CALIBRATION OF MICRO-SIMULATION TRAFFIC-FLOW MODELS
CONSIDERING ALL PARAMETERS SIMULTANEOUSLY

Alexander Paz, Ph.D., P.E. (Corresponding author)
Assistant Professor
Department of Civil and Environmental Engineering
University of Nevada, Las Vegas
E-mail: paz.alexander@gmail.com
Address: PO BOX 454015, Las Vegas, NV 89154-4015
Ph.: (702) 688-3878

Victor Molano, M.S. Student
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Nevada, Las Vegas
E-mail: victor.hugo.molano@gmail.com
Address: 3875 Cambridge St Apt 911, Las Vegas, NV 89119
Ph.: (702) 595-6110

Alauddin Khan, MBA, P.E., P.T.O.E,
Chief Performance Management Engineer
Nevada Department of Transportation
Carson City, NV 89712 USA
AKhan@dot.state.nv.us

Submitted: August 1, 2013
Word Count: 3,978 + 4 tables * 250 + 10 Figures* 250 + = 7,478

A paper submitted for presentation at the 93nd Transportation Research Board Annual Meeting
January 12-16, 2014 and publication in the Transportation Research Record: Journal of the
Transportation Research Board
This study proposes a methodology to calibrate simulation-based microscopic traffic flow simulation models. This methodology has the capability to calibrate simultaneously all the calibration parameters as well as demand patterns for any type of network. Global and local parameters were considered as well as performance parameters for driver behavior and vehicles. Demand patterns, in terms of turning volumes, were included in the calibration framework. The primary contribution of this paper is the simultaneous consideration of multiple performance measures, such as link counts and speeds, while calibrating all model parameters across various time periods. This represents a very comprehensive approach for the calibration of simulation-based microscopic traffic flow models. Previous studies claim to consider all model parameters. However, they do not consider multiple performance measures simultaneously. In addition, in the experimental framework, most of them used pre-calibrated parameters and demand patterns. A Simultaneous Perturbation Stochastic Approximation algorithm was used to search for the vector of the model’s parameters that minimizes the difference between actual and simulated network states. The simultaneous consideration of all model parameters and multiple performance measures was motivated by issues associated with convergence and stability. The effects of changing the values of the parameters were taken into consideration to adjust them slightly and simultaneously. This resulted in a small number of evaluations of the objective function. Three networks were calibrated with excellent results. The first network was an arterial network with link counts and speeds used as performance measurements for calibration. The second network included a combination of freeway ramps and arterials, with link counts used as performance measurements. The third network was an arterial network, with time-dependent link counts and speed used as performance measurements. The experimental results illustrate the effectiveness and validity of this proposed methodology. The same set of calibration parameters was used in all experiments.
INTRODUCTION

Micro-simulation models provide tremendous capabilities to model, at a high level of resolution, complex systems in a broad range of fields, including economy, sociology, physics, chemistry, and engineering (1). In the context of vehicular traffic systems, microscopic traffic flow models enable modeling many aspects of the actual system, including the maneuvers of individual vehicles and their interactions, the various types and characteristics of facilities, and the vast number of control settings. These capabilities are associated with a large number of modeling parameters that typically need to be tailored for each vehicular system. For example, driver behavior includes parameters associated with car following, lane-changing maneuvers, and gap acceptance. Thus, the quality of the model and the validity of its results are highly dependent on the correctness of the chosen parameters (2-8). Hence, it is important to consider all these model parameters simultaneously, with the aim to capture their intricate effects, thereby seeking convergence and stability of the solutions.

A broad number of optimization algorithms, ranging from genetic algorithms to finite difference stochastic approximation, have been used to determine an adequate set of model parameters for a particular traffic system (2-4, 9, 10). For example, the sequential simplex algorithm was used to calibrate parameters for car-following, acceleration/deceleration, and lane-changing behavior (4). However, only a subset of parameters was considered. Moreover, parameters associated with infrastructure and vehicle performance were not considered. The algorithm provided adequate results under congested conditions. However, under low-congestion conditions, manual calibration provided better results (4).

