Calibration of SUMO Microscopic Simulator for Sri Lankan Traffic Conditions

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Abstract: This research presents an automated calibration framework coupled with SUMO microscopic traffic simulation software to calibrate model parameters related to car-following and lane-changing models in heterogeneous traffic conditions. The calibration framework is based on a stochastic approximation algorithm named Simultaneous Perturbation Stochastic Approximation (SPSA). The proposed method is implemented for a link on an urban corridor in Colombo, Sri Lanka, by calibrating one car following and four lane change model parameters. The calibrated parameters provide a good fit to observed traffic speed measurements. Due to its automated model creation and calibration process, the methods can be easily extended to create and calibrate larger networks to better represent Sri Lankan traffic conditions in traffic simulation models.

Keywords: Calibration, SUMO, SPSA, Heterogeneous Traffic Conditions, Sri Lanka

1. INTRODUCTION

Traffic congestion has been a significant problem in urban transportation for many years. To counter traffic congestion, it is essential to implement effective traffic management and control strategies. Microscopic traffic simulations play an important role by providing a testbed for decision-makers to understand the suitability of different traffic control approaches. To make accurate decisions from traffic simulations, they must be properly calibrated for the specific network, rather than using the default model parameters provided in the simulation software (Yu and Fan, 2017). However, in Sri Lankan context, as in many developing countries, traffic simulations' calibration needs to represent the heterogeneous traffic conditions, poor lane discipline, and aggressive driving behavior for better results.

Model calibration is a process of adjusting the estimates of the different model parameters to better represent the actual traffic condition (Olstam and Tapani, 2011). This is an iterative process to be carried out until the difference between the observed and simulated traffic measurements is reduced to an agreed level. Due to the complex interdependencies between the model parameters and simulation outputs, the calibration of traffic simulation models is often considered as an optimization problem where the error between simulated and observed traffic measurements are minimized.

The motivation behind this research is to introduce and use such automated traffic model calibration approaches as a solution for the traditional trial and error approaches. In this research, a Stochastic Approximation (SA) algorithm named Simultaneous Perturbation Stochastic Approximation (SPSA) proposed by Spall (1998) was used to automate the calibration process.

Its generic problem formulation enables the SPSA to use any actual traffic measurements available for calibration. The SPSA is also computationally efficient algorithm that requires only two objective functions to be evaluated at a given iteration to calculate new estimates, regardless of the total number of parameters being calibrated. Therefore, this research methodology could be also applicable for calibrating larger microscopic traffic models.

The objectives of this research are twofold: 1) to develop a generic methodology of creating microscopic traffic simulation models with SUMO by taking advantage of the existing traffic data, 2) to develop a systematic and automated calibration procedure to calibrate such models using available true traffic measurements to estimate the model parameters to represent the actual traffic conditions closely.

2. LITERATURE REVIEW

The objective of traffic model calibration is to closely represent the simulation to the real-world data or ground truth. Balakrishna *et al.* (2007) argue that the direct use of the outputs of the simulation model helps to capture the nonlinear dependencies of the variables (model parameters) and the data (true measurements). For microscopic traffic model calibration, it would be ideal to have disaggregated data for the calibration. However, such data is costly and difficult to collect. Therefore, in practical applications, only aggregate traffic measurements will be available. A web-based survey conducted by Brackstone *et al.* (2012) reveals that some practitioners use personal experience in calibrating models where the simulation results of the initial estimates are used to modify the selected model parameters until a satisfactory calibration is reached. However, this approach is tedious and hard to replicate in a new model. Most importantly, it does not guarantee to achieve an optimal set of estimates.

A list of previous calibration work conducted using microscopic traffic simulation models is summarized by Yu and Fan (2017). According to the summary, Genetic Algorithm (GA), SPSA are widely used in previous work. A case study comparing GA and SPSA for calibrating microscopic models is presented by Ma *et al.* (2007). The research shows that SPSA can obtain a good set of calibrated model parameters in much less time compared to GA, while GA produces more stable solutions in the numerical experiments. Therefore, the modeler must decide the tradeoff between calibration accuracy and computational cost when selecting a calibration algorithm. Kostic *et al.* (2017) also highlights convergence issues of SPSA at higher dimensional calibration problems and proposes techniques and approaches to improve the performance of SPSA. This problem, in relation to transport modeling, has been studied intensely in dynamic demand calibration. Solutions such as W-SPSA (Antoniou *et al.* 2015) and PC-SPSA (Qurashi *et al.* 2020) have been proposed to overcome some shortcomings of the basic form of SPSA for higher-dimensional problems.

In the Sri Lankan context, Jayasooriya and Bandara (2018) used queue lengths to calibrate PTV Vissim model parameters. Eight parameters were considered in this study, and the error was minimized by changing parameter values manually. Vajeeran and Silva (2020) researched the effectiveness of the manual traffic control methods compared to the traffic signals. As a part of the study, the driver behavioral parameters were calibrated using a trial-and-error process. Simulated and observed queue lengths were used in the error minimization process. Therefore, in Sri Lanka, microscopic traffic simulation model calibration using automated methods has not been researched extensively.

3. METHODOLOGY

This study formulates the calibration problem as a generalized optimization problem given below.

$$\underset{\theta}{Minimize} \quad z(y, \acute{y}) \tag{1}$$

with $\acute{y} = f(x, G, \theta)$

subject to $\theta \in \Theta$

where:

$y, \acute{y}$	: Observed and simulated traffic measures
θ	: Parameters being calibrated
x	: Traffic demand
G	: Network
z	: Goodness of fit function
Θ	: Domain of allowable values for θ

Where the best possible values for θ are determined such that z is minimized by keeping x static.

