CALIBRATION OF MICRO-SIMULATION MODEL PARAMETERS FOR HETEROGENEOUS TRAFFIC USING MODE-SPECIFIC PERFORMANCE MEASURE

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ABSTRACT

Calibration is an essential pre-requisite to scenario evaluations using traffic micro-simulation models. In the context of mixed traffic operations, where different fast and slow moving vehicular modes form a heterogeneous environment, a well-calibrated model needs to give adequate importance to each mode in order to realistically replicate the complex interactions in the traffic stream. This paper presents a methodology for calibrating traffic micro-simulation model for such mixed traffic conditions. A combination of vehicle mode-specific travel time distributions is adopted as the performance measure for the calibration. In order to aid practitioners, each step of the methodology is demonstrated using VISSIM simulator considering a signalized corridor in the Kolkata metro city, India. The work includes Genetic Algorithm based optimization for obtaining mode-specific parameter sets. Kolmogorov-Smirnov test is carried out to compare the travel time distributions of different modes. The calibrated model is also validated considering several signalized approaches along the calibrated study corridor. The results show that the methodology is successful in developing a model for non-lane based mixed traffic operations with vehicle mode-specific optimized parameter sets.

Keywords: calibration, traffic micro-simulation, multi-modal traffic, VISSIM, genetic algorithm, K-S test

INTRODUCTION

Evaluation of alternative strategies for a road network is generally constrained by financial and legal implications which restrict the use of field experiments. In this regard, traffic micro-simulation models, hereby referred to as TMMs, have gained popularity as an essential tool for scenario evaluations (*1-3*). TMMs have a large set of parameters designed to describe the traffic and control operations. Majority of these parameters can be modified, and their default values can only replicate the performance of a disciplined and homogeneous traffic stream under standard operating environment. The efficiency of TMM lies in its ability to replicate the local characteristics (*4*). No single TMM can be expected to be equally accurate for all possible scenarios, and a poorly calibrated model is a prime reason for skepticism among policy-makers and non-modelers alike. Thus, researchers have realized the need for proper calibration which consists of selection and modification of input parameter values to reflect particular traffic scenarios (*4-6*) and "improve the ability of the model to accurately reproduce local traffic conditions" (*7*).

Significant contributions have been made in the recent past for TMM calibration (*4,8-11*). A comprehensive review of different TMM calibration methods (*12*) highlighted the most important issues and made recommendations for different steps, that include, formulation of calibration process, identification of important parameters, selection of goodness of fit measure, and model validation. Most of the calibration attempts on TMMs reported in literature have been limited to scenarios with relatively homogeneous traffic operations where a single set of modified parameter values could suitably replicate the entire traffic stream performance. However, the situation is significantly different in emerging economies, such as India, where different types of slow and fast moving vehicles form a mixed traffic environment to share the same road space. A properly calibrated TMM should provide useful information on individual driver responses to changing traffic and geometric conditions (*13*), and a single set of calibrated parameter values for all modes may not be able to reflect the complex interaction. Therefore, the paper aims to develop on the existing scholarship by proposing a calibration methodology that can help TMMs to replicate such mixed traffic scenarios. The methodology is applied on a case study considering Kolkata metro city, India using microscopic traffic simulator, VISSIM. An end-to-end validation of VISSIM for a heterogeneous traffic environment has been provided in this manuscript with a detailed discussion of each stage of the calibration methodology. While the methodology has been applied to a particular traffic environment, the work presented in this manuscript will be helpful for the planners and traffic engineers to carry out more rational traffic scenario analysis with appropriate TMM calibration in the context of multi-modal traffic operations.

The manuscript has been structured in four Sections. A brief introduction to the research problem has been highlighted in this section and a discourse of the proposed methodology is presented in the following section. Different steps of the calibration methodology have been discussed in details with a focus on the issues and recommendations already established in literature. In the next section, the applicability of the proposed methodology for a case study is explored and the relevant findings are reported. Finally, the major findings and outcomes of the study are summarized in the concluding section.

METHODOLOGY

The methodology is developed based on past evidences and experiences reported in literature. It also takes into account the research gaps related to TMM calibration in the context of emerging countries with mixed traffic operations. The proposed methodology is demonstrated in **Figure 1**. The steps have been discussed in details in the following subsections.

