leq NOPV \leq 4$. Average standstill distance (ASD) is the average distance between stopped cars and also between cars and other elements of networks, such as stoplights.
The default value for this parameter is 2 m. Here, we used 2 m as lower bound and 4 m as upper bound, i.e. $2 \leq \text{ASD} \leq 4$. Waiting time before diffusion (WTBD) is the amount of time which if reached, the vehicle that stops at the ESD during this time would be defused (eliminated from the network). In this paper, we used 40 s and 60 s as lower bound and upper bound of this parameter, respectively, i.e. $40 \leq \text{WTBD} \leq 60$. Minimum headway (MH) is the minimum distance to the vehicle in front that is needed for a vehicle to change lane and be in its desired route. The default value for MH is 0.5. Here, we chose our range to be between 0.2 and 2, i.e. $0.2 \leq \text{MH} \leq 2$.

Using these parameters and their range, we created 972 cases using these parameters. 5 simulation runs were performed for each setting and the result was averaged to represent the performance of that setting. Table 1 shows the values of the parameters used to run the microsimulation model. Since an accurate estimator for VISSIM outputs was needed, this high number of runs were necessary.

\textbf{Table 1: Parameters' values used in microsimulation runs}

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Min</th>
<th>Max</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESD</td>
<td>Emergency Stopping Distance</td>
<td>5</td>
<td>20</td>
<td>5,10,15</td>
</tr>
<tr>
<td>LCD</td>
<td>Lane-Change Distance</td>
<td>200</td>
<td>2000</td>
<td>400,800,1000,1500,2000</td>
</tr>
<tr>
<td>NOPV</td>
<td>Number Of Observed Preceding Vehicles</td>
<td>2</td>
<td>4</td>
<td>2,3,4</td>
</tr>
<tr>
<td>ASD</td>
<td>Average Standstill Distance</td>
<td>2</td>
<td>4</td>
<td>2,3,4</td>
</tr>
<tr>
<td>WTBD</td>
<td>Waiting Time Before Diffusion</td>
<td>40</td>
<td>60</td>
<td>40,50,60</td>
</tr>
<tr>
<td>MH</td>
<td>Minimum Headway</td>
<td>0.2</td>
<td>2</td>
<td>0.2,1,2</td>
</tr>
</tbody>
</table>

As it will be stated in following subsections, these parameters are not the only parameter used in the calibration process but are ones that we used to build our regression model. In order for microsimulation model to produce the best outputs for calculating charging lanes’ energy consumption, it is essential for us to find the best parameters that make VISSIM mimic the reality at all stations and for every time intervals. Using MSE or root mean square error (RMSE) for the entire corridor might not be a very accurate approach since it eliminates all the randomness that parameters causes at all stations during simulation runs. Fixed effect regression cannot reflect this randomness across stations and time intervals. Thus, we use a mixed/multilevel regression model (MRM).

Mixed regression model can capture heterogeneity among stations at different time intervals providing a better estimation for VISSIM results. To investigate this claim, first, let define some measure of performance. Assume \textbf{Absolute Difference} (AD) to be:

\[
AD_{t,s} = |F_{t,s}^{\text{sim}} - F_{t,s}^{\text{obs}}| \tag{8}
\]

Where, $|.|$ is the absolute value function. Using $AD_{t,s}$ as the dependent variable, the correlation of parameters with $AD_{t,s}$ was modeled. We refer to it as Model2. For the sake of comparison, we also used a fixed effect regression model to model the sum of absolute differences ($\sum_t \sum_s AD_{t,s}$) over main calibration parameters. We refer to this as Model1. To evaluate the prediction capability of models, we randomly chose 97 cases (10%) and eliminated them from the data set. Model1 and Model2 were estimated with the remaining cases. Equation (9) shows the solution for the fixed effect (Model1).