3.1 SPSA Algorithm

SPSA is generally used for large scale nonlinear problems with expensive objective function evaluations. In SPSA, the next set of estimates for the parameters are calculated as:

$$\hat{\theta}_{k+1} = \hat{\theta}_k - a_k \hat{g}_k(\hat{\theta}_k) \tag{2}$$

Where $\hat{\theta}_{k+1}$ represents the estimated parameters through the evaluated gradient $\hat{g}_k$ at the k^{th} iteration by perturbing $\hat{\theta}_k$. a_k defines the minimization step size, predefined using the hyperparameters. Perturbation of $\hat{\theta}_k$ calculates two sets of intermediate estimates in the form of $(\hat{\theta}_k + c_k\Delta_k), (\hat{\theta}_k - c_k\Delta_k)$, used to obtain two measurements of the objective function. Here, c_k governs the magnitude of the perturbation and Δ_k is a Monte Carlo random vector with the dimensions of the number of parameters being calibrated. Each element of the Δ_k vector is independently generated from a zero-mean probability distribution. In SPSA, the variables are perturbed simultaneously, so the gradient can be approximated by using only two evaluations of the objective function regardless of the number of parameters to be estimated.

$$\hat{g}_k(\hat{\theta}_k) = \frac{y(\hat{\theta}_k + c_k\Delta_k) - y(\hat{\theta}_k - c_k\Delta_k)}{2c_k} \begin{bmatrix} \Delta_{k1}^{-1} \\ \Delta_{k2}^{-1} \\ \vdots \\ \Delta_{kp}^{-1} \end{bmatrix} \tag{3}$$

a_k and c_k are defined based on the guidance given in Spall (1998) by carefully selecting the values for hyperparameters $c, \gamma, a, A,$ and α. With k being the iteration number, the hyperparameters of the algorithm define the pattern of reductions in c_k and a_k for each increment of the iterations.

$$c_k = c \,/\, k^{\gamma} \quad , \quad a_k = a \,/\, (k + A)^{\alpha}$$

Such that:

$$a_k, c_k > 0 \quad , \quad a_k, c_k \to 0 \text{ as } k \to \infty$$

$$\sum_{k=1}^{\infty} a_k = \infty \quad , \quad \sum_{k=1}^{\infty} \frac{a_k^{\,2}}{c_k^{\,2}} < \infty$$

3.2 SUMO Simulator

In this study, the SUMO (Simulation of Urban Mobility) microscopic traffic simulator was used as the modelling software. SUMO is a free, open-source, portable, microscopic, and continuous multi-modal traffic simulation package designed to handle large networks. SUMO has various capabilities and number of tools to support modler's requirements (Lopez *et al,* 2018).

3.3 Calibration Workflow

Figure 1 describes the workflow of the calibration algorithm. The initial estimate used in the calibration can be set to the simulator's default values or an initial set of values based on modeler's judgement if no prior estimations are available for the model parameters in concern. The estimates from the previous iteration are perturbed at a given iteration, as mentioned in subsection 3.1. The perturbed estimates are passed to the SUMO simulator to get the speed outputs for each perturbed estimate set to evaluate the objective function. After the gradient approximation step and the estimation of new model parameters, the simulator runs again to evaluate the objective function with new estimates. Therefore, for a given iteration, three simulation runs are required.