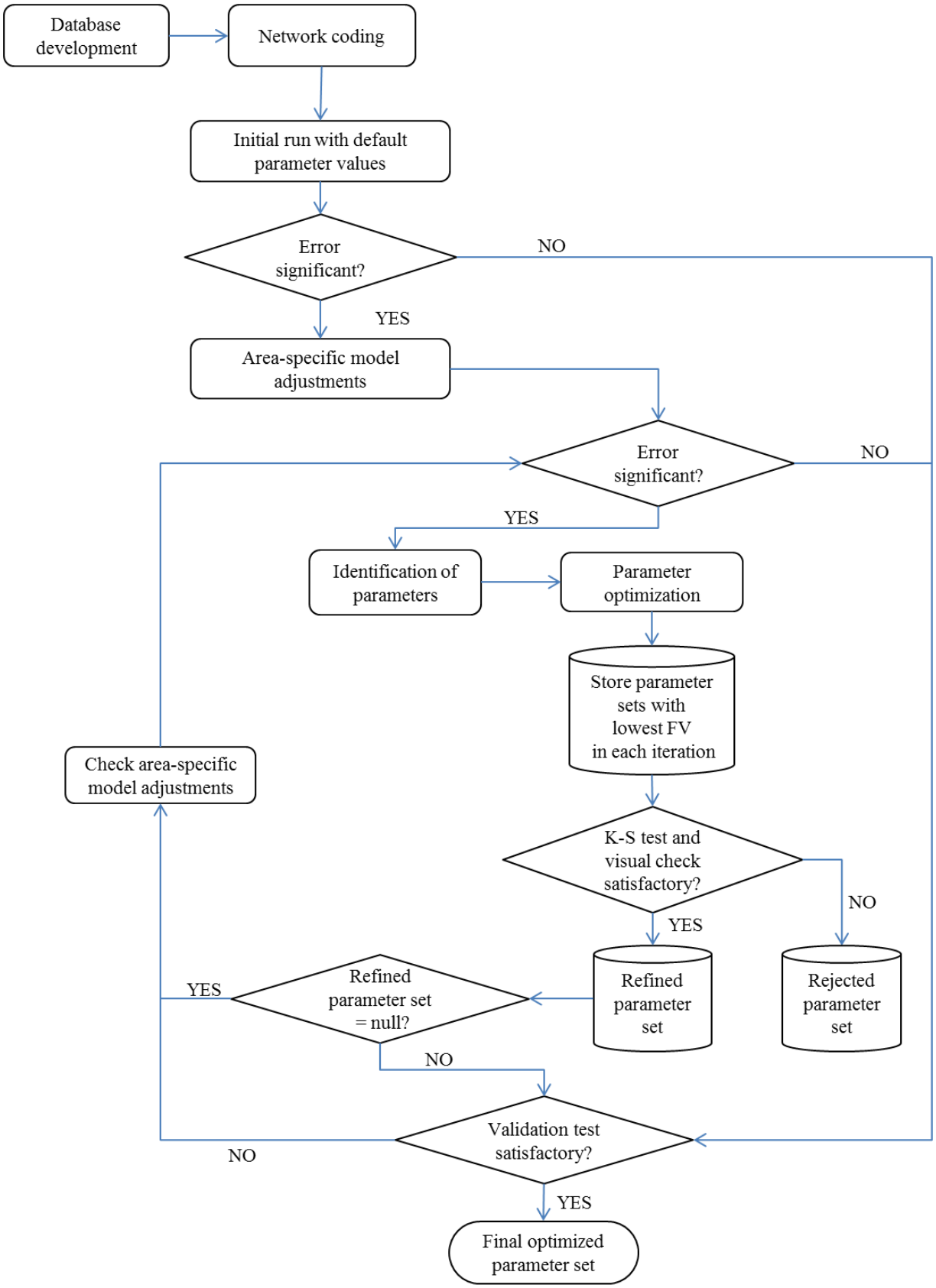


Figure 1 Proposed TMM Calibration Methodology

Database Development & Network Coding

This is a pre-calibration step which involves collection of relevant field inputs and coding the road network in the TMM based on the field data. VISSIM requires a range of input parameters for developing the model. These can be classified further into uncontrollable and controllable parameters (*3*). This stage deals with incorporation of all the uncontrollable parameters (e.g., road geometry, traffic flow, signal program) that needs to be provided only once and doesn't require any further modification. Moreover, a performance measure, hereby referred to as Measure of Effectiveness (MOE), was identified for fine-tuning a specific set of controllable parameters and comparing the performance of the simulation model with the field conditions.

Initial Run with Default Parameter Values

After the network coding has been performed, a set of initial runs with default values of the simulation parameters is carried out to check if there is any significant variation of simulation outputs from the field MOE. A significant variation justifies the need for calibration.

Area-specific Model Adjustments

In order to replicate some aspects of the traffic stream, there are a few model parameters which require modification, but optimization under an iterative process may not be necessary. These include the desired speed distributions of respective modes, the lane changing and lateral behavior, especially of smaller vehicles, etc. This stage includes identification and modification of such parameters to improve the model performance.

Identification of Parameters for Optimization

Any TMM has a large set of adjustable input parameters. However, modifying all parameters is likely to make the calibration process inefficient and also increase the complexities (*13*). As per the FHWA guidelines for TMM calibration (*7*), the parameters should be divided into two categories: (i) parameters that the analyst is certain about and does not wish to adjust and (ii) parameters that the analyst is less certain about and willing to adjust. The final list of adjustable parameters should ideally be selected to satisfy the following three objectives (*12*): (i) the parameter space is large enough to address various behavioural elements, (ii) small enough such that each parameter could receive adequate individual attention, and (iii) small enough to ensure computational feasibility. Hence, in order to improve the efficiency and cater for the time constraints, this step involves selection of a set of parameters for calibrating the TMM.

Parameter Optimization

This is the most crucial step of the methodology which involves optimization of selected parameters to replicate the field conditions. Studies have been reported to demonstrate different approaches for TMM parameter optimization. All adopted techniques may be classified into three broad categories: manual search, mathematical optimization, and heuristic search. Initial attempts to optimize parameters were generalized, trial-and-error based, and lacked in providing a more direct approach. Moreover, manual search techniques are highly time-exhaustive in comparison to other methods (*14*). In a more recent study (*2*), a further objective approach was demonstrated where it was attempted to develop linear regression models to relate the selected parameters as independent variables to the MOE. However, developing regression models is a simplification technique leading to approximation, and the variations due to model stochasticity were not adequately addressed. Since most calibration processes are multi-parameter optimization of the objective function, and there may be a correlation among parameters, it is preferable to adopt a

heuristic based automated procedure that is capable of solving a multi-dimensional problem without using derivatives and requiring less iterations (*9*,*10*,*12*). Different heuristic-based search algorithms are available in literature for optimization of multi-dimensional problems. In the present context, Genetic Algorithm (GA) has been applied extensively and successfully (*9*-*10*,*15*-*16*). GA is a population-based probabilistic search and optimization technique that has the capability to examine many candidate solutions concurrently using less iteration and, therefore, has advantage in exploring all feasible parts of non-differentiable spaces, thereby increasing the probability of obtaining a global optima. Hence, GA is adopted in this study and different operators such as selection, crossover and mutation are specified (*17*).

Developing the fitness function is another critical aspect of parameter optimization. A review of available literature indicated that the fitness function was developed based on aggregate measures, such as, average travel time (*9*), average delay (*18*-*19*), etc. Even in cases where non-parametric tests were conducted, the fitness function considered only one parameter value, such as the p-value while performing a Kolmogorov-Smirnov (K-S) test (*10*). The p-value of K-S Test is again based on the maximum distance between the cdf of two datasets. However, since a large parameter set considering several modes is involved in the optimization process, such single-point measure will not help the GA to optimize efficiently. Therefore, in the present study, a "misfit function" (*16*) was developed to minimize the error between the travel time distributions from TMM and the real world system. The Fitness Value (FV) for the GA-based optimization was defined as shown in **Equation 1**. Instead of a single point, the distributions of simulated and field-observed travel time for a particular mode were compared considering several percentile points to make the optimization process more efficient and robust. An error term was also introduced based on the K-S test statistic, so that parameter sets with similar percentile errors but producing more comparable travel time distributions have better fitness values.

$$FV = \sum_i \sum_j \frac{\left|P_{sim,ij} - P_{field,ij}\right|}{P_{field,ij}} * e_i$$

$$e_i = \begin{cases} 1.00 & if\ p_i < 0.01 \\ 0.50 & if\ 0.01 \le p_i < 0.05 \\ 0.00 & if\ p_i \ge 0.05 \end{cases} \qquad (1)$$

$P_{field,ij}$ and $P_{sim,ij}$ are the jth percentiles of the field and simulated travel time distributions of the ith mode, p_i and e_i are the asymptotic p-value and the error term respectively associated with the K-S test statistic for the ith mode. The null hypothesis was that the field and simulated travel time data were from the same continuous distribution. If FV obtained for a particular parameter set was found to be lower than previously obtained FVs, then that FV along with the parameter set values were stored for further evaluations.