Genetic Algorithms (GA) were used for the calibration of global and local capacity and occupancy parameters (11, 12). A sequential approach was used to update global and local parameters. Simultaneous Perturbation Stochastic Approximation (SPSA) algorithms also have been proposed. J. Lee used SPSA algorithms to calibrate model parameters using distributions to generate input for various stages (13). The calibration capabilities of GA and SPSA algorithms were shown to be similar; however, SPSA algorithms were less computationally intensive (11).

In addition, SPSA and Finite Difference Stochastic Approximation algorithms have been proposed for the calibration of time-dependent Origin-Destination matrices considering various time intervals. Balakrisna et al. proposed SPSA-based calibration framework to consider all model parameters (14). However, in their experiments, driver-behavior parameters were pre-calibrated. Other important performance measures, such as speed, were not considered. In contrast to previous studies, the proposed methodology in this paper seeks to calibrate, simultaneously and explicitly, all model parameters while concurrently considering multiple performance measures, such as link counts and speed as well as multiple time periods.

This study proposes a methodology to calibrate simultaneously all model parameters and demand patterns, based on link counts and speeds. This is in contrast with previous studies in which either only a subset of model parameters were considered, a single performance measure was used, or demand patterns were pre-calibrated. In addition, multiple time periods are explicitly considered with target performance values for each period. The proposed methodology implements a SPSA algorithm to determine an adequate set of all model parameters and turning volumes.

The SPSA was chosen based on its computational efficiency and ability to handle large numbers of parameters (13-20). Only two traffic-flow simulation evaluations per iteration of the SPSA are required to update all model parameters. Running a low number of traffic-flow simulations represents important savings in terms of time and other resources. Comparative
studies between SPSA and other algorithms can be found in the literature (14, 15, 18). In
addition, the SPSA algorithm was used to calibrate and optimize various transportation
applications (11, 13, 21).

METHODOLOGY

Formulation of the Calibration Problem
The calibration problem for all model parameters, $\theta$, was formulated using a mathematical
programming approach. The analysis period was divided into a number $T$ of discrete time
periods. The objective function, normalized root mean square (NRMS), as denoted by Equation
1, is the sum over all calibration periods of the average of the sum over all links $I$ of the root
square of the square of the normalized differences between actual and simulated link counts and
speeds. The normalization enables the consideration of multiple performance measures, in this
case, link counts and speeds. The calibration problem was formulated as follows:

Minimize $NRMS = \frac{1}{\sqrt{N}} \sum_{t=1}^{T} \left( W \sum_{i=1}^{N} \left( \frac{V_{i} - \bar{V}(\theta)_i}{V_i} \right)^2 + (1 - W) \sum_{i=1}^{N} \left( \frac{S_{i} - \bar{S}(\theta)_i}{S_i} \right)^2 \right)$

Subject to:

Lower bound $\leq \theta \leq$ Upper bound

Where:

$V_i$ = actual link counts for link $i$

$\bar{V}(\theta)_i$ = simulated link counts for link $i$

$S_i$ = actual speeds for link $i$

$\bar{S}(\theta)_i$ = simulated speeds for link $i$

$N$ = total number of links in the model

$T$ = total number of time periods $t$

$W$ = weight used to assign more or less value to counts or speeds based on the reliability of
the corresponding data

Calibration criteria
The calibration criteria for this study were based on guidelines from the Federal Highway
Administration. The difference between actual and simulated link counts should be less than 5%
for all links, and the GEH statistic (22) should be less than 5 for at least 85% of the links, where:

$$GEH = \sqrt{\frac{2(V_i - \bar{V}(\theta)_i)^2}{V_i + \bar{V}(\theta)_i}}$$

$V_i$ = actual link counts at the link $i$
\( \hat{v}(\theta_i) \) = simulated link counts at the link \( i \)

**Simultaneous Perturbation Stochastic Approximation algorithm**

The SPSA algorithm is an iterative approach that uses gradient estimations of the objective function to determine an optimal solution. Details of its implementation are provided by James C. Spall (16-18, 20). In each iteration of SPSA, the vector of model parameters was updated using Equation 3:

\[
\theta_{k+1} = \theta_k - a_k g_k \theta_k
\]  

(3)

where:

\( \theta_{k+1} \) = vector of updated parameters at iteration \( k+1 \)

\( \theta_k \) = vector of initial parameters at iteration \( k+1 \)