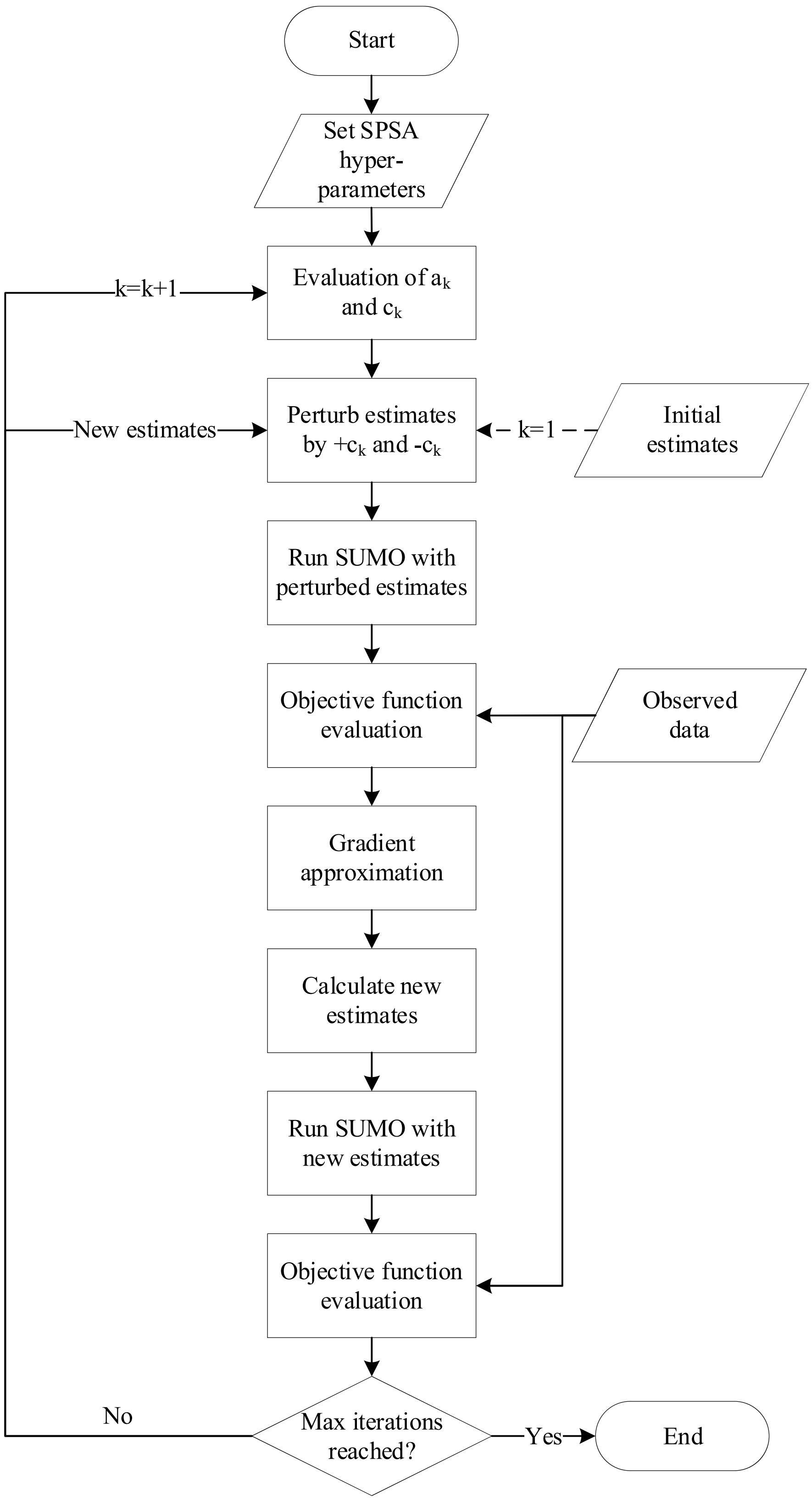


Figure 1. Flowchart of SPSA

The simulated outputs are compared with the observed traffic measurements using a goodness of fit measure. The mean absolute percentage error (MAPE) is used in this study.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \quad (4)$$

where,

y_i : simulated value
$\hat{y}_i$: observed value
i : is ranging from the number of measurements captured $[1,2,\dots,n]$

3.4 Using the Traffic Counts with SUMO

The traffic data need to be processed into a SUMO readable .xml file format to run the simulations, as illustrated in Figure 2.

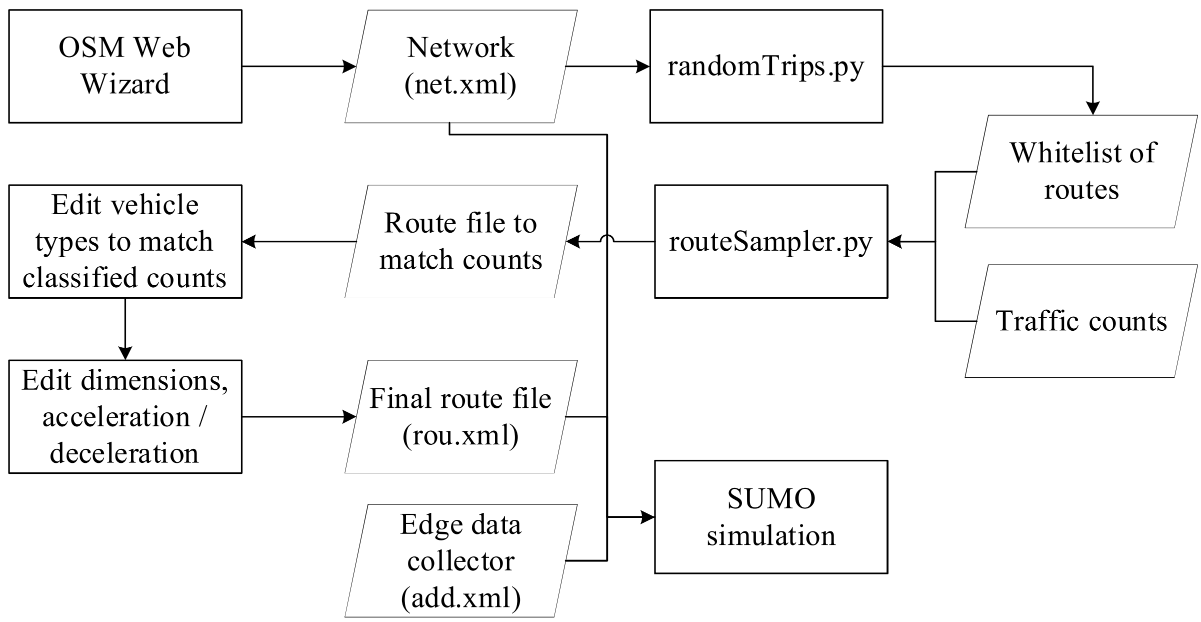
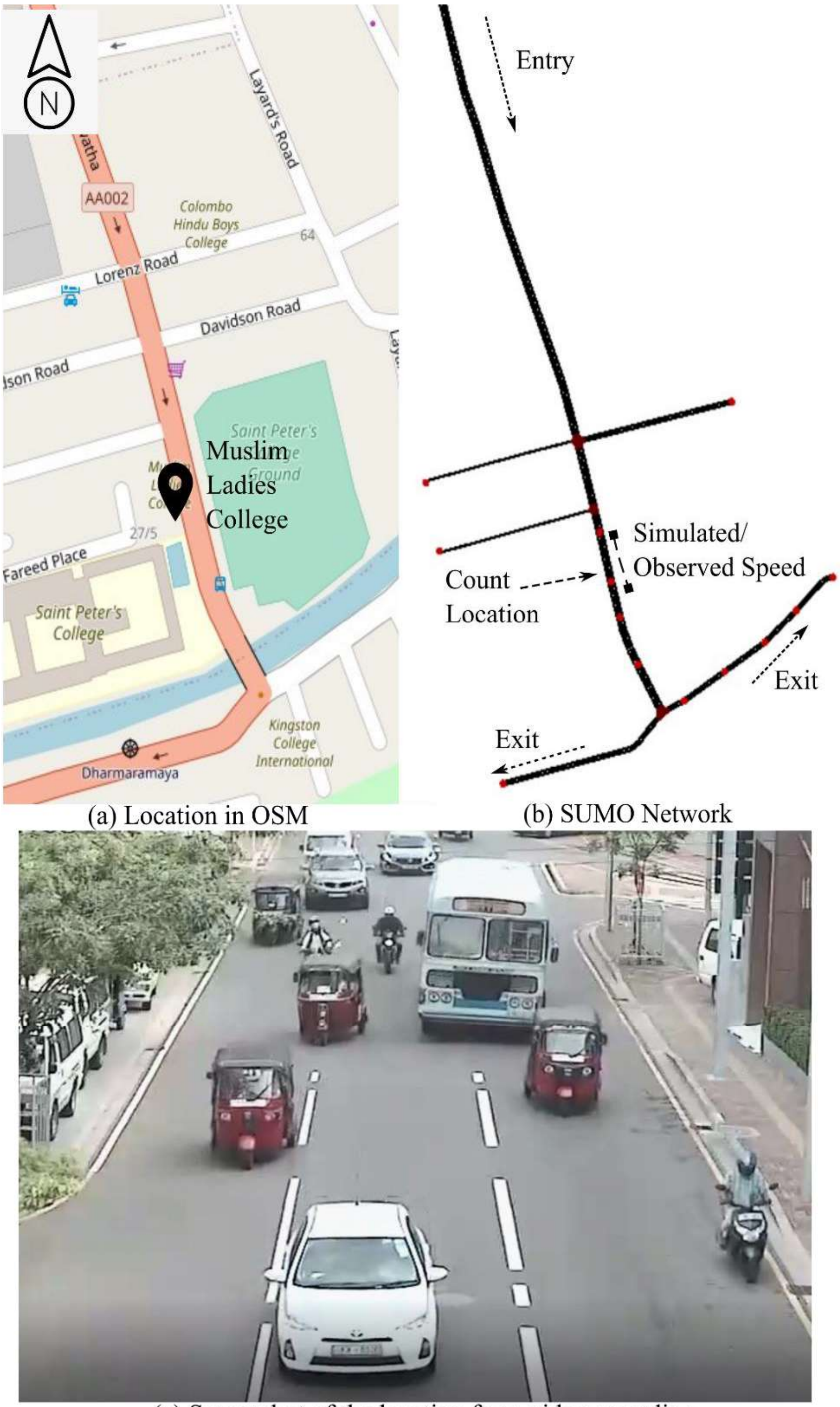