Non-Parametric Test & Visualization Check

Based on the GA procedure, parameter sets which provide an acceptable error are initially selected. Simple goodness-of-fit test statistics, as used in the previous stage, are helpful to create a primary selection of optimized parameter values. In the next stage, it is necessary to test to what extent the optimized values aid to replicate the field operations in terms of the field-measured distribution of mode-specific travel times. In this regard, non-parametric tests have been recommended by researchers as it is not necessary to make any prior assumption about the distribution of the underlying population while applying such techniques (*10*). K-S test is one such

non-parametric two-sample test where the test statistic is based on the maximal difference between the cumulative distribution functions and may be used to test the validity of the calibrated model by investigating the hypothesis whether simulated and observed outputs are drawn from the same distribution (*20*). Three specific advantages (*12*) of using the K-S test over other non-parametric tests include: (i) the test is sensitive to the difference of shape between the compared distributions, instead of difference of a certain measure of central tendency, (ii) contrary to many two-sample tests, the problem of pairing each observed measurement with a specific simulated measurement does not occur when using the K–S test since it compares the respective probability density curves, rather than directly applying to the two samples, and (iii) this test statistic is not sensitive to small errors as it is based on the cumulative probability density function. K-S Test has also recently been applied by several researchers to successfully calibrate TMMs (*9,17*). Hence, K-S Test is incorporated in this step to compare field and simulated travel time distributions for each mode. Another important component of micro-simulation is to ensure that the model is also performing visually similar simulations as compared to the field conditions. Thus a visual validation has been recommended as a first step of validation in several studies (*9,12*). Hence, a visualization check is included in this step to select a final parameter set with visually satisfactory results. This ensures selection of a further refined set of optimized parameters.

Validation

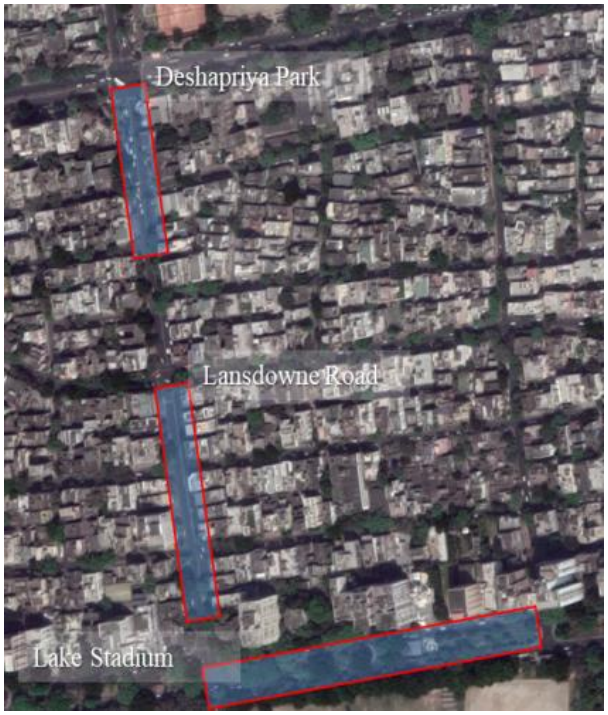
The final step involves validation of the calibrated model by applying the final optimized parameter set to different traffic scenarios with similar operating conditions. K-S Test is again used in this stage to compare the mode-specific travel time distributions in the new traffic scenarios selected for validation.

APPLICATION

The proposed calibration methodology was successfully applied considering several urban signalized approaches in the Kolkata metropolitan city, India as a case study. The different steps with reference to the case study are demonstrated in the following subsections to aid practitioners to replicate the methodology for other case-specific conditions. The relevant findings have also been discussed in brief with respect to each step of the methodology.

Database Development & Network Coding

A 200 m stretch of one direction of an effectively four-lane dual carriageway (excluding on-street parking) was selected as the study corridor for replication in the micro-simulation interface. The selected stretch (**Figure 2a**) is a part of the Lansdowne road located in the Kolkata metropolitan area, India. Mixed operations of different fast and slow moving vehicles prevail on the selected corridor. The road geometric characteristics were recorded and coded in the micro-simulation framework based on manual field measurements and satellite images of the study corridor. The stop line location and signal timing plans were also incorporated in the model as per field conditions. The traffic signal operates as a two-phase system with a cycle length of 80 seconds. The intervals for each phase follow the sequence: Green (30 s)-Amber (4 s)-Red (42 s)-Flashing Red (4 s).



(a)

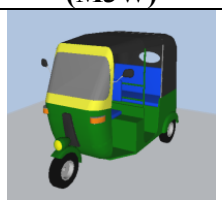
(b)

Figure 2 (a) Satellite view of the study stretch, & (b) Travel time section

The vehicle composition on the study corridor comprises of bicycle (or two-wheeler, 2W), motorbike (or motorized two-wheeler, M2W), auto-rickshaw (or motorized three-wheeler, M3W), car, mini bus and large bus. Apart from the conventional vehicles, viz. car, 2W and M2W, other types, those specific to the Indian traffic, either are not included or have distinctly different design and dimensions in the TMM. As a result, these vehicle types, as indicated in **Table 1**, were

modelled and incorporated in the TMM. The dimensions of these unique vehicle types were collected as primary data from the field. minibus, private bus and low-floor bus were considered as a single mode, BUS. Hence, five specific modes were considered in the study, viz., CAR, 2W, M2W, M3W, BUS. The turning movements at the intersection approach of the study corridor were recorded to provide the mode specific routing decisions in the simulation framework.Volume input was provided to the TMM as per the peak hour flow rate which was observed during 09:30 - 10:30 a.m.

Table 1 Vehicle types specific to study area incorporated in simulation model

Vehicle Type	Autorickshaw (M3W)	Ambassador Taxi	Mini Bus	Ordinary Private Bus	Low Floor Bus
3D View					
Vehicle Dimension (m x m)	2.6 x 1.3	4.3 x 1.7	6.8 x 2.2	12 x 2.6	12 x 2.6

VISSIM includes distribution of vehicle acceleration and deceleration performances as a function of the speed profile. Specific distributions can be assigned to specific modes. The default acceleration/ deceleration distributions available in TMMs do not adequately match the field distributions (*21*). Therefore, a GPS-based data logger was used to obtain acceleration and deceleration distributions for incorporation in the simulation framework. The device was attached to the windscreen of different modes on a clear day to ensure good satellite transmission and appropriate triangulation of vehicle location.