\( a_k \) = gain coefficient at iteration \( k+1 \) calculated using Equation 4

\( g_k \theta_k \) = estimated gradient at iteration \( k+1 \).

\[
a_k = \frac{a}{(k+1+A)^\alpha}
\]  

(4)

where \( a, A, \) and \( \alpha \) are empirical non-negative coefficients. These coefficients affect the convergence of the SPSA algorithm. The simultaneous perturbation and gradient estimate are represented by \( g_k \theta_k \), and is calculated using Equation 5.

\[
g_k \theta_k = \frac{y(\theta_k+c_k \Delta_k)-y(\theta_k-c_k \Delta_k)}{2c_k} [\Delta_{k1}^{-1}, \Delta_{k2}^{-1}, \Delta_{k3}^{-1}, \ldots, \Delta_{kp}^{-1}]^T
\]  

(5)

Here, \( c_k \) is calculated using Equation 6,

\[
c_k = \frac{c}{(k+1)^\gamma}
\]  

(6)

where \( c \) and \( \gamma \) are empirical non-negative coefficients.

The elements in the random perturbation vector \( \Delta k = [\Delta_{k1}^{-1}, \Delta_{k2}^{-1}, \Delta_{k3}^{-1}, \ldots, \Delta_{kp}^{-1}]^T \) are Bernoulli-distributed, with a probability of one-half for each of the two possible outcomes. The SPSA algorithm is implemented using the following steps (18):

Step 1: Set counter \( k \) equal to zero. Initialization of coefficients for the gain function \( a, A, \) and \( \alpha \) and calibration parameters \( \theta_0 \).

Step 2: Generate the random perturbation vector \( \Delta k \).

Step 3: Evaluate the objective function plus and minus the perturbation.

Step 4: Evaluate the gradient approximation \( g_k \theta_k \).

Step 5: Update the vector of calibration parameters using Equation 3 along with the corresponding constraints denoted by Equation 2.
Step 6: Check for convergence. If convergence is achieved, stop; otherwise, set counter $k = k + 1$ and repeat Steps 1-6. Convergence is achieved when all the criteria in Table I are satisfied or the maximum number of iterations is reached.

**Convergence Criteria**

Convergence is reached when the inequality in Equation 3 is satisfied or a user pre-specified maximum number of iterations is reached. At convergence, the calibration criteria are expected to be satisfied or a significantly better model is obtained.

$$
\sum_{k=n}^{k=N} \frac{\sqrt{\sum (NRMS_{AV} - NRMS_k)^2}}{N} < \rho
$$

where:

- $NRMS_{AV}$ = average NRMS of the last $k-N$ iterations
- $NRMS_k$ = NRMS at $k$ iteration
- $k$ = iteration counter
- $n$ = pre-specified integer
- $\rho$ = pre-specified convergence condition

**EXPERIMENTS AND RESULTS**

**Micro-simulation Model**

The proposed methodology was tested using CORSIM models, which integrates two different models to represent a complete traffic system, FRESIM for freeways and NETSIM for surface streets (23, 24). The *Traffic Analysis Toolbox Volume IV: Guidelines for Applying CORSIM Micro-simulation Modeling Software* (8) describes a procedure for the calibration of micro-simulation traffic-flow models, with a focus on CORSIM. The suggested procedure in these guidelines uses three sequential and iterative steps, including the calibration of (i) capacity at key bottlenecks, (ii) traffic volumes, and (iii) system performance. However, the guidelines do not suggest any particular methodology to perform the calibration in an efficient and effective manner. For example, issues associated with convergence and stability of the solutions are not discussed. Nevertheless, alternative studies have proposed and developed practical procedures to accelerate the calibration process, which typically is time consuming (25). However, stability and convergence continue to be issues.

**Calibration Parameters for CORSIM Models**

The calibration of CORSIM models can involve Driver Behavior and Vehicle Performance parameters (23, 24). These parameters can be defined exclusively for surface streets or freeways or both models simultaneously. In addition, the resolution of these parameters can be defined as global or link-based. This study considered all types of parameters and levels of resolution. In addition, parameters related to demand patterns were included.

