A New Calibration Methodology for Microscopic Traffic Simulation Using Enhanced Simultaneous Perturbation Stochastic Approximation (E-SPSA) Approach

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ABSTRACT

Traffic simulation models can represent real-world conditions, such as delays, travel times, queues, and flows. However, accurate evaluation of these traffic conditions is highly dependent on the selection of model parameters and the calibration methodology.

Most previous calibration studies have focused on minimizing the sum of the differences between the observed data and simulation output during a certain time period on a typical day. However, to capture a realistic distribution of all possible traffic conditions, a more general calibration methodology that can be used with any traffic condition is required.

This paper proposes a new calibration methodology—the Bayesian sampling approach in conjunction with the application of the SPSA stochastic optimization method (Enhanced SPSA or E-SPSA)—that enables the modeler to enhance calibration by considering statistical data distribution. A microscopic simulation model based on PARAMICS, developed by Quadstone Limited, is used in conjunction with the proposed methodology. Instead of calibrating with input data for certain time periods, calibration is performed with the data obtained from a complete input distribution. Mean square variation (MSV) was used to evaluate accuracy of the proposed E-SPSA calibration approach. On the basis of the MSV of flows, the MSV value of the E-SPSA methodology was found to be 0.940, which was greater than the variation of speed obtained from SPSA-only (0.897) or from a variation approach proposed by Sanwal et al. (1) (0.888). Thus, this proposed methodology not only makes it possible to overcome some of the limitations of previous calibration approaches, but also improves the results of simulation model calibration by accurately capturing a wide range of real-world conditions. Future work will focus on testing the proposed calibration methodology using more extensive data sets and models developed using simulation tools other than PARAMICS.
INTRODUCTION AND MOTIVATION
Calibration studies have been performed for various traffic simulation tools. In general, the modeler starts by using default parameters, which might not always represent the observed conditions of the modeled network. To accurately represent real traffic conditions, the default parameters are changed in accordance with a theoretically sound calibration methodology until various observations, such as flows or travel times, match observed values. Lee et al. (2), Schultz and Rilett (3), Park and Qi (4), Kim et al. (5), and Ma and Abdulhai (6) used genetic algorithms (GAs) to calibrate microscopic simulation tools. Ciuffo et al. (7) used the OptQuest/Multistart algorithm (OQMS) for simulation-based calibrations and the analytical stationary traffic flow model for model-based calibration. Kim and Rilett (8) used the simplex algorithm, whereas Kundé (9) used the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm to calibrate a model developed in DynaMIT-P, a mesoscopic simulation tool. Ding (10) and Ma et al. (11) calibrated a network model using PARAMICS, and Balakrishna et al. (12) conducted a calibration study of a microscopic simulation model developed using MITSimLab, while employing the SPSA algorithm.

The above studies generally focused on determining the effectiveness of their optimization methodologies and minimizing the objective function, which is generally the sum of the differences between the observed and simulated data during a certain period of time of a typical day. However, this approach cannot capture a realistic distribution of all possible traffic conditions and may produce inaccurate calibration results. Hollander and Liu (13) mentioned that a comparison of the distributions between the observed and simulated data using the K-S test is a better validation method than the examination of individual observations. Lee and Ozbay (14) performed the calibration of a macroscopic simulation model based on the cell transmission model and compared its output with the distribution of the observed values from using the K-S test. This approach was found to improve the results of simulation calibration by accurately capturing realistic distribution of the observed traffic characteristics.