Previous studies related to calibration of VISSIM simulator for mixed traffic scenarios have been limited to use of aggregate measures such as delay, average speed, and flow, as MOE (*18-19,22-23*). However, it has been reported by several researchers that use of aggregate measures as MOE does not utilize the full potential of TMMs to reflect the stochastic nature of traffic operations (*12,21*). This is due to the fact that calibrations based on aggregate measures fail to reproduce a representative distribution of the model outputs as they only reproduce the mean values. On the contrary, use of disaggregate level vehicle data, in the form of field-measured distributions as MOE, has enabled researchers to calibrate TMMs in a more robust and effective manner (*21,24*). Vehicle travel time and delay are the most commonly adopted MOE for TMM calibration. In order to avoid approximations in field and simulation platform, it is desirable to consider travel time as MOE for the model calibration process (*25*). Therefore, mode specific distribution of travel time was chosen as the MOE for the study. The travel time distributions of different modes within the same traffic stream were found to be different as can be observed from **Figure 3**. Frequency with respect to travel time ‘t’ seconds indicates the percentage of vehicles for a particular mode passing the selected road section with a travel time equal to or less than ‘t’ seconds. A K-S test was conducted to compare the travel time distributions. The test statistic (**Equation 2**) is the maximum distance between distributions.

$$D = \sup_x \left|F_i(x) - F_j(x)\right| \qquad (2)$$

where, $F_i(x)$ and $F_j(x)$ are the respective cumulative distribution functions, hereby referred to as cdf, of the i-th and j-th modes. For all combinations of modes, the test statistic, D, was found to be higher than the critical test statistic, D*, at 0.05 level of significance.

A summary of the test results is presented in **Table 2**. The test results revealed that the differences between distributions were statistically significant. Moreover, several other microscopic characteristics, such as, lateral and longitudinal spacing between vehicles (*26*), discharge headway (*27*), etc. are also mode-specific in such scenarios. This is a unique feature of mixed traffic environment which entails the need for adopting a different TMM calibration methodology in order to replicate such mode-specific traffic behaviour. Other necessary inputs, viz., vehicle inflows, routing decisions, traffic signal plans, etc., were also collected for the study approach. GPS-based data logger was used to obtain mode-specific acceleration and deceleration distributions for incorporation in the simulation framework. During early morning lean period, the free-flow speeds of different modes were recorded at mid-block section.

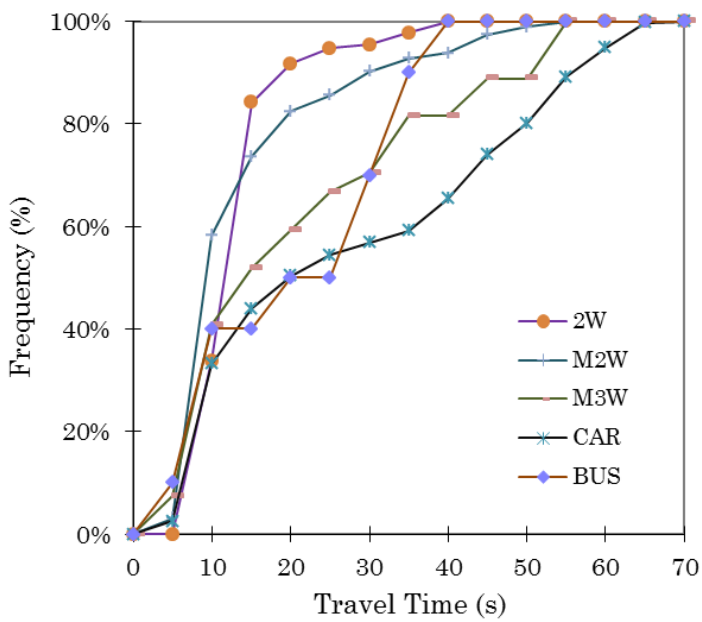


Figure 3 Field-observed mode-specific travel time distributions

Table 2 Summary of K-S test statistic values for observed travel time distributions

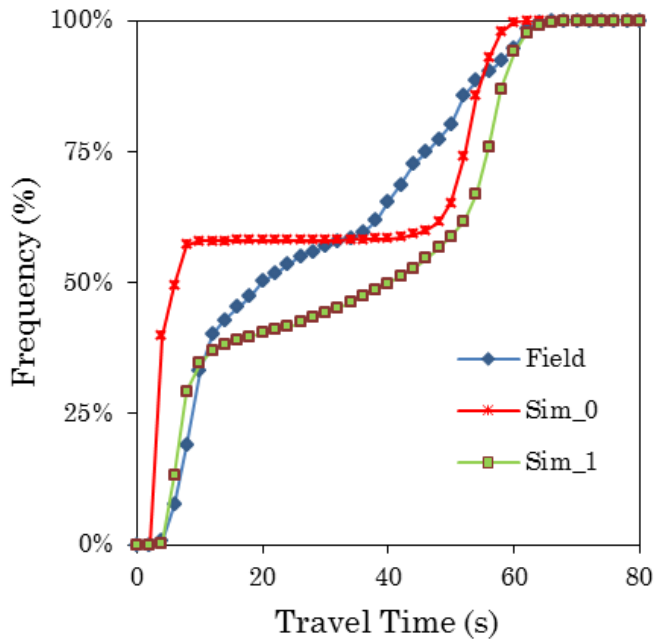
Mode	2W	M2W	M3W	CAR	BUS
2W	0	0.244 (0.153)	0.325 (0.240)	0.414 (0.134)	0.447 (0.240)
M2W	---	0	0.232 (0.210)	0.336 (0.117)	0.356 (0.210)
M3W	---	---	0	0.554 (0.143)	0.593 (0.240)
CAR	---	---	---	0	0.673 (0.210)
BUS	---	---	---	---	0

Values in parenthesis indicate the critical test statistic value at 0.05 significance level

Initial Run with Default Parameter Values

After incorporation of all basic inputs, the network was simulated multiple times and travel time outputs from the simulation framework were compared. K-S Test was conducted and the results indicated significant differences in travel time distributions for all modes. As an example, the cumulative distribution function (cdf) of field ('Field') and simulated travel time

('Sim_0') for CAR are demonstrated in **Figure 4a**. The average Car travel times from the field and simulation were 27.3 and 25.8 seconds respectively. Although, the average values are comparable and the mean absolute percentage error (MAPE) is only 5.5%, there are clear variations among the two distributions which were further confirmed by the K-S test statistic of 0.428 which was higher than the critical value of 0.110 at a significance level of 0.01. This shows that calibration considering only a single average value does not necessarily yield a realistic representation of the field conditions and, therefore, they lack in robustness. Similar results were obtained for other modes. Hence, further steps were adopted for improving the TMM in terms of field conditions.