Table 1 shows all the different parameters used for the calibration of CORSIM models. Several studies have conducted sensitivity analysis for the calibration of CORSIM models (7). These studies have showed that the maximum non-emergency deceleration rate, for example, does not affect the outcomes of a specific FRESIM model. However, the specific vehicle distributions improve the accuracy of the model (7). Driver-behavior parameters were found to
affect the time to breakdown and the flow on ramps. Flow-related parameters showed low effects. The calibration parameters have different effects for specific networks and conditions. 

The interaction between these parameters is very complex, and might vary from model to model. As a starting point, the proposed methodology used a set of default values for the parameters listed in Table 1. This decreased the effort during the selection of the calibration parameters and setup. In order to avoid unrealistic values, during calibration, the value of the selected parameters was adjusted while constraining their boundaries.

**TABLE 1 Calibration Parameters for NETSIM and FRESIM Models**

<table>
<thead>
<tr>
<th>NETSIM Model – Surface streets</th>
<th>Vehicle Performance</th>
<th>Demand Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Driver Behavior</strong></td>
<td><strong>Vehicle Performance</strong></td>
<td><strong>Demand Patterns</strong></td>
</tr>
<tr>
<td>• Queue discharge headway</td>
<td>• Speed and acceleration characteristics</td>
<td>• Turn movements in surface streets</td>
</tr>
<tr>
<td>• Start-up lost time</td>
<td>• Fleet distribution and passenger occupancy</td>
<td></td>
</tr>
<tr>
<td>• Distribution of free-flow speed by driver type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Mean duration of parking maneuvers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Lane change parameters</td>
<td>• Maximum left and right turning speeds</td>
<td></td>
</tr>
<tr>
<td>• Maximum left and right turning speeds</td>
<td>• Probability of joining spillback</td>
<td></td>
</tr>
<tr>
<td>• Probability of joining spillback</td>
<td>• Probability of left turn jumpers and laggers</td>
<td></td>
</tr>
<tr>
<td>• Probability of left turn jumpers and laggers</td>
<td>• Gap acceptance at stop signs</td>
<td></td>
</tr>
<tr>
<td>• Gap acceptance at stop signs</td>
<td>• Gap acceptance for left and right turns</td>
<td></td>
</tr>
<tr>
<td>• Gap acceptance for left and right turns</td>
<td>• Pedestrian delays</td>
<td></td>
</tr>
<tr>
<td>• Pedestrian delays</td>
<td>• Driver familiarity with their path</td>
<td></td>
</tr>
<tr>
<td>• Driver familiarity with their path</td>
<td>• Speed and acceleration characteristics</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Turn movements on freeways</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>FRESIM Model - Freeways</th>
<th>Vehicle Performance</th>
<th>Demand Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Driver Behavior</strong></td>
<td><strong>Vehicle Performance</strong></td>
<td><strong>Demand Patterns</strong></td>
</tr>
<tr>
<td>• Mean start-up delay at ramp meters</td>
<td>• Speed and acceleration characteristics</td>
<td>• Turn movements on freeways</td>
</tr>
<tr>
<td>• Distribution of free-flow speed by driver type</td>
<td>• Fleet distribution and passenger occupancy</td>
<td></td>
</tr>
<tr>
<td>• Incident rubbernecking factor</td>
<td>• Maximum deceleration</td>
<td></td>
</tr>
<tr>
<td>• Car-following sensitivity factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Acceptance parameters for a lane-change gap</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Parameters that affect the number of discretionary lane changes</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Experimental Setup and Results**

Three experiments were designed to test the capabilities of the proposed methodology to calibrate based on vehicle counts and speeds simultaneously.
First Experiment: Pyramid Highway in Reno, Nevada

In this experiment, a CORSIM model for a portion of the Pyramid Highway in Reno, Nevada, was calibrated. Figure 1 (a) shows a Google Map of the Pyramid Highway. Figure 1 (b) illustrates the corresponding CORSIM model. This portion of the highway is located between Milepost 1.673 and 5.131. The calibration focused on speeds and link counts for the entire simulation. The weight factor in the objective function was set to 0.7. This value was constant for the first two experiments because link counts were obtained by using more accurate methods for the data collection than for speeds. In addition, sensitivity analysis was conducted; with $W = 0.5$ and $W = 1.0$, the difference between actual and simulated link counts increased significantly. This implies that considering speeds data, even less reliable than counts, and related objectives contributes to the overall performance of the model and calibration process.