For the calibration of microscopic simulation models to accurately represent real traffic conditions, the parameter values need to be calibrated for each input datum generated from an observed distribution. However, calibration with the entire data from multiple days and a wide range of time periods is too computationally intensive and cannot reflect the uncertain demand caused by variations in input data. In most previous studies, the sum of differences between observed data and simulated output were used to measure goodness of fit. Most of these previous studies failed to note that having the same mean for the observed data distribution as for the simulated output does not imply that these distributions are identical. In addition, this traditional approach cannot create a series of data to be compared with simulation output when the demand is uncertain. Waller et al. (15) studied the influence of demand uncertainty and compared the use of a single determined value for future demand with true expected future performance. Molina et al. (16) used the Bayesian approach to overcome these problems and predicted the behavior of traffic at a signalized intersection in Chicago. The Bayesian analysis method proposed by Molina et al. (16) enables finding the posterior distribution of the parameters of demand (\(\lambda\)) and turning probability (P) given the data (C), denoted by \(\pi(\lambda, P | C)\), that is acquired from a prior distribution for \(\lambda\) and P, with the data densities given for \(\lambda\) and P. However, they did not use a stochastic optimization method to find “best” values for the calibration parameters.

This paper considers calibration in the context of a wide range of likely demand conditions. Thus, it proposes a new and enhanced calibration methodology based on applying Bayesian sampling techniques in conjunction with the SPSA stochastic optimization method, which we call Enhanced SPSA (E-SPSA), to achieve more effective calibration of microscopic traffic simulation models.

PROPOSED METHODOLOGY FOR THE CALIBRATION OF A MICROSCOPIC SIMULATION MODEL
We propose the use of the Bayesian sampling approach in conjunction with the SPSA approach proposed by Spall (17). Flows and speeds are obtained using a microscopic simulation model based on PARAMICS, which was developed by Quadstone Limited. The objective function is shown below:
The basic steps of our proposed methodology can be summarized as follows:

1. Increment iteration: \(\text{iteration} = \text{iteration} + 1\)
2. Compare the output of a simulation for the demand \(I_k\) given \(h_k\) and \(r_k\) in the current iteration—namely, flows—with the observed distribution of flows to determine the statistical similarity between the two distributions (where \(k = 1, 2, ..., 100\)). If it is satisfactory, terminate the iterative process and proceed to the validation step. Else return to Step 1.
3. Perform validation test. If satisfied, then stop. Else return to Step 1.

Figure 1 shows a flowchart of the proposed combined E-SPSA calibration and validation methodology.
DESCRIPTION OF THE STANDARD SPSA ALGORITHM

Search algorithms can be divided into two general categories: gradient and gradient-free. The stochastic root-finding algorithm proposed by Robbins-Monro (18) is generally used for nonlinear problems when the gradient function is available. When measuring the gradient is impossible, as with simulation, a gradient-free approach is applied. The finite-difference (FD) approximation is the best-known gradient approximation method; however, the FD approximation is performed only when the noise measurements of the loss function are available. The well-known SPSA algorithm introduced by Spall (17), (19), (20) has an inherent advantage that can be exploited in both stochastic gradient and gradient-free settings—it can be applied to solve optimization problems that have a large number of variables. Spall (21) performed the optimization work to control signal timing using the SPSA algorithm, and its effectiveness was proved. A dynamic multi-ramp metering control using the SPSA algorithm was performed by Luo (22), and the effectiveness of SPSA therein was shown for freeway operations. The application of the SPSA algorithm to the calibration of simulation can be also found in Kundé (9), Ding (10), and Balakrishna et al. (12).

The SPSA algorithm is an applicable stochastic optimization method for multivariable equations, and the standard SPSA algorithm has the following form:

\[
\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \hat{g}_k(\hat{\theta}_k)
\]

Here, \( \hat{g}_k(\hat{\theta}_k) \) estimates the gradient \( g(\theta) = \partial L(\theta) / \partial \theta \), based on the loss function (usually termed “objective function”) measurements at \( \theta = \hat{\theta}_k \) at the \( k^{th} \) iteration.