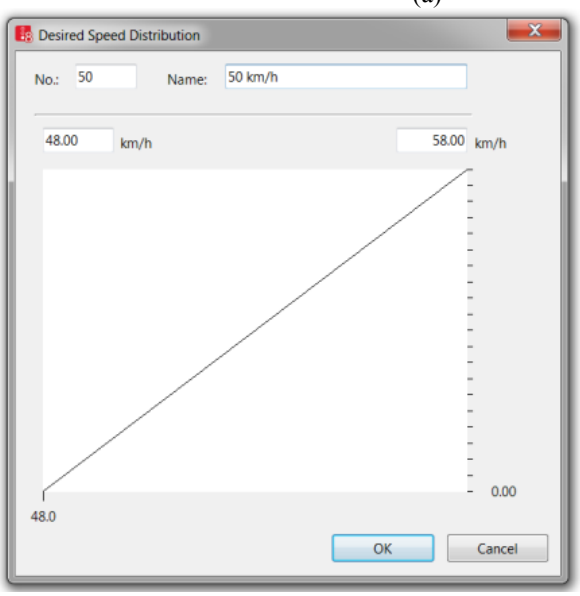


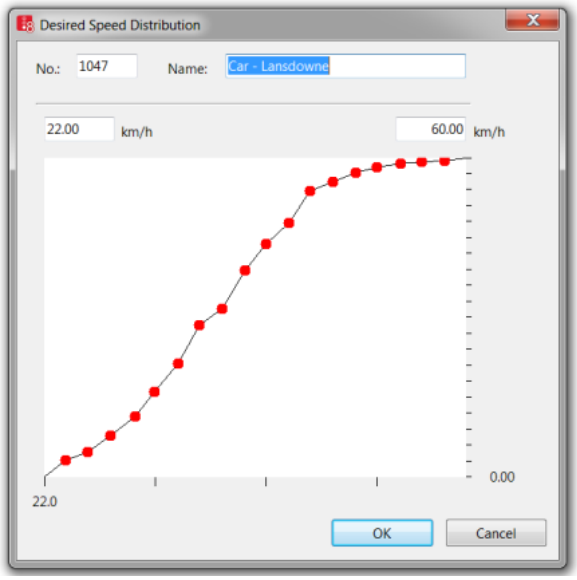
Field: field distribution;

Sim_0: Simulated distribution with default parameter values;

Sim_1: Simulated distribution after area-specific adjustments

(a)





(b) (c)

Figure 4 (a) cdf of field and simulated travel times of CAR (b) Default desired speed distribution of CAR and (c) Modified desired speed distribution of CAR

Area-specific Model Adjustments

At this stage, several adjustments were made to address some field conditions. Field conditions refer to the type of road, traffic control and adjoining land use that will influence the driver behaviour. Further fine-tuning of area-specific adjustments may be required at a later stage, if the parameter optimization procedure is unable to produce a valid set of optimized parameters. This involves making adjustments to the desired speed distributions and lateral behaviour of different modes as discussed below.

In order to account for stochasticity in traffic stream and driver behaviour, VISSIM micro-simulator considers a desired speed distribution for different modes instead of a single free flow speed for a particular facility (*28*). Recent studies have identified desired speed distribution as an important parameter that has a significant effect on travel speed and influences the traffic performance (*9,29-30*). Therefore, in order to develop the desired speed distribution for each mode, a section was identified on the midblock section of the study corridor and video-graphic survey was carried out to record vehicle movements in free flow conditions during the early morning lean periods. As an example, default and modified CAR desired speed distributions are demonstrated in **Figure 4b** and **Figure 4c** respectively. It may be observed that the range of field distribution is higher in comparison which may be attributed to heterogeneity in driver and vehicle performances within the same mode.

VISSIM simulator adopts a rule-based algorithm for lateral vehicular movements (*1*). The lateral behavior of vehicles is a key aspect in heterogeneous traffic mix where there is a substantial share of small vehicles. These small vehicles, such as 2W and M2W, perform higher degree of lateral movements in order to occupy any available space between larger vehicles and move up a congested vehicle stream. Hence, in order to accommodate similar behavior in the simulation platform, “Minimum longitudinal speed” and “minimum lateral distance while overtaking” were modified for the respective modes. The lateral clearances also vary with respect to different mode pairs. For example, the lateral gap between a small vehicle and a car will be different from that of a car and a bus. Therefore, the lateral gap values for each pair of modes have been incorporated based on a past study for similar heterogeneous traffic environment (*27*). Mixed traffic streams in emerging countries, such as India, are also characterized by a lack of lane discipline. This aspect was achieved by modifying the “Desired position at free flow” parameter from “Middle of lane” to “Any” to allow for the vehicles to occupy any position laterally along the available length of the carriageway. The small vehicles occasionally violate the Stop-line and make stops slightly downstream of the Stop-line. This aspect has already been discussed in previous studies (*19*) and was also addressed in this study by considering a second Stop-line for the small vehicles in advance of original Stop-line.

Simulation runs were again carried out and comparison of the new results with the previous runs indicated that the simulated vehicle performances were nearer to the field conditions. A visual comparison of cdf of CAR travel time for field conditions (‘Field’) with respect to initial simulation scenario (‘Sim_0’) and post-adjustment simulation scenario (‘Sim_1’) can be made from **Figure 4a**. After modifying the desired speed distributions, it is evident that the flow regime uninterrupted by the traffic signal is now well represented in the model from the overlap of the simulated cdf on the field cdf at low travel time values. However, there are significant variations in the second regime which demands the need for further calibration. K-S test statistic of 0.213 was obtained which, although lower than the previous simulation results, was still higher than the critical value of 0.110 at a significance level of 0.01. Similar observations were obtained for other modes which justify the need for further calibration.