The model included 126 arterial links, but freeways were not included. Link counts and speeds were available only for 45 of these links. Coefficients for the SPSA algorithm were selected using guidelines from the literature (18). These values affected the convergence of the algorithm.

Figure 2 illustrates how the objective function was minimized. The noisy trajectory was a consequence of the stochastic perturbation applied to all calibration parameters to obtain the
gradient approximation at each iteration. The characteristics of the traffic model made the function noisier due to rounding. The $NRSM$ was 0.042 before calibration and 0.010 after calibration. The calibration process stopped around the 80th iteration, when a stable region was found.

![Normalized root mean square plot](image)

**FIGURE 2** Objective function for the first experiment.

Figure 3(a) shows the actual and simulated counts and speeds before calibration. These values present poor initial conditions, especially for the volumes over 1,500 vehicles per hour (vph). Figure 3(b) shows the actual and simulated counts and speeds after calibration. The proposed methodology is able to reduce the gap between actual and simulated counts. The results illustrate larger improvements for the large counts. Figure 3(a) clearly shows that links with counts over 1,500 vph were improved, while the values with good initial conditions were slightly modified.

As illustrated in Figure 3(a), simulated speeds differ greatly from actual speeds; the simulation model underestimates many speed values. After calibration (Figure 3(a), the speeds were improved for 23 of the links. The rest of the speeds were kept close to the initial values, with a variation less than 1 mile per hour (mph). This can be associated to the relative large value of the weight assigned to the counts in the objective function ($W = 0.7$). In addition, the experimental results showed that link counts were more sensitive than speeds to changes in the calibration parameters.

The GEH statistics for the models before and after calibration are shown in Table 2. It is clear that the calibration model significantly improves the GEH statistic. All the links reach a GEH statistic less or equal to 5, thereby satisfying the calibration criteria. The results show that the three calibration criteria were satisfied. In general, the proposed methodology was able to improve significantly the model outcomes.

Table 2 summarizes the calibration results for the first experiment. The total difference between actual and simulated link counts is 6% for all links in the network.
FIGURE 3 Actual vs. simulated counts and speeds before (a) and after (b) calibration.

TABLE 2 Summary of Calibration Results for the First Experiment

<table>
<thead>
<tr>
<th></th>
<th>NRMS</th>
<th>Total link counts</th>
<th>GEH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before calibration</td>
<td>0.042</td>
<td>45,359</td>
<td>&lt; 5 for 74% of the cases</td>
</tr>
<tr>
<td>After calibration</td>
<td>0.010</td>
<td>55,882</td>
<td>&lt; 5 for 100% of the cases</td>
</tr>
<tr>
<td>Actual</td>
<td></td>
<td>59,610</td>
<td></td>
</tr>
</tbody>
</table>

Second Experiment: I-75 in Miami, FL

In this experiment, a portion of I-75 in Miami, FL was calibrated. A total of 375 freeway ramps and 334 arterial links were included in the model. Data was available for 353 freeway ramps and 59 arterial links for a morning peak period of one hour. The coefficients of the SPSA algorithm were the same as those used in the first experiment. All the calibration parameters in the network were included as well as the turning volumes for freeways and arterials. The weight factor in the objective function was set to 0.7.

Figure 4(a) shows the Google map of I-75 highway in Miami, Florida. Figure 4(b) illustrates the corresponding CORSIM model. Figure 5 illustrates the trajectory of the objective function for this experiment. The NRMS goes from 0.270 to 0.245. Figure 6(a) illustrates the link counts for the ramp segments in the model before calibration, and Figure 6(b) shows the link counts for the ramp segments in the model after calibration.
counts for the ramps after calibration. These results clearly show that the calibration process significantly reduces the difference between actual and simulated link counts. It is clear that the calibration model significantly improves the $GEH$ statistic. 99.6% of the links reach a $GEH$ statistic less or equal to 5, thereby satisfying the calibration criteria.

![Image](a) ![Image](b)

**FIGURE 4** In Miami, Florida, Highway I-75 using (a) Google Map and (b) a CORSIM model.
Figure 5. Objective function for the second experiment.

Figure 6. Links counts before (a) and after (b) calibration for freeway ramps in the network.