The new value of \( \theta \), obtained for every iteration, is calculated by subtracting the product of step size and the gradient at the present value from the previous value of \( \theta \), as shown in equation (3). With simultaneous perturbation, loss measurements are obtained by randomly perturbing the elements of \( \hat{\theta}_k \). Assuming that \( \theta \) is \( p \)-dimensional, the SP gradient approximation step can be expressed as follows:

\[
\hat{g}_k(\hat{\theta}_k) = \frac{L(\theta + c_k \Delta_{k1}) - L(\theta - c_k \Delta_{k1})}{2c_k \Delta_{k1}} \ • \ • \ • \\
\hat{g}_k(\hat{\theta}_k) = \frac{L(\theta + c_k \Delta_{k2}) - L(\theta - c_k \Delta_{k2})}{2c_k \Delta_{k2}} \ • \ • \\
\hat{g}_k(\hat{\theta}_k) = \frac{L(\theta + c_k \Delta_{kp}) - L(\theta - c_k \Delta_{kp})}{2c_k \Delta_{kp}} \\
\hat{g}_k(\hat{\theta}_k) = \frac{L(\theta + c_k \Delta_{k}) - L(\theta - c_k \Delta_{k})}{2c_k} \Delta_{k}^{-1} \Delta_{k}^{-1} \ldots \Delta_{kp}^{-1} \ldots \Delta_{lp}^{-1}
\]

Here, the \( p \)-dimensional random perturbation vector \( \Delta_{k} = [\Delta_{k1}, \Delta_{k2}, ..., \Delta_{kp}]^T \) is user-specified and its components are usually \( \pm 1 \) Bernoulli variables.

DESCRIPTION OF Bayesian SAMPLING METHODOLOGY

This study proposes an enhanced simulation calibration methodology that combines the stochastic optimization algorithm and Bayesian sampling techniques. The main purpose of using sampling methodology is to incorporate time-varying conditions from a probabilistic distribution of demand. In our problem, the output of PARAMICS is
generated as a result of the randomly sampled origin–destination (O-D) demands and input parameters calibrated in
the previous iteration. The objective of the E-SPSA analysis is to find the best simulation parameters given
randomly sampled demand values. This study, in the way it performs the sampling of demand, is similar to
the methodology proposed by Molina et al. (16) in that the initial distribution (prior distribution in the case of Molina et
al. (16)) of demands is obtained by the Bayesian sampling technique.

IMPLEMENTATION DETAILS OF THE PROPOSED E-SPSA CALIBRATION METHODOLOGY

Data Collection
In traffic simulation models, the vehicular demand is modeled by using traffic zones. For freeway segments, these
zones are usually placed at a segment upstream of the segment under study. If the study segment is relatively short
and the flow is observed on all sections, the demand generated from the zone will, on an average, be equal to the
flow observed at the segment under study. Thus, it can be assumed that the flow observed at a point on the freeway
has resulted from the same amount of demand generated at a zone upstream of the segment. In this study, the
demand matrices were generated by using the traffic counts (i.e., flows from loop detectors).

A new demand matrix is formed from flows that are randomly selected from the distribution of observed flows,
which is the prior distribution. Thus, a generated demand matrix is effectively a sample from the initial distribution.
However, depending on the existence of intermediate ramps, a random demand matrix can be formed from the
distribution of observed flows for the two distinct geometries. The basic calibration procedures of demand
originating from a single zone and of demand originating from several zones may differ slightly because of the
sampling methodology. For the ramp scenario, the prior distribution is obtained from the relationship between the
flow on the mainline and that on a ramp. To take into account the existence or lack of correlation between demands,
the demand matrix needs to be generated using conditional or independent samples, respectively.

Because the goal in this paper is to introduce a new calibration methodology, a well-accepted but easy-to-implement
traffic condition was chosen for the simulation. The calibration of a single zonal demand case was performed to test
the effectiveness of the proposed E-SPSA approach. It is clear that the proposed calibration methodology can be
implemented in conjunction with any other road condition.

Data were obtained from the database of the Freeway Service Patrol project for a portion of the I-880 freeway in
Hayward, California (Skabardonis et al. (23)). Data from 6:00 AM to 10:00 AM weekdays were collected over a
period that ranges between September 27 and October 29, 1993 (reflecting at capacity and uncongested conditions)
and aggregated into 5-minute counts. Data for all time periods for 16 different days were employed.

