Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2017) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2016 Shanghai. 10-15 July 2016

A methodology for calibration of vehicle class-wise driving behavior in heterogeneous traffic environment

Palak Maheshwary[a,*], Kinjal Bhattacharyya[b], Bhargab Maitra[c] , Manfred Boltze[d]

[a]*Assistant Engineer, Jacobs Engineering, Kolkata-700091, India*
[b]*Research Scholar, Dept.of Civil Engg, IIT Kharagpur, Kharagpur-721302, India*
[c]*Professor, Dept.of Civil Engg, IIT Kharagpur, Kharagpur-721302, India*
[d]*Professor, Dept.of Civil and Environmental Engg, TU Darmstadt, Darmstadt-64287, Germany*

Abstract

In developed countries, traffic microsimulation is already a widely accepted tool for the evaluation and assessment of alternative design schemes, e.g. for different signal timing plans for a road network. However, for developing countries, replicating heterogeneous and non-lane based traffic in a microsimulation model is gaining increased importance and still remains a challenge. The present study demonstrates a methodology to calibrate vehicle class-wise driver behavior in an urban Indian scenario using data from a midblock section and an intersection approach in Kolkata. The study area was modeled using the VISSIM microscopic simulator. The sensitive parameters affecting the driver behavior are identified for every vehicle type using latin hypercube sampling, taking vehicle specific travel time as a performance measure. Further, a single criteria and multi criteria calibration approach based on a genetic algorithm is highlighted in this paper.

Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

Keywords: Microsimulation; Heterogeneous; Class-wise; VISSIM; Driver behavior; Latin hypercube; Multi criteria; Genetic Algorithm.

1. Introduction

With the advancements in computational technology over the last few decades, microscopic traffic simulation has become a popular tool among researchers for the evaluation of different alternative designs and management strategies for a road network before actually implementing them on the field. Field implementations generally have legal and financial constraints associated to them while traffic simulation is a cost-effective, objective, and flexible approach to analyze and evaluate transportation systems (Rakha et al, 1996). When compared to analytical models,

Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

microscopic simulation models can keep a track of individual vehicle movements and interactions on a second to sub second basis (FHWA, 2004) and they are quite helpful in realistic representation of complex traffic behaviors.

In developing countries such as India, absence of lane marking, no lane discipline, haphazard movement near intersections, disorganized movement of a varied mix of vehicle types, is a commonly observed scenario which is difficult to replicate using traditional analytical models thus creating a widespread demand for microscopic simulation models (Mathew and Radhakrishnan, 2010). However, the efficiency and acceptability of a traffic simulation model in evaluating different scenarios lies in its ability to reflect the local study area's network, infrastructure, and driver characteristics. This can be achieved by model calibration which may be defined as the process of selecting the best set of model input parameters. Such calibration should address the most important differences between the model's default assumptions, and those conditions actually observed locally in the field. The calibration should determine to what extent the model user is able to, or is required to, modify or fine-tune the default input parameter values, that describe the underlying mechanics, in order to accurately reflect the field-measured and observed local traffic conditions (Park & Schneeberger, 2003; Rakha et al., 1996).

Microscopic traffic flow simulation software contains several independent parameters to describe the traffic control operation, traffic flow characteristics, and drivers' behavior (Park and Schneeberger, 2003). It is difficult, cumbersome and expensive to estimate some of these parameters directly from the field. Hence, in general, these parameters are kept at their default values which reflect a well-disciplined and homogeneous traffic environment. Thus, in order to replicate different complex traffic scenarios, the values of these parameters need to be modified and adjusted by the user by following a defined procedure of calibration. However, adequate research has not been conducted to explain the heterogeneous traffic environment and subsequently incorporate them while undergoing calibration. Therefore, the aim of this study is to evolve a well-defined methodology through a step-by-step approach for calibration of driving behavior for heterogeneous traffic. As different microscopic simulation platforms have different parameters and/or variables to explain the inbuilt mechanism of driver behavior, the calibration methodology developed in this study particularly focuses on the VISSIM microscopic simulator.

The paper has been structured in seven sections. After portraying a background and need for the study in the Introduction, a brief review of the works and identification of gaps related to calibration of driving behavior in heterogeneous traffic conditions is discussed in Section 2 with reference to VISSIM microscopic simulator. A methodology of calibration of driver behavior is explained in Section 3, followed by a brief description of the heterogeneous traffic corridor selected for the study and the database developed for a demonstration of the calibration methodology for the selected study corridor in Sections 4 and 5 respectively. Discussions based on statistical analysis of results at different stages of calibration are presented in Section 6. The paper is concluded with a summary of the work highlighting the major findings and contributions in Section 7.

2. Previous works on VISSIM Calibration

In the early stages of traffic flow micro-simulation, researchers calibrated simulation models on a trial-and-error basis and often used default parameters for replicating diverse traffic scenarios resulting in large errors in the model outputs as reported by Park and Schneeberger (2003). In the recent years, in order to improve the reliability of traffic micro-simulation models, several studies have projected the need of an accurate calibration of micro-simulation models, and they have proposed general requirements and guidelines on calibration (Hourdakis et al 2003, Park and Schneeberger 2003, Dowling et al 2004, Park and Qi 2005). In the process, procedures have evolved from simple time-consuming manual calibration to more efficient automated processes with an objective to develop a realistic and acceptable calibrated model for end users. Table 1 is a comprehensive database of a majority of the available techniques that have been used in different stages of calibration of a microscopic traffic flow simulation model. It may be mentioned that these studies focused primarily on homogeneous traffic conditions and related aspects. Only a few studies have been reported in literature with regard to the calibration of heterogeneous traffic conditions (Mathew and Radhakrishnan 2010, Manjunatha et al 2013, Siddharth SMP, 2013). The different studies reported in literature related to calibration using VISSIM are discussed in brief as summarized in table 1.