Identification of Parameters for Optimization

Replication of driving behavior is one of the most important attributes towards TMM calibration in light of the local traffic conditions. VISSIM incorporates the Wiedemann car-following model which is a psycho-physical car-following model (*1*). Over the years, several researchers have carried out different sensitivity analysis tests to identify the critical parameters to which the model performances are sensitive. A significant number of studies have been carried out for urban Indian traffic scenario, as well. A majority of these studies (*18-19,22-23*) have identified several parameters of the Wiedemann '99 car-following model as the critical parameters. The parameters that were observed to be critical across several sensitivity studies include CC0 (standstill distance), CC1 (headway time), CC2 (longitudinal acceleration), CC3 (threshold for entering 'following'), CC7 (oscillation during acceleration), CC8 (desired acceleration at 0 kmph), maximum look ahead distance, and number of observed vehicles. Accordingly, these eight parameters for each of 5 modes were selected in the present study for performing optimization. A detailed description of the parameters is available in the literature (*28,31*).

Parameter Optimization

As discussed in the previous section, Genetic Algorithm was adopted in this study. A code was developed in MATLAB R2015b to operate VISSIM through the COM interface by modifying the selected parameter values and obtain outputs. A population size of 100 was considered, and the first set of chromosomes was randomly generated. A TMM provides inputs in a stochastic nature to reflect the random variations in the field, i.e., random numbers are adopted for generation of vehicles, route selection, and driving behaviour (*7*). Therefore, it is generally insufficient or inaccurate to use the model outputs based on only a single run (*12,32*). Only a few studies reported in literature have used three to five runs while carrying out the calibration process (*9,14*). Therefore, in the present study, three runs using different random seeds were carried out for each chromosome to address the stochastic nature of the TMM. Simulation outputs were extracted, and the FV for each chromosome was obtained as per **Equation 1**.

An initialization period or warmup time of 30 minutes was adopted before extracting outputs to ensure that the system reaches an equilibrium state (*7*). As discussed previously, **Equation 1** was adopted to obtain the FV. Subsequently, tournament selection procedure was carried out to create the mating pool. Multiple-point alpha-blend crossover with a probability of 0.80 and random mutation with a probability of 0.03 were successively carried out to create the new population set for the next iteration. Initially, on a trial basis keeping all other GA parameters fixed, different number of iterations was carried out from 20 to 60 iterations and it was observed that the best FV was obtained between 40 and 50 iterations in all cases. Therefore, the same steps were iterated 50 times, and the parameter sets were stored whenever a chromosome yielded a lower FV lower as compared to the previous iterations. Based on three runs for each parameter set, a population size of 100 for each generation, and 50 generations in the GA optimization framework, a total of 15000 runs of the VISSIM model was executed. The entire optimization process required approximately 27 hours in an Intel i7 (4th Generation) 64-bit processor with 8 GB RAM. The parameter sets which yielded the lowest FVs were selected as an initial list of optimized parameter sets for further analysis.

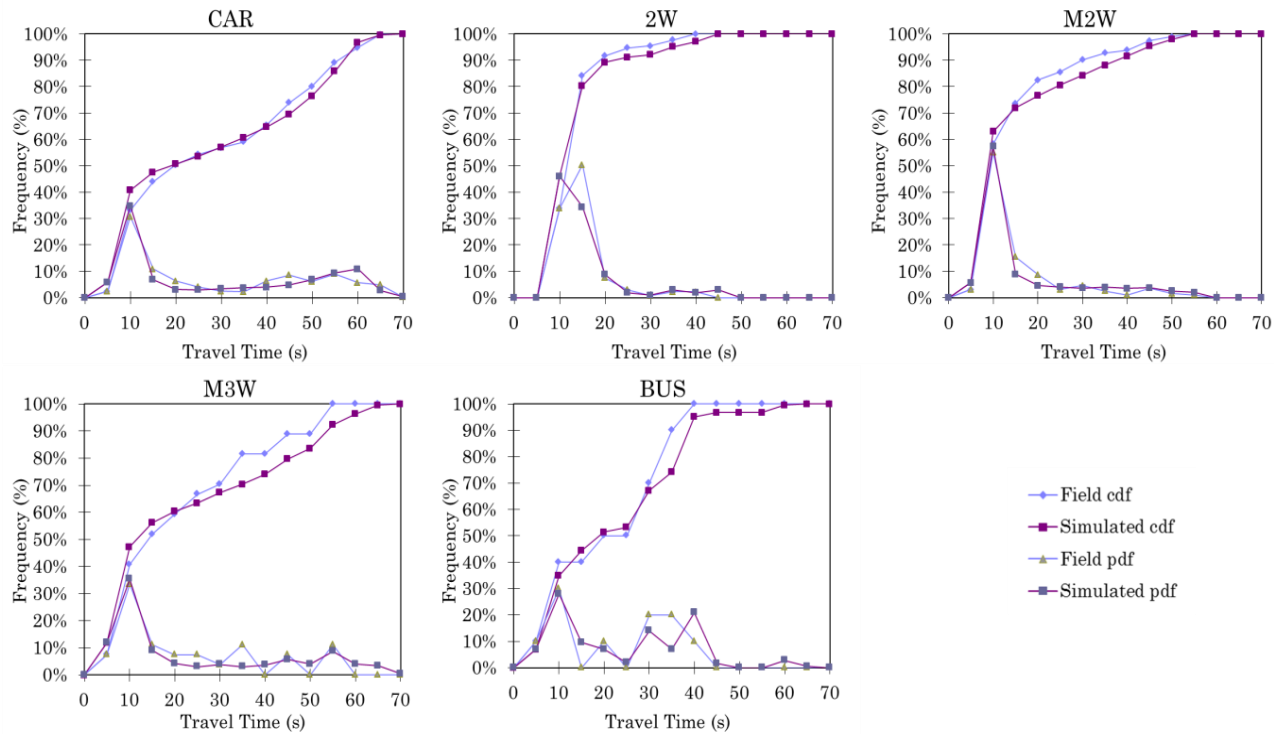


Figure 5 Mode-specific Field and Calibrated Model Travel Time Distribution

Non-Parametric Test and Visualization Check

In order to select the final set of optimized parameters, 30 runs were adopted for each selected parameter set and K-S Test was carried out to compare the mode-specific travel time distributions.The parameter set for which the K-S Test statistic was found to be lower than the critical value at a significance level of 0.10 for all modes was selected as the final optimized set. **Figure 5** shows the mode specific simulated and field-observed travel time distributions and **Table 3** shows the K-S Test outputs for the final selected optimized parameter sets. The critical test statistic is different for different modes due to variations in sample size with respect to each mode. The findings show that the TMM is well calibrated considering every mode separately.