![Histogram of Flow (6:00-10:00)](image)

Figure 2 Histogram based on the distribution of the 16 days of observed demand (21)
The network was created in the PARAMICS model based on the data from the Freeway Service Patrol study (23). The selected freeway segment is a five-lane one-way road with length 2.7 km. The layout of the study segment is shown in Figure 3.

![Figure 3 Layout of the study segment modeled using PARAMICS](image)

**Demand Matrix Generation from the Observed Distribution of Demand**

Selecting a best-fit distribution for the data histogram is crucial to accurate data analysis because an inappropriate distribution causes incorrect input data generation. How well the selected distribution matches the data distribution is determined by a goodness-of-fit test such as the Kolmogorov-Smirnov (K-S) test, Anderson-Darling test, or Chi-Square test. Easyfit software (24) was used to determine the best-fit distribution for the data set and to compensate for uncertainties. In addition, the software shows the parameter values and the results of a goodness-of-fit test for 40 different distributions.

Easyfit software determined the beta distribution whose parameter values are $\alpha_1=3.56$, $\alpha_2=2.18$, $a=944.5$, and $b=2100.5$ to be the best fit for our data set (where $a$ indicates the minimum value and $b$ the maximum value of the data). Figure 4 shows a histogram of the data, with the distribution-fitting.
The obtained beta distribution is compared with the observed data distribution, using the K-S test (Miller et al. (25)). The K-S test is appropriate in our case because its critical values do not rely on the distribution’s shape. In addition, the effectiveness of small errors can be avoided by investigating the probability (Hollander and Liu (13)). However, the K-S test is applicable only to continuous distributions and is normally more sensitive around the center of the distribution (26). Kim et al. (5) performed the K-S test to ensure that the distribution of the simulation travel time represented real traffic conditions. In contrast, Anderson-Darling is only applicable to a few types of distributions and a chi-square test requires sufficient sample size (27).

The null hypothesis states that there is not a statistically significant difference between the beta distribution and the observed flow distribution. On the basis of the results of the K-S test, summarized in Table 1, the null hypothesis cannot be rejected at any reasonable confidence levels, i.e., the sampling from the beta distribution can be assumed to represent the distribution from the data histogram. However, for the Anderson-Darling test, the null hypothesis can be rejected at confidence levels of less than 95 percent (Table 2).

<table>
<thead>
<tr>
<th>Table 1 Results of the K-S Test</th>
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<td>Kolmogorov-Smirnov test</td>
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<td>P-Value</td>
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<td>Critical Value</td>
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<th>Table 2 Results of the Anderson-Darling Test</th>
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<td>Anderson-Darling test</td>
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<td>Sample Size</td>
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Determination of the Optimal Parameters that Minimize the Error using the Enhanced SPSA Algorithm

PARAMICS is capable of controlling individual vehicle movements that address model input parameters, such as car-following parameters, seed value, signpost distance, lane-changing, and time step of simulation per second. Among the parameters, driver behavior factors—mean target headway and mean reaction time—directly influence the car-following model and the lane-changing model. Many studies of microscopic calibration have been performed with these two parameters, to modify simulation results (Ma and Abdulhai (6); Gardes et al. (28)). Thus, for input data \( I \), the parameter values of PARAMICS—mean target headway and mean reaction time—are determined using the SPSA algorithm.

In most previous studies, simulation calibration was performed with a single input datum \( I \) obtained at one point in time and parameter values were optimized using a specific methodology, such as the genetic, simplex, or trial-and-error method (Lee et al. (2); Kim and Rilett (8); Gardes et al. (28); Toledo et al. (29)). However, a simulation model calibrated using traffic data obtained from a limited time period over certain days under an unknown input distribution might not be able to represent the traffic conditions on other days. A more robust approach is to calibrate for the entire range of the input data \( (I) \), to enable representing a complete range of possible traffic conditions \( (i = 1, 2, ..., n) \). However, this method requires considerable computing resources to run the simulation for each replication of demand. In addition, because traffic flow is variable and none of the predicted future traffic counts can be observed, there are limitations in accurately representing predicted traffic conditions with predetermined parameter values that are optimized using a certain day’s data. Therefore, rather than calibrating using input data from certain time periods only, calibration with the data obtained from a complete input distribution is deemed to be necessary.