\[
AD = e^{(5.37+0.027 \log(\text{ESD})-0.30 \log(\text{LCD})+0.13 \log(\text{NOPV})+0.063 \log(\text{MH})+0.17 \log(\text{ASD})-0.014 \log(\text{WTBD})} \tag{9}
\]

where, $e^x$ is the exponential function. All of the variables are 99% significant. It should be noted that Model2 cannot be written as a closed form and any prediction take place through software packages. To compare the modeling results, let $M1$ and $M2$ be the sum of absolute differences, predicted by Model1 and Model2, respectively. Figure 2 depicts, AD, M1, and M2 over a 100 best (lowest) (a) and a 100 worst (highest) (b) values of AD. Figure 2 (c) shows the same thing over 97 randomly chosen cases. As it can be seen, M2 is closely mimicking VISSIM’s outputs for lower values of AD; it is a better estimation than M1 in highest
values of AD, but might not be as much efficient as it is in the lower values of AD. For the randomly chosen cases, in 78% of cases (lower values of AD), Model2 has far better predictive capabilities. Since the objective of calibration is to find the values of parameters such that the value of AD becomes minimum, it can safely be concluded that Model2 has better prediction capability.

Moreover, since Model2 is predicting for every time intervals at all station, we can use it to eliminate settings with maximum AD above 15%. In other words, this model gives two criteria for choosing the best solution: 1) mean absolute differences and 2) maximum absolute differences. Although this surface function is a better estimation of VISSIM outputs, it cannot be used instead of microsimulation models. Also, the outputs of the microsimulation model are dependent on many other variables that cannot be used in the surface function (due to the multiplicative increase in the number of runs). Above mentioned surface function is only developed to evaluate the initial solution for following GA.

**Genetic Algorithm**

GA is one of the commonly used methods for calibration of microsimulation models [7, 17, 18]. In this study, we used GA as our final step in the model calibration procedure. The cost function here is to minimize the average $AD_t$, plus the average absolute difference between observed and simulated average speed along all the stations and during the simulation period. Another criterion used to accept the solution as a near optimum solution was maximum $GEH$ statistic; it can be calculated using the following formulation [19]:

$$GEH_{h,s} = \frac{2(f_{h,s}^{obs} - f_{h,s}^{sim})^2}{f_{h,s}^{sim} + f_{h,s}^{obs}}, \quad \forall h, s$$

(10)

where, $f_{h,s}^{sim}$ and $f_{h,s}^{obs}$ are simulated and observed flow at hour $h$ at station $s$, respectively. there are 24 genes, which represents 24 parameters, in each chromosome. These genes are listed in Table 2. Gene 1 and 2 are adjusting the vehicle input based on original O-D demand and estimated O-D demand. $\delta_1$ is used to calculate vehicle inputs based on original O-D demand and estimated O-D demand. Mathematically,

$$OD = OD_{original} + \delta_1(OD_{Estimated} - OD_{original})$$

(11)

where, $OD$, $OD_{original}$, and $OD_{Estimated}$ are vehicle inputs, original and estimated O-D demands, respectively. Alongside, $\delta_2$ adjusts the warm-up period traffic volume based on first time-interval traffic volumes. Mathematically,

$$OD_t^w = \delta_2 OD_t^w, \quad \forall w, \forall t \in \{1, ..., 6\}$$

(12)

Using this gene helps minimize the over-load and under-load of the network at the beginning of data gathering. Parameters (genes) 3 through 8 are the same as that described in the previous section. In some cases, the range is changed due to observations made in the previous subsection. Parameters (genes) 9 through 17 are the car following parameters in Wiedemann car-following model. Parameters (genes) 18 through 24 are parameters controlling lane changing behavior.
Figure 2: Plot of AD, M1, and M2 against different iterations.
Table 2: List of genes, their definition, and the minimum and maximum value