Animation output is a powerful tool in TMM because it enables to qualitatively assess the overall performance of the calibrated system (*7*). Several runs were taken in the TMM using the optimized parameter sets to check if the traffic performance is visually similar to the local field scenario. Visual similarity was ensured considering the following: small vehicles displayed similar seeping behaviour as observed in the field, there were no unrealistic gaps between vehicles, there was no overlap between vehicles, and there was no unrealistic lateral behaviour among different modes. A comparison of the simulation run with the field operations is demonstrated in **Figure 6** by taking screenshots of the simulation platform and video files respectively, and it was inferred to be visually satisfactory.

Validation

This is the final stage of the methodology to investigate the applicability of the calibrated model in similar traffic environments. The optimized parameter values were applied to different scenarios to check if the calibrated model was able to yield acceptable results for such scenarios. Two new signalized approaches were selected; these were the upstream and downstream

approaches of the 2-lane study corridor selected for calibration (**Figure 2a**). They were similar to the calibrated section of the corridor in terms of lane configuration and traffic composition with similar vehicle modes operating in all the scenarios. Mode-specific travel time distributions were again extracted for 100m stretches for the two locations, and the networks were coded in the simulation platform. Multiple simulation runs were taken and, in both cases, K-S Test showed that the distributions were similar for all vehicle modes (**Table 3**). Since the share of M3W was very low for Lake Stadium approach, it was excluded for that road segment. It was inferred from the results that the calibrated model parameters are robust and may be applied in similar traffic and control environment.

Video Screenshot

Simulation Screenshot

Figure 6 Visualization Check of Calibrated Model

Table 3 Summary of K-S Test Results for different Signalized Approaches

Mode	D*	$D^{*}_{, Critical}$ (0.01 Level of Significance)	Hypothesis
Calibration Stretch – Lansdowne Approach			
CAR	0.076	0.082	Accept
2W	0.122	0.161	Accept
M2W	0.060	0.124	Accept
M3W	0.112	0.338	Accept
BUS	0.158	0.503	Accept
Validation Stretch 1 – Lake Stadium Approach			
CAR	0.080	0.084	Accept
2W	0.147	0.292	Accept
M2W	0.109	0.148	Accept
BUS	0.157	0.332	Accept
Validation Stretch 2 – Deshapriya Park Approach			
CAR	0.067	0.076	Accept
2W	0.131	0.161	Accept
M2W	0.089	0.107	Accept
M3W	0.159	0.292	Accept
BUS	0.161	0.481	Accept

D*: K-S Test Statistic

Optimized Parameter and Implications

The applied methodology was successful in developing a calibrated model with due consideration of all modes operating in a mixed traffic environment. Although several attempts have been made in the recent past for TMM calibration in similar traffic scenarios, the studies were not exhaustive and different modes have not been adequately addressed in the calibrated models. All these concerns have been carefully addressed in the present study, and the optimized parameter values of the calibrated model are demonstrated in **Table 4**.

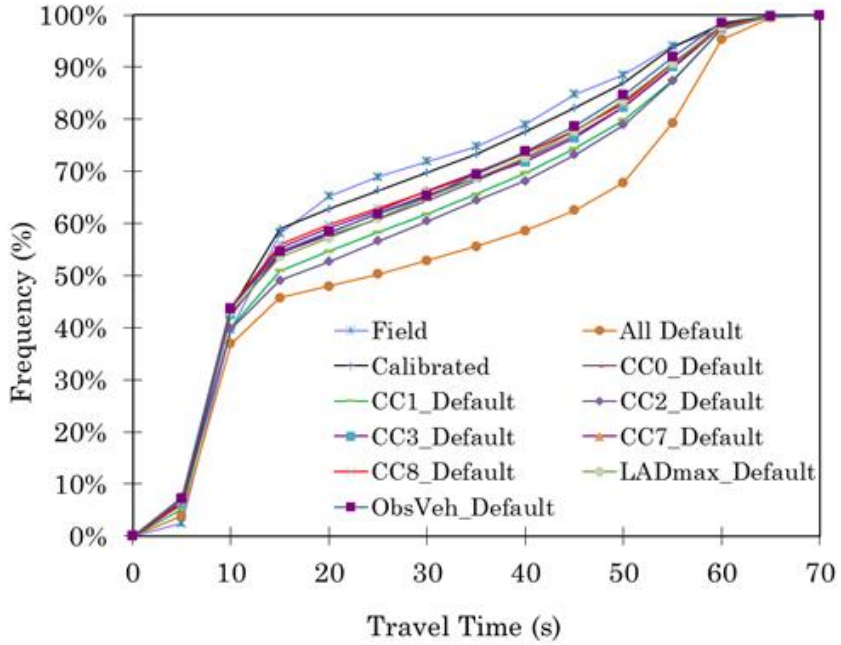
Considering the traffic operations in urban India, some case-specific observations may be made from the optimized parameter values for different modes. While the default values of CC0 and CC1 represent the safe standstill distance and headway time respectively for a relatively homogeneous and lane-based traffic stream, it is evident from the calibration that, in the present context, other than BUS, Indian vehicles tend to maintain smaller safety distances and headways in congested conditions. The smaller vehicles, such as 2W, M2W, maintain the least safety gaps as they occupy the available spaces in the congested vehicle streams. These findings are in agreement with the previous calibration attempts for Indian traffic (*18-19*). In terms of following variation (CC2), in comparison to the default value of 4 metre representing stable conditions, CAR shows least variations, while BUS and M3W show significantly more variations while following other vehicles. 2W and M2W are quicker to react to the preceding slower vehicles and, as a result, CC3 values are obtained to be higher for these vehicular modes with respect to the default values. A stable default value of oscillation during acceleration (CC7) is 0.25. However, M2W, being small and less stable, show the highest oscillation during acceleration

(CC7), while, on the other hand, 2W is a non-motorized mode and hence, its desired acceleration from standstill (CC8) is much lower as compared to the other modes and the default value. CAR and M2W are more prone to overtake other vehicle modes and as a result the maximum look-ahead distance for these two modes is higher in comparison to the other modes and close to the default value. CAR and BUS can generally better predict other vehicles' movements and, as a result, Observed Vehicles value is higher for CAR and BUS, while, on the other hand, it is on the lower side for 2W and M2W modes with reference to the default value. Therefore, the optimized parameter values obtained from the calibration methodology indicate logical and realistic variations from the default values with respect to different modes.