In this paper, based on the randomly sampled \( "m" \) number of input data points, which cover the whole range of the input distribution, the mean target headway \( (h_j) \) and mean reaction time \( (r_j) \) are optimized using the SPSA algorithm for each sample, and the distributions of \( h_i \) and \( r_i \) given the values of \( I \) \( (i = 1, 2, ..., n, j = 1, 2, ..., m, m < n) \) are determined. Based on the optimized values of \( h_j \) and \( r_j \) as a function of demand, the trend lines and their functional representations are also obtained for both of them. These relationships for the mean target headway distribution given demand \( (h_i | I) \) and for the mean reaction time given demand \( (r_i | I) \) are shown in Figure 5.

![Mean Target Headway Distribution](image)

Figure 5 (a)
Analysis of the Simulation Output for the Optimized Input Parameters

A simulation output is a function of input data given mean target headway and mean reaction time, denoted by $F(I_k|\lambda, r)$. One hundred sampled input data ($I_k$) and optimized parameter values, given $I_k$, were the inputs to PARAMICS, and the outputs of the simulation were compared with the observed data distribution obtained from real data. For each sample, the generated sample data $I_k$, the mean target headway, and the mean reaction time were calculated using the estimated equations shown in Figure 5. The K-S test was performed as a goodness-of-fit test to compare the distribution obtained from the simulation outputs using the optimized input parameters with the distribution obtained using observed data.

Statistical Comparison of the Distributions Obtained Using Simulated and Observed Data

The Kolmogorov–Smirnov (K-S) test was performed to ensure that the distribution of the simulation results represented real traffic conditions. A comparison was made between the observed data distribution and the distribution of the simulation results acquired from 100 sampled input data and their optimal parameter values. The K-S test value for flow distribution was 0.059, which is less than any of the critical values obtained from the K-S table shown in Table 3. This result indicates that there is no statistically significant difference between the two distributions and thus the calibrated simulation model represents real-world conditions. Figure 6 shows a probability comparison between the observed data and simulation results.

<table>
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<th>Table 3 Results of the Kolmogorov-Smirnov Test</th>
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Comparison of the Degree of Deviations

The E-SPSA methodology was evaluated against the SPSA-only calibration method and a variation approach proposed by Sanwal et al. (1). It is difficult to compare the calibrated model performance with the similar performance results found in other calibration papers. However, the mean square variation (MSV) that Sanwal et al. (1) used is a good method to compare the degree of deviation from the observed values. Fitness criteria for MSV are

\[ R_{fit}^2 = 1 - \frac{E[(v - v_m)^2]}{E[v_m^2]} \]

(where \(v_m\) and \(v\) denote measured speeds and model speeds, respectively). A value close to one indicates that the model’s estimations are close to real-world measurement.

The MSV value of the E-SPSA methodology was 0.940, which was better than those obtained from the SPSA-only methodology (0.897 for October 18, 1993) or the variation approach (0.888). In other words, on the basis of the MSV values, the SPSA-only methodology produced only slightly more accurate results than did the approach of Sanwal et al. (1). Thus, it can be safely stated that neither of these approaches can match the E-SPSA methodology in accurately representing a complete range of traffic conditions.

Validation Test

After the K-S test was satisfied for the calibration step, a validation test was performed for the data of a time period that was not used for the calibration study. For the 15-minute flow range of 1200–1400 vehicles, eight different days’ simulation output distributions were compared with the observed data distributions. Figure 7 shows a comparison between the observed data and simulation probability results.
The K-S test was performed to verify the null hypothesis that there is not a statistically significant difference between the distribution of the simulation results and that of the observed flow. Based on the K-S test, the value of the flow distribution, 0.028, was less than the critical value of 0.192 obtained from the K-S table at the 95% confidence level. This demonstrated that the observed and simulated flow distributions have an acceptable level of similarity (fit) with each other.