Figure 2. Workflow to create SUMO Simulation

The workflow begins with the road network in the interested study area downloaded using 'Open Street Map (OSM) Web Wizard', a built-in tool in SUMO installation. The network is edited to represent the actual number of lanes per direction, connection between edges. The network is then used as an input to 'randomTrips.py' to generate candidate routes for the vehicles. The candidate routes and the traffic counts are then used as an input to 'routeSampler.py', which produce a route file that matches the vehicle counts and the time intervals. This output file is then edited via a Python script to represent the classified counts for the given intervals. After that, the dimensions of different vehicle types and corresponding acceleration and deceleration values were changed if necessary. This finalized route file and road network are then used as inputs in the SUMO simulator. An edge-based state dump is also defined as an additional file (add.xml) to collect the required simulation outputs.

4. CASE STUDY

A three-lane, one-way traffic road segment of a 2 km section of the Duplication road corridor in Colombo, Sri Lanka, was selected as the case study area, as shown in Figure 3.



(a) Location in OSM (b) SUMO Network

(c) Screenshot of the location from video recording

Figure 3. Case study area

The selected section was used to test the proposed simulation framework to calibrate selected car-following and lane-changing model parameters. The number of vehicles enters/exit from the three by-lanes are neglected due to their low volumes. Therefore, the simulation was set up such that all the vehicles enter the network from the topmost edge of the network and leaves the network from one of the two exit edges. In addition, the disturbances for the traffic flow from other factors (e.g., pedestrian movement, on-street parking) were observed to be minimum from the site visits and the video recordings (Figure 3 (c)). Therefore, in this study, the impact of such disturbances on traffic flow is considered insignificant.

4.1 Data Collection and Preparation

4.1.1 Traffic counts

A video recording of the vehicles passing a count location near Muslim Ladies College, as shown in Figure 3, was used to obtain a classified count for each 5-minute interval. Two-hour data from 07:00 am to 09:00 am were extracted from the video footage collected on 20th August 2020 for model creation and calibration. Altogether 4,387 vehicles were counted in these two hours. The vehicle composition for the period of data collection is given in Table 1.

4.1.2 Speed data

Google Apps Script was used to capture the average speed of the selected road segment on the same day and same period for validation purposes. Speeds were captured every 5 mins, providing 24 measurements for two hours. Within a simulation, the first five minutes was considered as a warm-up period. Therefore, the observed and simulated measurements during that interval were not considered for the calibration. Similarly, the last two measurements were not considered in the calibration due to the lack of interaction between vehicles as the vehicles gradually start to leave the simulation towards the latter part of the simulation. Therefore, a total of 21 actual measurements were compared against the simulated traffic speeds for the calibration.

4.1.3 Characteristics of vehicle types

The length and width of each of the vehicle categories found on Sri Lankan roads were measured as shown in Table 1.

Table 1. Vehicle composition and dimensions

Vehicle Type	SUMO Vehicle Class	Composition (%)	Length (m)	Width (m)
Motorcycle	Moped	21.6	2.0	0.9
Three-wheeler	-	35.9	2.5	1.5
Cars	Passenger	31.4	4.3	1.8
Van	Passenger	3.3	5.3	2.1
Minibus	Bus	1.2	7.0	2.4
Large bus	Bus	4.9	10.8	2.9
Light goods	Truck	0.8	3.7	1.8
Medium goods	Truck	0.6	6.2	2.3
Heavy goods	Truck	0.2	8.5	3.0

In most situations, default values for each vehicle classes were used, including the acceleration and deceleration values except for three-wheelers, taken from Bokare and Maurya (2017).

4.2 Experimental Setup

4.2.1 Model parameter selection

Car following and lane changing manoeuvres can be considered as the most common driving behaviour on urban roads. Car following models describe the longitudinal movement of the vehicles, whereas the lane changing models describe lateral movements of the vehicles.