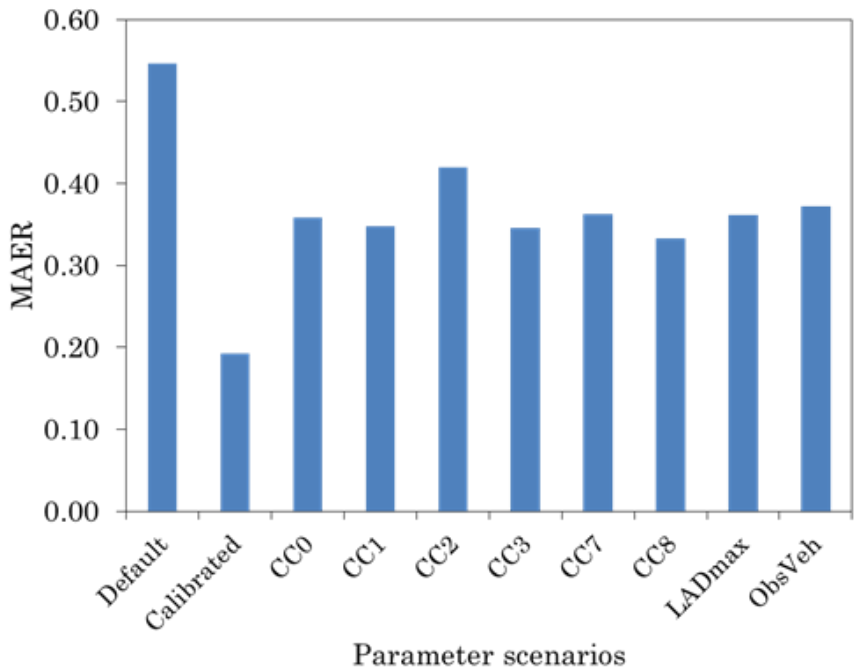
Table 4 Mode-specific Optimized Parameter Values of the Calibrated VISSIM Model

Parameter	Default	CAR	2W	M2W	M3W	BUS
CC0 (m)	1.50	0.80	0.17	0.38	1.01	1.96
CC1 (s)	0.90	0.58	0.70	0.33	0.38	1.73
CC2 (m)	4.00	0.50	0.76	3.00	5.91	5.00
CC3	-8.00	-4.20	-10.50	-7.10	-6.00	-5.60
CC7	0.25	1.14	0.70	1.48	0.60	0.32
CC8 (m/s^2)	3.50	2.64	0.98	1.66	4.00	4.00
Maximum Look Ahead Distance (m)	250	265	112	220	100	190
Observed Vehicles	4	4	1	2	3	5

A scenario analysis was carried out by keeping one optimized parameter at their default values in each scenario. In all scenarios, the outputs from the simulation were significantly different from the field outputs. **Figure 7a** presents a comparison of the travel time distribution of all vehicles under different scenarios of optimized parameter values. A comparison of Mean Absolute Error Ratio (MAER), as demonstrated in **Figure 7b**, also shows that the MAER was obtained to be greater than 0.30 for all scenarios except for the calibrated conditions, with the highest being reported for the default conditions.



(a)



(b)

Figure 7 (a) Simulated travel time cdf and (b) MAER for different scenarios

CONCLUSION

A comprehensive methodology for calibration of traffic micro-simulation model is demonstrated in this study. The methodology adopts a GA-based optimization technique and gives due consideration to each mode operating in a multi-modal traffic environment. The proposed methodology is of particular importance in the context of mixed traffic scenarios prevailing in many emerging countries. The methodology was successfully applied with respect to a case study

for a typical urban scenario in Kolkata city, India. An end-to-end validation for a heterogeneous traffic environment is presented with a detailed discussion of each stage of the methodology.

A single-point measure was observed not to be effective in capturing the actual field conditions. Hence, a new fitness function was developed in this study and mode specific distribution of travel time from the model outputs were compared with the field observations for similar modes, first at different percentile points and then applying a non-parametric test. The test results and visual checks indicated that the calibrated model was able to replicate all modes and a mode-specific optimized parameter value set was suggested. The model was also validated considering two intersection approaches along the same two-lane corridor having similar geometric characteristics and comparable traffic composition which show that the calibrated model was robust in nature.

Each step of the methodology has been clearly explained and demonstrated to aid traffic engineers to directly apply this methodology for model calibration in the case of emerging countries or multi-modal mixed traffic scenarios. Practitioners may be able to apply the mode-specific optimized parameters for scenarios with similar geometric and multi-modal traffic characteristics as presented in this paper. Although the methodology has been demonstrated in this paper with respect to VISSIM simulator, the experience gained in the process is expected to be of interest to researchers working in TMM calibration as a similar approach can be applied considering other platforms.

The optimized parameter values showed significant variations from the default values which exhibit the requirement of unique parameter value sets for different vehicle modes.Moreover, a scenario analysis was carried out by keeping one optimized parameter at default value under each scenario and comparing the model outputs with the field outputs which showed that it was necessary to fine-tune all the parameters under study to obtain a properly calibrated model for mixed traffic.

The present study has been conducted considering mode-specific travel time distribution as the MOE for a signalized approach. The study can further be extended by conducting a network-level demand-based calibration covering a network of intersections. The objective function can also be augmented by considering additional mode-specific performance measures, such as discharge characteristics, and also investigating the effect of side friction and bus stops. Other heuristic algorithms may also be explored to find a more efficient calibration algorithm for similar traffic scenarios. It may also be mentioned that the range of traffic heterogeneity may vary significantly across different scenarios and the present calibration methodology has been applied for a certain kind of heterogeneous traffic operation. The traffic represents urban traffic where commercial vehicle is negligible and there is a considerable share of non-motorized transport. While the primary objective of validation in the present study was to ensure if it performs satisfactorily in a similar environment, it will be interesting to investigate the future the applicability of the validated model across a range of heterogeneous traffic scenarios and identify the situations where the calibration methodology may be again applied to develop new set of optimized parameter values due to a significant change in driving behaviour. Finally, a few sets of optimized parameter values may be developed to represent various traffic environments prevailing in an urban setup.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows:
Study conception and design: K. Bhattacharyya, B. Maitra; data collection: K. Bhattacharyya; analysis and interpretation of results: K. Bhattacharyya, B. Maitra, M. Boltze;
Draft manuscript preparation: K. Bhattacharyya, B. Maitra, M. Boltze.
All authors reviewed the results and approved the final version of the manuscript.

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