Figure 7(a) illustrates the link counts for the arterials before calibration. Figure 7(b) shows the link counts for the ramps after calibration. These results show that there is significant improvement for links with large link counts. The calibration model significantly improves the GEH statistic. Seventy-six percent (76%) of the freeway ramp links reach a GEH statistic less or equal to 5.
Figure 6 and Figure 7 together show that the calibration methodology provides better results for freeway ramps than for arterials. This could be a consequence of having more data available for freeway ramps than for arterials, thereby giving more weight to the ramps.

Table 3 shows the ‘before’ and ‘after’ GEH statistics. As illustrated, the calibration improves the statistics, especially for the highest GEHs. However, some GEH values need to be improved because they are over 5.

### TABLE 3 Summary of Calibration Results for the Second Experiment

<table>
<thead>
<tr>
<th></th>
<th>Total link counts (vph)</th>
<th>GEH</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>FREEWAY</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before calibration</td>
<td>234,928.2</td>
<td>&lt; 5 for 86% of the cases</td>
</tr>
<tr>
<td>After calibration</td>
<td>257,454.1</td>
<td>&lt; 5 for 99.6% of the cases</td>
</tr>
<tr>
<td>Actual</td>
<td>271,908</td>
<td></td>
</tr>
<tr>
<td><strong>ARTERIALS</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before calibration</td>
<td>61,097</td>
<td>&lt; 5 for 66% of the cases</td>
</tr>
<tr>
<td>After calibration</td>
<td>68,927</td>
<td>&lt; 5 for 76% of the cases</td>
</tr>
<tr>
<td>Actual</td>
<td>80,524</td>
<td></td>
</tr>
</tbody>
</table>

*Third Experiment: Network from McTrans Sample Data Sets*

In this experiment, a network with arterials from the McTrans official web page was calibrated. A total of 20 arterial links were included in the model. Data was available for all the arterial links. Figure 8 shows the CORSIM model for this experiment.
The total simulation time was one hour divided into four time periods $t$ of 15 minutes each ($T = 4$). In this experiment, all parameters for all the links for all four time periods were updated. The coefficients of the SPSA algorithm were the same as those used in the previous experiments. All the calibration parameters in the network as well as the turning volumes were included. The weight factor in the objective function was set to 0.7.

Figure 9 illustrates the trajectory of the objective function corresponding to the third experiment. The initial NRMS value was 0.51, and the minimum obtained after 100 iterations of the optimization algorithm was 0.09.
Figure 10 illustrates the link counts and speeds before and after the calibration results for all links in the network for the first time period of the simulation. These results clearly show that the calibration process significantly reduces the difference between actual and simulated link counts and speeds.

Similar to Figure 10, Table 4 shows the summary of link counts and speeds for all links in the network for the second, third, and fourth simulation time periods. Relative to the ‘before calibration’ results, the calibrated results were significantly closer to the actual values. In addition, all links had a GEH statistic below the threshold limit of ‘5’ for all time periods. Speeds were improved for most links, especially for values less than 20 mph.

In this experiment, optimal parameters for the model were determined in order to reproduce time-dependent link counts and speeds. The calibrated parameters took a single value during the entire simulation process; that is, they were not time-dependent. In contrast, the link counts and speeds were time-dependent. These results illustrate the ability of the proposed calibration methodology to adjust model parameters so as to calibrate the time-dependent link counts and speeds. The summary of the results are showed in Table 4. Tables including values for the parameters before and after calibration are provided in (26).

FIGURE 9 Objective function for the third experiment.
CONCLUSION
This study proposed a methodology for the calibration of micro-simulation traffic-flow models. The design and implementation of this methodology sought to enable the calibration of generalized models. The calibration methodology was developed independent of characteristics for any particular microscopic traffic flow simulation model. At this point in the model development, the proposed methodology minimized the difference between actual and simulated time dependent link counts and speeds by considering all model parameters and turning volumes simultaneously.

The methodology used the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm to determine the calibrated set of model parameters. Previous studies have proposed the use of the SPSA algorithm for the calibration of vehicular traffic systems; however, few parameters were considered, and the calibration typically was based on a single performance measure, usually link counts. The simultaneous consideration of all model parameters and multiple performance measures was motivated by issues associated with convergence and
stability. During the experiments, the proposed algorithm always reached convergence and stability.