'Krauss' model, the default car-following model of SUMO, is used for this study. Krauss model has six parameters, and four of them (minGap, accel, decel, emergencyDecel) are vehicle class specific. For those parameters, the default values given for each vehicle class were used. The model parameter 'tau' intends to model driver's desired time headway and default value of 1 second was used in this study. The model parameter 'sigma' governs the stochastic driving behaviour. When 'sigma' is not equal to zero, vehicles randomly vary their speeds based on a random number. This parameter was considered for the calibration as it can be used to model the imperfectness of driving. The default acceptable value range for 'sigma' is between 0 and 1. For this study, the possible value range for 'sigma' was further restricted to accept values between 0.25 and 1, so that randomness due to driver imperfection is guaranteed throughout the simulation runs.

The lane-changing model in SUMO is based on four different motivations (strategic, cooperative, tactical, and regulatory) for lane changing (Erdmann, 2015). From the video recordings, it was clear that certain vehicle types do sharp manoeuvres to gain speed. Therefore, model parameters that represent driver's 1) willingness to change lanes to gain speed and 2) willingness to encroach laterally on other drivers was considered as two model parameters. Two other lane-changing parameters were selected to represent the strategic and cooperative lane changing behaviours.

Brief definitions for the selected model parameters, their acceptable value range for the simulator, and the initial guess assigned for the model parameters for each vehicle type are given in Table 2.

Table 2. SUMO model parameters used in the calibration (DLR, 2021)

Model parameter	Definition	Value range	Default value	Initial guess*
sigma	The driver imperfection (0 denotes perfect driving)	[0-1]	0.5	0.9
lcSpeedGain	The eagerness for performing lane changing to gain speed (higher values result in more lane changing)	[0-inf)	1.0	1.0
lcPushy	Willingness to encroach laterally on other drivers	[0-1]	0	0.5
lcStrategic	The eagerness for performing strategic lane change – higher values result in earlier lane-changing	[0-inf)	1.0	0.5
lcCooperative	The willingness to perform cooperative lane changing. Lower values result in reduced cooperation	[0-1]	1.0	0.5

* Authors initial guesses

The sub-lane model in the SUMO simulator was activated to simulate the lack of lane discipline as suggested by Sashank *et al.* (2020) for calibrating model parameters for Indian 'lane-less' traffic conditions. The sub-lane model accepts one parameter called 'lateral-resolution' that divides the regular lanes into sub-lanes with a minimum value of the given lateral resolution. In this study, the parameter's value was fixed at 1.0 meters, which is based on the width of the vehicle type that has the least width (motorcycle) with a small buffer.

4.2.2 Stochastic aspects of the experiment

Stochasticity in microscopic traffic simulations is an important aspect of reproducing reality (DLR, 2021). Microscopic traffic simulation models have higher computational complexity compared to both mesoscopic or macroscopic traffic models. Therefore, ensuring the stochastic aspects of the simulation and the calibration while keeping the computational time to a manageable level is important. The following steps were followed in this study to ensure the stochastic aspects of the experiment:

1. For a given simulation run, each vehicle enters the simulation from the least occupied lane with a maximum possible speed. This behaviour and a value for ‘sigma’ always greater than zero will ensure the randomness for each simulation run.

2. Once the error is reduced to a certain acceptable level, SPSA is restarted with different random seeds to ensure that the error reduction is consistent regardless of the random seed chosen in SPSA. Once a set of feasible solutions are identified, multiple simulations are run for the same set of estimates using different random seeds of the simulator to identify the best set of estimates.

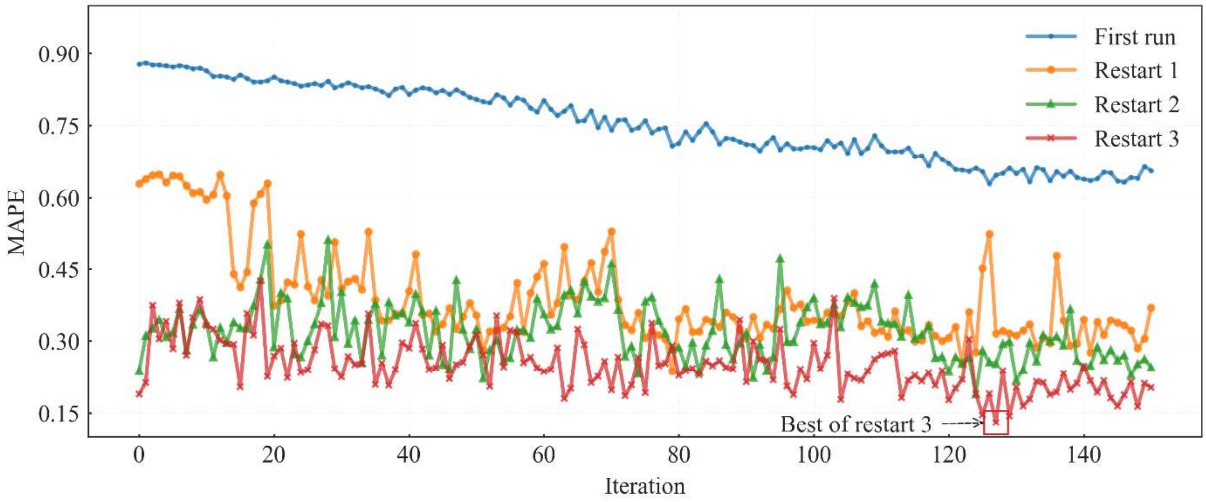
4.2.3 Hardware and software

The calibration procedure was implemented in Windows 10 platform with an AMD Ryzen 5 processor and 8GB RAM. The scripts were implemented in python 3.9. The execution time for 150 iterations was about 8 hours and 25 mins.