<table>
<thead>
<tr>
<th>#</th>
<th>Gene</th>
<th>Definition</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\delta_1$</td>
<td>Vehicle input correction coefficient</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>$\delta_2$</td>
<td>Warm-up-period vehicle-input adjustment coefficient</td>
<td>0.5</td>
<td>2.5</td>
</tr>
<tr>
<td>3</td>
<td>ESD</td>
<td>Emergency Stopping Distance</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td>4</td>
<td>LCD</td>
<td>Lane-Change Distance</td>
<td>300</td>
<td>1500</td>
</tr>
<tr>
<td>5</td>
<td>NOPV</td>
<td>Number Of Observed Preceding Vehicles</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>6</td>
<td>ASD</td>
<td>Average Standstill Distance</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>WTBD</td>
<td>Waiting Time Before Diffusion</td>
<td>30</td>
<td>60</td>
</tr>
<tr>
<td>8</td>
<td>MH</td>
<td>Minimum Headway</td>
<td>0.2</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>CC1</td>
<td>Headway time distribution</td>
<td>0.5</td>
<td>30</td>
</tr>
<tr>
<td>10</td>
<td>CC2</td>
<td>'Following' variation</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>CC3</td>
<td>Threshold for entering 'Following'</td>
<td>-20</td>
<td>0</td>
</tr>
<tr>
<td>12</td>
<td>CC4</td>
<td>Negative 'Following' threshold</td>
<td>-5</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>CC5</td>
<td>Positive 'Following' threshold</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>14</td>
<td>CC6</td>
<td>Speed dependency of oscillation</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>15</td>
<td>CC7</td>
<td>Oscillation acceleration</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>16</td>
<td>CC8</td>
<td>Standstill acceleration</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>17</td>
<td>CC9</td>
<td>Acceleration at 80 km/h</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>18</td>
<td>CoopLnChgSpeedDiff</td>
<td>Cooperative lane change - maximum speed difference</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>19</td>
<td>CoopLnChgCollTm</td>
<td>Cooperative lane change - maximum collision time</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>20</td>
<td>MaxDecelOwn</td>
<td>Maximum deceleration (own)</td>
<td>-10</td>
<td>-0.02</td>
</tr>
<tr>
<td>21</td>
<td>MaxDecelTrail</td>
<td>Maximum deceleration (trail)</td>
<td>-10</td>
<td>-0.02</td>
</tr>
<tr>
<td>22</td>
<td>AccDecelOwn</td>
<td>Accepted deceleration (own)</td>
<td>-10</td>
<td>0</td>
</tr>
<tr>
<td>23</td>
<td>AccDecelTrail</td>
<td>Maximum deceleration (trail)</td>
<td>-10</td>
<td>0</td>
</tr>
<tr>
<td>24</td>
<td>CoopDecel</td>
<td>Cooperative deceleration</td>
<td>-10</td>
<td>0</td>
</tr>
</tbody>
</table>

After explaining genes, finding a good way of creating an initial population is of the essence. Although GA can start with any solutions and works all its way to near optimum ones, it is instructed to work with a known good solution instead of randomly generated ones since it increases the algorithm efficiency. However, the initial population cannot be without randomness since randomness guarantees gene diversity which helps to find near-optimum solutions [20]. To this end, we generated 100 individuals in a random manner. Then, 50 individuals were selected randomly to be evaluated through Model2. If the criteria was satisfied ($AD_{ts}/F_{obs}^h \leq 0.15$ and $\max_t(AD_{ts}/F_{obs}^h) \leq 0.15$ ), the individual was accepted as a member of initial solution. If not, that chromosome would be replaced by another randomly generated one who passes the evaluation step. This process repeats until 50 good initial solutions is found. This process helps us to have both good individuals and random individuals at the same time. After generating the initial population, other steps of GA are as follows:

- **Step 1:** (Chromosome Evaluation) run VISSIM using the information of each newly added chromosome, five times. Use the average of these five times to calculate cost function and GEH. Sort chromosomes in an ascending order based on their cost function.
- **Step 2:** (Selection of parents) use prioritized random selection (selection of a better chromosome is more probable) to select 25 pairs of parents. If any of these pairs are the same, replace them with a new one which is not the same with others.
- **Step 3:** (Crossover) choose a gene randomly for each pair of parents. Swipe the genes that come after that between two parents. These newly made chromosomes are offspring.
- Step 4: (Mutation) for each offspring, generate a random number. If the number is less than \( \rho \), which is mutation rate, mutate a gene randomly (choose a gene in that chromosome and assign a random value to it). Otherwise, do nothing.

- Step 5: (Updating the population) replace the last 50 individuals in the last generation (previous population) with offspring. If the criteria are met, stop otherwise go to step one.

In this study, we choose 0.2 as the mutation rate. For stopping criteria, if maximum GEH is below 5, the stopping criteria are met whether cost function is below 10% or a certain number of iteration is reached. We choose 25 as the maximum number of iteration based on our different runs of the algorithm. Figure 3 shows the convergence plot of the GA.