CONCLUSIONS AND FUTURE RESEARCH

This paper proposed a new calibration methodology using the Bayesian sampling approach in conjunction with the SPSA stochastic optimization method. This methodology enables the use of a wide range of traffic conditions from an observed data distribution. It also considers uncertainties. Data were obtained for a portion of the I-880 freeway in Hayward, California and aggregated into 5-minute counts for 16 different days. The input distribution was estimated using Easyfit software.

The section of I-880 was first modeled in PARAMICS and then calibrated using the proposed methodology. The simulation results of a microscopic model varies in sensitivity based on the input parameters such as geometries, signposting, or factors related to the behavior of drivers. Thus, the calibrated parameters for a single demand matrix might not generate accurate results for other demands that are likely to occur depending on the time of the day, day of the week, the month, or the season.

The E-SPSA approach allows for the calibration of a simulation model for the whole range of input data and helps to determine the optimized parameter values for this wide range. In this paper, based on “m” number of sampled data points from the complete distribution of demands that covers the whole range of the input distribution, input parameters were optimized using a well-known stochastic optimization algorithm, SPSA, at each iteration \((h_i, r_i | I_j)\) (where \(j = 1,2,...,m\)). The distributions of \(h_i\) and \(r_i\) given \(I_j\) \((h_i, r_i | I_j)\) were assumed to follow the trend lines shown in Figure 5.

The distribution of simulation output for 100 samples of input data \((I_k)\) was compared with the distribution of the observed data. The optimized parameter values given \(I_k\) were determined from Figure 5. The K-S test was used to ensure that the distribution of the simulation results represented real traffic conditions. The K-S test value for flow distribution was 0.059, which was less than any of the critical values obtained from the K-S table, that is, the calibrated simulation model can capture real-world conditions.

The MSV measure used by Sanwal et al. (1) was applied as an evaluation criterion to compare the degree of deviations from the observed values. The MSV value of the E-SPSA methodology was 0.940 after parameter fitting, whereas the values of the SPSA-only methodology and the variation approach were 0.897 for October 18, 1993 and 0.888, respectively. Thus, it can be safely stated that neither of the latter approaches can match the E-SPSA methodology in accurately representing a complete range of traffic conditions.

A validation test was also performed to verify that the parameter values obtained from E-SPSA were applicable to data from days that were excluded from the calibration dataset. For the 15-minute flow range of 1200–1400 vehicles, the simulation output distributions for eight different days were compared with the observed data distributions. Based on the K-S test, the value of the flow distribution (0.028) was less than the critical K-S value (0.192) obtained from the K-S table at the 95% confidence level, i.e., the simulated flow distribution was not statistically different from the observed flow distribution.

This analysis showed that calibration based on E-SPSA can capture day-to-day randomness of traffic because it employs a wide range of data obtained from a representative probability distribution of traffic over different days and periods within a day. On the other hand, there are limitations in capturing traffic conditions accurately for the complete input distribution when calibrating using SPSA-only or the variation approach. This is because these methods require considerable computational time to run the simulation for each input and still cannot reflect day-to-day randomness of traffic flow, mainly due to a lack of robust sampling needed to guarantee an accurate representation of the complete input distribution. Therefore, E-SPSA, which uses Bayesian sampling, was found to
improve the results of simulation calibration by accurately capturing a wide range of time-dependent real-world conditions, overcoming the limitations of previous calibration studies.

Future research tasks include testing the proposed E-SPSA methodology for larger and more networks and for other microscopic traffic simulation tools such as CORSIM and VISSIM. Other simulation parameters and more extensive data sets will be used to test the strengths and weaknesses of the methodology.
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