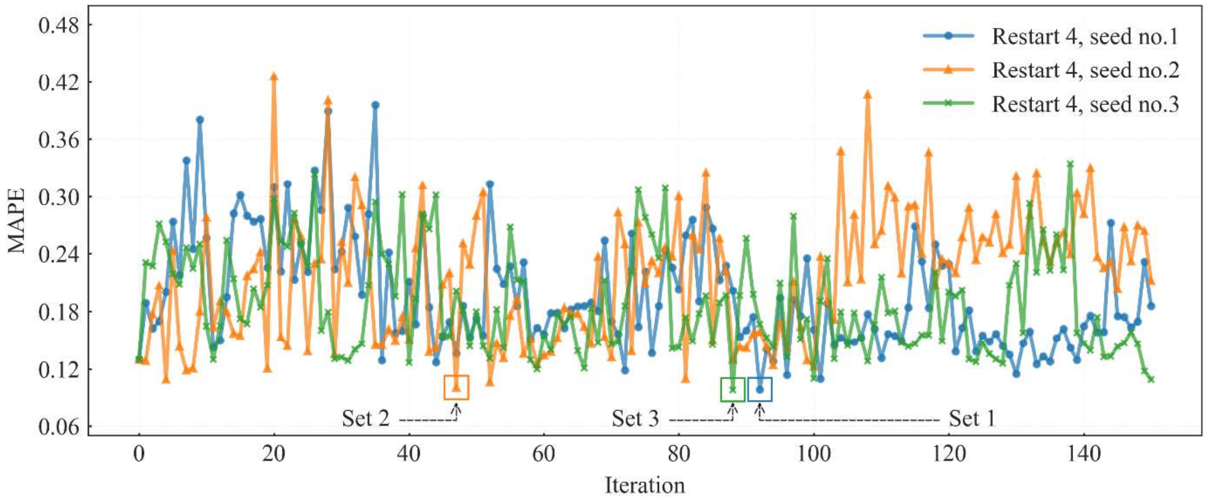
5. VALIDATION OF RESULTS

5.1 Convergence

In comparing the goodness of fit value (MAPE) with the number of iterations, the model parameter estimates that provided the lowest MAPE or the highest goodness of fit have been identified as a feasible solution for the next step of the experiment. The error reduction using the SPSA algorithm was done in stages and the results are given in Figure 4.



(a) Initiate SPSA algorithm and restart with previously calibrated solution



(b) Restarting SPSA algorithm with different random seeds

Figure 4. Change of MAPE with the iterations

Figure 4 (a) shows how the error has been reduced starting from the initial guess. For all these experiments, the random seeds used in the SPSA algorithm and the simulator were fixed. The initial guess produced a MAPE of 0.87. Over the iterations of the first run, the algorithm was able to reduce the MAPE to 0.62. The error reduction has been plateaued after the 120th iteration. Therefore, it was decided to limit the number of iteration to 150 for a given calibration. The parameter estimates that provided the best results (lowest MAPE) from the previous calibration was used as the initial guess for the next calibration run. This feedback method, named as ‘algorithm restart', helps improve the convergence of SPSA and avoid local minima (Kostic *et al.* 2017). Three algorithm restarts were performed and each restart was able to reduce the error compared to the previous run, as shown in Figure 4 (a). Algorithm restart 3 produced the lowest error with a MAPE value of 0.13, annotated in Figure 4 (a).

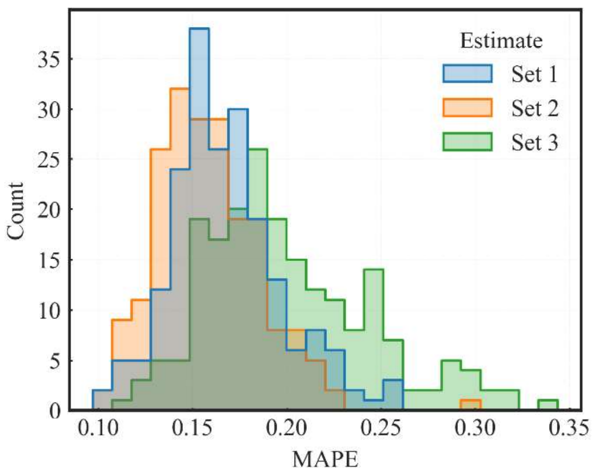
Figure 4 (b) shows the result of algorithm restart 4. The best results from algorithm restart 3 was used as the initial guess for restart 4. In addition, restart 4 was repeated three times using three different random seeds while keeping the random seed of the SUMO simulator unchanged. Though the error reduction in restart 4 was minimum, it was able to reduce the MAPE further. Three sets of experiments belong to three different seeds at iteration 92, 47 and 88, respectively (as shown in Figure 4 (b)) produced their lowest values as shown in Table 3 and considered the candidate solutions from the calibration.

Table 3. Candidate estimates for calibrated model parameters

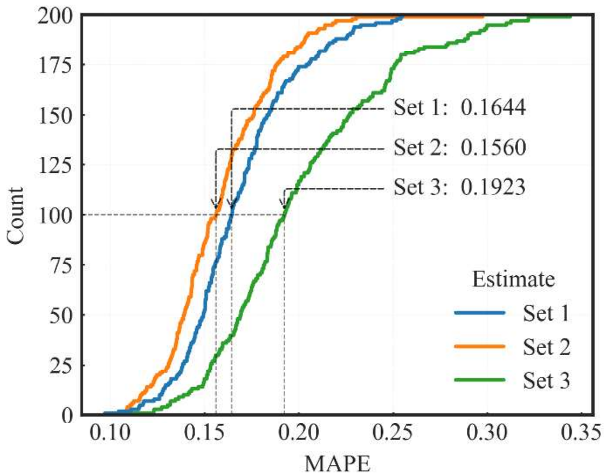
Model parameter	Calibrated estimates		
	Set 1	Set 2	Set 3
sigma	0.84032494	0.79383816	0.76949289
lcSpeedGain	6.02258474	5.22275400	6.84867586
lcPushy	0.92484981	0.79390518	0.94947069
lcStrategic	5.69255636	5.91387018	7.63341656
lcCooperative	0.99917092	0.99917092	0.99729995
MAPE	0.0986	0.1006	0.0981

5.2 Selection of Best Estimates

The candidate solutions were then tested by changing the random seed of the simulator. Each candidate solution was tested with 200 random seeds, and the resulting MAPE values were calculated and given in Figure 5.