As far as the initial solution is concerned, GA starts with both cost function (16.24%) and maximum GEH (5.68) near acceptable limits. Moreover, the algorithm shows to have sharp decreases at the beginning and milder ones at the end. It shows that after iteration 17 the cost function is not improving; however, since both cost function and maximum GEH are within acceptable range (the former is below 15% and the latter is below 5), it can safely be assumed that the maximum number is large enough. It might be true that a better solution can be found if the number of iterations is increased; however, the computational cost would be severe since finding a better solution is not guaranteed. In the final iteration, the value of \( \delta_1 \) and \( \delta_2 \) are the same among the ten best chromosomes and are equal to 0.977 and 0.915, respectively. It shows that path flow estimator can provide a much tightened lower bound for vehicle inputs when there are no other data available. In the end, the best chromosome was used as the accepted value for parameters. Following section is dedicated to results of the calibrated model and conclusion.

Figure 3: Plot of cost function, maximum GEH, and average GEH against iteration number.

RESULTS AND CONCLUSION

Using the above-mentioned calibration and O-D estimation procedure would result in a very close resemblance between simulated data and field data. Figure 4 shows the results of the calibrated microsimulation model and field data versus time interval for different stations along I-710 southbound. Simulation results are the average of 50 different runs with different random seeds.

Figure 4 shows that traffic flow in all the stations is in the close vicinity of field data. Additionally, the maximum GEH is 4.20 which satisfies the acceptable criteria (GEH<5) [14]. There are no unrealistic bottlenecks along the way and no unrealistic on-ramp queueing in the corridor. In some station, the simulated flow is more closely mimicking the field data compared with other stations. It can be explained by the location of these stations which is either further away from upstream on-ramps or the upstream on-ramps do not have high traffic volumes. Also, if they are placed in the vicinity of a short weaving area the traffic can oscillate more sharply compared to other places along the network.
Speed is also closely mimicking the field data; however, in some stations, the speed obtained from the simulation model is noticeably lower or higher than the field data in some time intervals. It also can be explained by the existence of on-ramps and weaving areas. For instance, station 2 (Figure 4 (b)) is placed right after a high volume weaving area; as its volume increases over time the traffic randomness makes it hard to duplicate what is observed in the reality. To get better results in stations similar to station 2, station-wide fine-tuning is necessary which is out of the focus of this paper.

In this study which is a part of feasibility analysis of electric truck roadways for some of the major corridors near Los Angeles, California, we tried to use a new method to calibrate a microsimulation model of I-710 southbound in order to overcome the lack of necessary data and provide results that can realistically mimic the field data. For this purpose, O-D demand data from existing planning model was used as an original seed for O-D estimation method. Alongside, PeMS data was collected for every five minutes for six station along the I-710 southbound to facilitate both O-D estimation and parameters calibration. For O-D estimation, a path-flow-estimator based method was used to minimize the differences between simulation results and field count data. Next step to calibrate the model was to create a good estimator for estimating the outputs of microsimulation model. Considering the fact that regression models are widely used in the literature [21, 22], a mixed effect regression model was used to evaluate the correlation between 6 main parameters and absolute differences between the simulated traffic volume and field data. This estimator was used later to evaluate the initial population of GA.

As a final step, GA was used to minimize the absolute differences between the simulated traffic volume and field data. GA also provided us with two adjustment factor; the first factor used to determine how close the vehicle inputs should be to the estimated O-D demand and the second one used to calculate vehicle inputs related to the warm-up period. The results demonstrate that, first, O-D demand estimator adjust the O-D volume correctly and, second, the parameter calibration process is capable of finding good values for parameters with the aim to minimize the differences between field and simulated data. All the steps of this paper were coded in MATLAB; VISSIM simulation runs were facilitated through VISSIM-COM.

To continue this research it is essential to use the procedure in other networks, evaluate the computational cost, and try to optimize the algorithm more which are not within the scope of this paper. After all calibration processes, the calibrated microsimulation model would be used in estimating the energy consumption of electric trucks traveling through I-710 south-bound which plays a chief role in designing wireless charging lanes dedicated to freight shipment.
Figure 4: Simulated/observed traffic count and average speed data versus time interval for six stations along I-710 south bound. (a) station 1; (b) station 2; (c) station 3; (d) station 4; (e) station 5; (f) station 6;
Reference