**TABLE 4 Summary of the Calibration Results for the Third Experiment**

<table>
<thead>
<tr>
<th>Time period 1</th>
<th>Before calibration</th>
<th>After calibration</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total link counts(vph)</td>
<td>10,126</td>
<td>17,136</td>
<td>17,276</td>
</tr>
<tr>
<td>GEH</td>
<td>&lt; 5 for 10% of the cases</td>
<td>&lt; 5 for 100% of the cases</td>
<td></td>
</tr>
<tr>
<td>Time period 2</td>
<td>Before calibration</td>
<td>After calibration</td>
<td>Actual</td>
</tr>
<tr>
<td>Total link counts(vph)</td>
<td>13,498</td>
<td>22,625</td>
<td>22,891</td>
</tr>
<tr>
<td>GEH</td>
<td>&lt; 5 for 10% of the cases</td>
<td>&lt; 5 for 100% of the cases</td>
<td></td>
</tr>
<tr>
<td>Time period 3</td>
<td>Before calibration</td>
<td>After calibration</td>
<td>Actual</td>
</tr>
<tr>
<td>Total link counts(vph)</td>
<td>10,502</td>
<td>17,820</td>
<td>18,767</td>
</tr>
<tr>
<td>GEH</td>
<td>&lt; 5 for 0% of the cases</td>
<td>&lt; 5 for 100% of the cases</td>
<td></td>
</tr>
<tr>
<td>Time Period 4</td>
<td>Before calibration</td>
<td>After calibration</td>
<td>Actual</td>
</tr>
<tr>
<td>Total link counts(vph)</td>
<td>10,533</td>
<td>17,939</td>
<td>19,013</td>
</tr>
<tr>
<td>GEH</td>
<td>&lt; 5 for 0% of the cases</td>
<td>&lt; 5 for 95% of the cases</td>
<td></td>
</tr>
</tbody>
</table>

This methodology was tested using CORSIM models. However, there is nothing preventing the implementation of this methodology to calibrate other models. Three different vehicular traffic systems were calibrated, taking into consideration all their model parameters by using various performance measures, including link counts and speeds. The first experiment included arterials, using as performance measures link counts and speeds. The second system included both arterials and freeways. Considering arterials and freeways represented a significant challenge because two different models with different parameters needed to be considered simultaneously. The third experiment included time-dependent link counts and speeds for four time periods during this experiment; in addition, global, individual, and time-dependent parameters were considered.

The experimental results illustrated the effectiveness of the proposed methodology. The three vehicular traffic systems used in this study were successfully calibrated; specifically, the calibration criteria were satisfied after the calibration was performed. The results from the first and third experiment showed that speeds improved after calibration; in fact, the quality of the second vehicular traffic system improved significantly. However, further sensitivity analysis of the parameters used by the SPSA algorithm is required to achieve better results and satisfy the calibration criteria. Further, as the number of parameters required for calibration increases, the complexity of the optimization problem also increases as well as the complexity to determine the set of required optimization coefficients.

The same set of calibration parameters was used in all the experiments. Therefore, any effort during parameter selection was reduced. The results improved for the entire model, and all calibrated parameters were within reasonable boundaries. Similarly, no irregularities were observed using the graphical user interface. The calibration software developed in this study can be downloaded, along with a user’s guide and examples, using this link:
http://faculty.unlv.edu/apaz/files/Calibration%20Tool%20Demo.zip. Hence, readers can replicate the results from this study. The calibration tool developed as part of this study used an optimization algorithm that required a set of coefficients to find the appropriate set of CORSIM model parameters. A time-consuming sensitivity analysis of these coefficients was required to achieve desired results.

A bi-level optimization framework was required to enable the simultaneous calibration of traffic flow and SPSA parameters. The first level of the bi-level framework represented the existing calibration tool developed as part of the existing project, whose objective was the calibration of CORSIM models under saturated conditions. The Simultaneous Perturbation Stochastic Approximation (SPSA) optimization algorithm was used to determine the appropriate calibration parameters. The second level of the proposed bi-level framework corresponds to future research, which objective will be to automate the sensitivity analysis that is required to find the right set of optimization coefficients for the SPSA algorithm.

REFERENCES