(a) Histogram



(b) ECDF

Figure 5. Statistical comparison of the error distribution

The histogram for error distribution is shown in Figure 5 (a), and the empirical cumulative distribution function (ECDF) is shown in Figure 5 (b). Since the distributions are not symmetric, median values are used as an appropriate central tendency measure. It can be seen that the lowest MAPE values got in from the calibration (Table 3) are largely different from the median

MAPE values when the simulation is performed using multiple different random seeds. From the ECDF plot in Figure 5 (b), and the overall statistical summary provided in Table 5, it is clear that estimate set 2 is consistent in producing lower MAPE values than the other two sets of estimates.

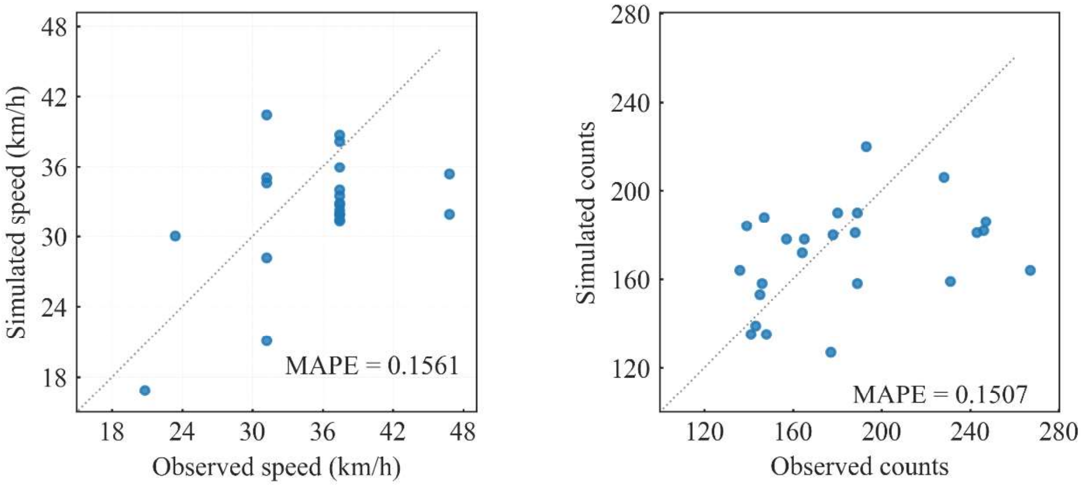
Table 4. Statistical comparison of candidate estimates

Calibrated estimates	Mean	Median	Standard deviation
Set 1	0.1680	0.1644	0.0294
Set 2	0.1581	0.1560	0.0278
Set 3	0.2005	0.1923	0.0446

Therefore, set 2 was considered as the best set of estimates for the model parameters to describe the traffic scenario used for this case study.

5.3 Comparison with Observed Traffic Measurements

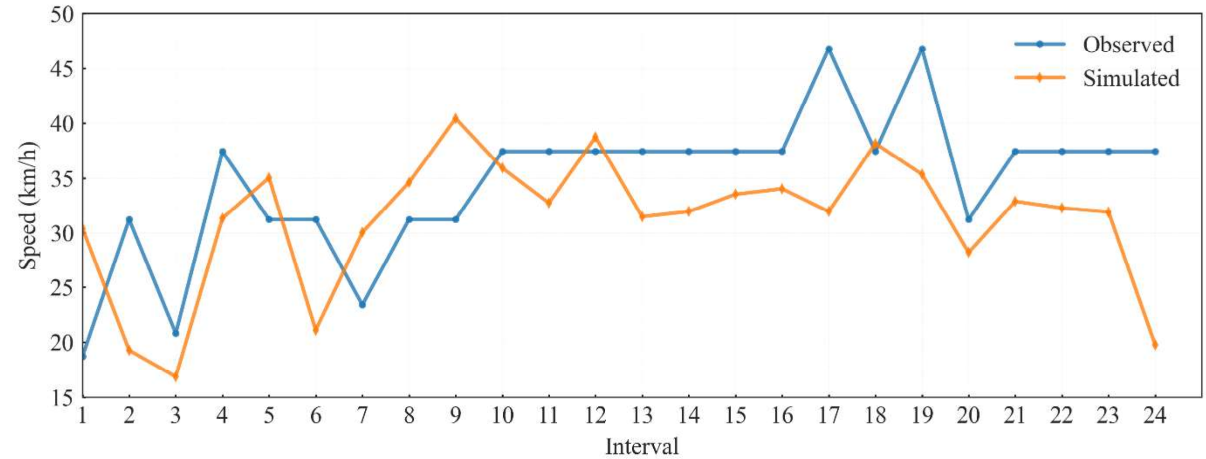
The scatter plots in Figure 6 (a) and (b) shows the calibrated model's simulated speeds and traffic counts compared to their observed counterparts. The diagonal line represents the case of perfect calibration. In Figure 6, a fair scenario is considered where the MAPE for the speeds is closer to the median MAPE, summarized in Table 4.



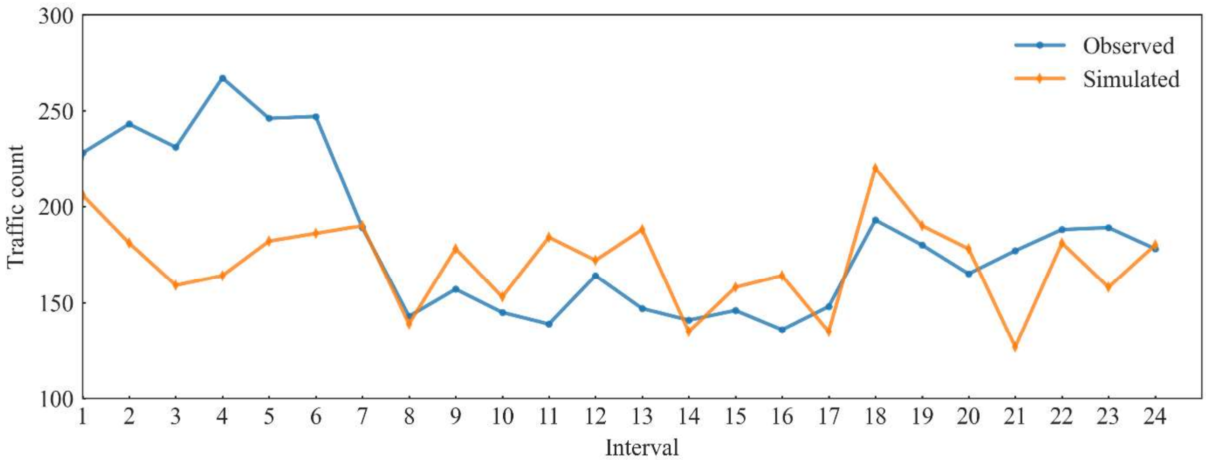
(a) Traffic speeds (b) Traffic counts

Figure 6. Calibrated model – Goodness of Fit

Figures 6 (a) and (b) show that the simulated values match well with the observed data. Speed values show more symmetry over the diagonal line, indicating that the calibration is successful. However, the scatter plot for traffic counts shows some data points with higher observed values. The main reason for this is that 278 vehicles (3.72% of total flow) have left the simulation after the planned simulation time of the simulation. In the experiment, the traffic counts were matched only once, and the calibration was done using the speed values for the objective function evaluation. However, according to the results, it is clear that it is important to consider traffic counts also in the calibration process to improve the overall accuracy of the calibration. A similar comparison of the simulated traffic measures is made with their observed values, including their respective time intervals in Figure 7.



(a) Comparison of observed and simulated speeds



(b) Comparison of observed and simulated counts

Figure 7. The calibrated model compared with the observed data over times intervals

Figure 7 (a) clearly shows that the simulated speeds obtained with the calibrated model parameters compare well with the observed speeds. The measurements from interval 2 to 22 were considered to evaluate the objective functions. The simulated speeds closely follow the observed speeds, especially from interval 3 to 21. However, the simulated traffic counts match well with the observed values from interval 7 onwards. This suggests that the calibrated model closely follows the reality for around 1 hour of the total simulation period.

5.4 Discussion

Using SPSA based calibration procedure, the study reduced the MAPE between simulated and observed speeds up to 0.15. The calibration of the car-following and lane-changing model parameters could be further improved, for example, using different variants of SPSA, better selection of model parameters, using more true measurements, and using different objective functions.

Table 5. Comparison of default and calibrated model parameters

Model parameter	Default	Calibrated
sigma	0.5	0.7938
lcSpeedGain	1.0	5.2227
lcPushy	0.0	0.7939
lcStrategic	1.0	5.9138
lcCooperative	1.0	0.9991

According to the summary given in Table 5, most of the calibrated parameter estimates are largely different from the simulator's default values. The car-following model parameter 'sigma' shows a higher value than the default value. It indicates that a higher driver imperfectness can simulate the traffic flow closely.

The calibrated estimates for lane change model parameters are also different to the default values. The drivers are more eager to do a lane change to gain speed than the default settings of the simulator. Also, drivers are more willing to encroach laterally on other drivers. The video recordings used for traffic counts justify higher values for 'lcSpeedGain' and 'lcPushy' as certain vehicle types (e.g., motorcycles, three wheelers, and cars) do quick lane change manoeuvres to gain speed by avoiding a slow leading vehicle. A higher value for strategic lane changing suggests that drivers are more eager to perform a strategic lane change. The calibrated value for corporate lane changing is similar to the default value of the model parameter, suggesting that it is reasonable to use the default estimate of the parameter.

6. SUMMARY AND CONCLUSION

Calibration of microscopic traffic simulations is a complex problem that requires an optimization algorithm based automated calibration procedure that provides significant advantages compared to trial-and-error methods. This study aims to understand the possibility of calibrating the SUMO simulator to match traffic conditions in Sri Lanka. An automated calibration procedure based on SPSA was used. Simulated and observed speeds were used to evaluate the objective function. The developed methodology is tested in a smaller urban corridor in Colombo, Sri Lanka, where actual traffic data were available.

The simulator-based case study proves that SPSA based automated calibration procedure can calibrate the model parameters to match the observed speed measurements. The corresponding set of estimates that produced the error distribution with the lowest median value (MAPE: 0.1560) considered as the calibrated estimates for one car-following and four lane-changing model parameters. The calibrated estimates well explained the traffic conditions compared to the observed speed and flow data. For the case study used in this research, results suggest that the drivers' random speed variatons are higher. Moreover, the drivers' willingness to change lanes in order to gain speed and as well as their willingness to encroach laterally on other drivers were also found to be higher.

One important future work is to test out the calibration procedure for a larger network with more traffic measurements at multiple locations. In the current study, the model parameters were calibrated such that the estimate of a particular model parameter is common for all vehicle types. For a larger network, this can be extended such that each model parameter is calibrated separately for different vehicle types, preferably by using variants of SPSA.

It is also important to look at how different model parameters change at different traffic conditions (e.g., peak/off-peak, urban road/expressway) so that these calibrated model parameters can be used for model creation and as a set of initial guesses for further calibration.

It is also argued that simulating heterogeneous traffic conditions with weaker lane discipline is difficult using conventional models (Papathanasopoulou and Antoniou 2018). The development of technology and the availability of high-quality traffic data enables the development of advanced data-driven microscopic traffic simulation models. The data-driven models help to easily include additional variables rather than relying on fixed formulas used in conventional microscopic simulation models. Therefore, it is important to incorporate such methods and compare the results between conventional models and data-driven methods.

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