Table 1. Different stages and techniques for calibration of traffic flow micro-simulation models

Stages of Calibration	List of Techniques Adopted for each Stage				
Field data collection	Manual	Video recordings	Traffic Management Centres	Detector stations	GPS based equipment
Network coding	Vissim	Corsim	Transim	Paramics	
Comparing simulated results and field observations	Statistical Confidence limits	Qualitative Analysis	Quantitative Analysis	Pattern Recognition	
Identifying sensitive parameters & range setting	Trial and error	Experience/ Judgment	Literature Review	Anova/ LHS+Anova	EE Method
Calibration using optimization methods	Heuristic trial and error	Linear Regression	Simplex Algorithm	Genetic Algorithm	SPSA
Model validation	Different temporal data	Different MOE's	Visual animation checks		

A general calibration framework in VISSIM has been presented by the researchers in the past. For instance, Hellinga's (1998) eight-step procedure set forth a general set of guidelines for the calibration and validation process which was further elaborated by Park & Schneeberger (2003) explaining calibration and validation of VISSIM for signalized intersections in the U.S.A. based on a linear regression model. Dowling et al (2004) present a calibration of key global capacity parameters followed by parameters affecting the route choice. Additionally, various parameter optimization algorithms have been applied in the process of calibration; amongthese, the Genetic Algorithm (GA) has emerged to be a very popular technique. For example, Zizhou et al (2005) used a Genetic Algorithm to find a suitable combination of VISSIM parameters for a study conducted on an Expressway in Shanghai. Park and Qi (2005) proposed a general methodology to calibrate VISSIM using an actuated signalized intersection as a case study.

Calibration using GA has also proven to be effective in the limited number of studies involving heterogeneous traffic. Mathew and Radhakrishnan (2010) suggested a methodology for calibrating parameters for heterogeneous traffic operations prevalent in developing countries like India. The calibration procedure includes the identification of sensitive parameters, setting the selected parameter ranges heuristically, and the tuning of selected parameters using GA. Three four-legged signalized intersections with heterogeneous traffic operations were modelled and the models were calibrated and validated using stopped delay as the measure of effectiveness (MOE).The approach was later modified by Manjunatha et al (2013) who introduced the concept of multi-parameter sensitivity analysis along with GA for calibration. Additionally, a brief idea of multi-criteria calibration was also presented by taking delay as MOE with bounds on Link Capacity. Siddharth SMP (2013) also developed a methodology on calibrating heterogeneous traffic conditions in India using VISSIM to minimize the differences between simulated and field-observed flow values with reference to two intersections in Chennai city. The common factor that is missing in the calibrated parameter outputs is the distinct difference in the drivers' behavior for different vehicle categories.

The driver behavior forms a significant part of calibration process when heterogeneous traffic is involved. In a country like India, driver behavior is not the same for all vehicle types; it is largely vehicle class dependent which has not been taken into account in the previous studies. The output/MOE is yet another factor which is generally expected to be different based on vehicle category. In the previous works related to calibration of VISSIM, calibration was generally done for the traffic stream as a whole. For instance, if speed is the MOE, calibration was done in such a way that average stream speed matches the observed values instead of calibrating speed for every vehicle separately. Moreover, in most of the studies, intersection approaches have been the only focus for calibration in heterogeneous traffic conditions until now. No attempts have been made to calibrate other sections of a road. This study attempts to overcome these gaps by proposing a detailed methodology to calibrate vehicle-class wise driver behavior in VISSIM. The proposed methodology is demonstrated with reference to a relatively heterogeneous traffic corridor in Kolkata city as a case study.

3. Methodology

The proposed procedure for the calibration of microscopic traffic flow simulation models broadly includes 4 stages as demonstrated in fig1: Pre-Modelling (i.e. definition of study objectives, selection of study area, determination of MOEs, field data collection and extraction), Initial Modelling (network coding, comparison of simulation with default values and field results), Calibration (identifying calibration parameters and ranges, experimental design for calibration and finally optimization e.g. using GA), Validation and Visualization (using a different set of flow data for validating the calibrated model, visualization check for realistic animations to identify the best parameter set).

3.1. Pre-Modelling

This is the first stage dealing with initial steps before actually modelling the network. This includes the selection of a traffic micro-simulation platform, the identification of a suitable MOE, and accordingly collecting and processing the data required from the field. All the three sub-tasks are interdependent in a way that the MOE is identified such that it is consistent with the study goals, available field data and simulation model capabilities. Out of all the available simulation models, VISSIM is the most preferred as it is universally applicable, and its varied features and parameters make it quite flexible to model heterogeneous traffic conditions (Mathew and Radhakrishnan 2010, Manjunatha et al 2013). Hence, VISSIM has been selected for the purpose of this study. The subsequent stages are discussed considering VISSIM as the selected micro-simulation platform.

3.2. Initial Modelling

The second stage deals with network coding and once the simulation model is set up, simulation runs may be performed with default parameter values followed by a comparison of the model output with the observed field values. If the differences are significant, it shall justify the need for calibration and subsequent steps may be followed.

3.3. Calibration

There are some parameters that cannot be measured directly on the field. These include several driver behavior parameters that affect the output significantly in case of heterogeneous traffic and hence need to be calibrated so that the on-field conditions can be replicated. This is further explained in five sub-steps as shown in figure 2.

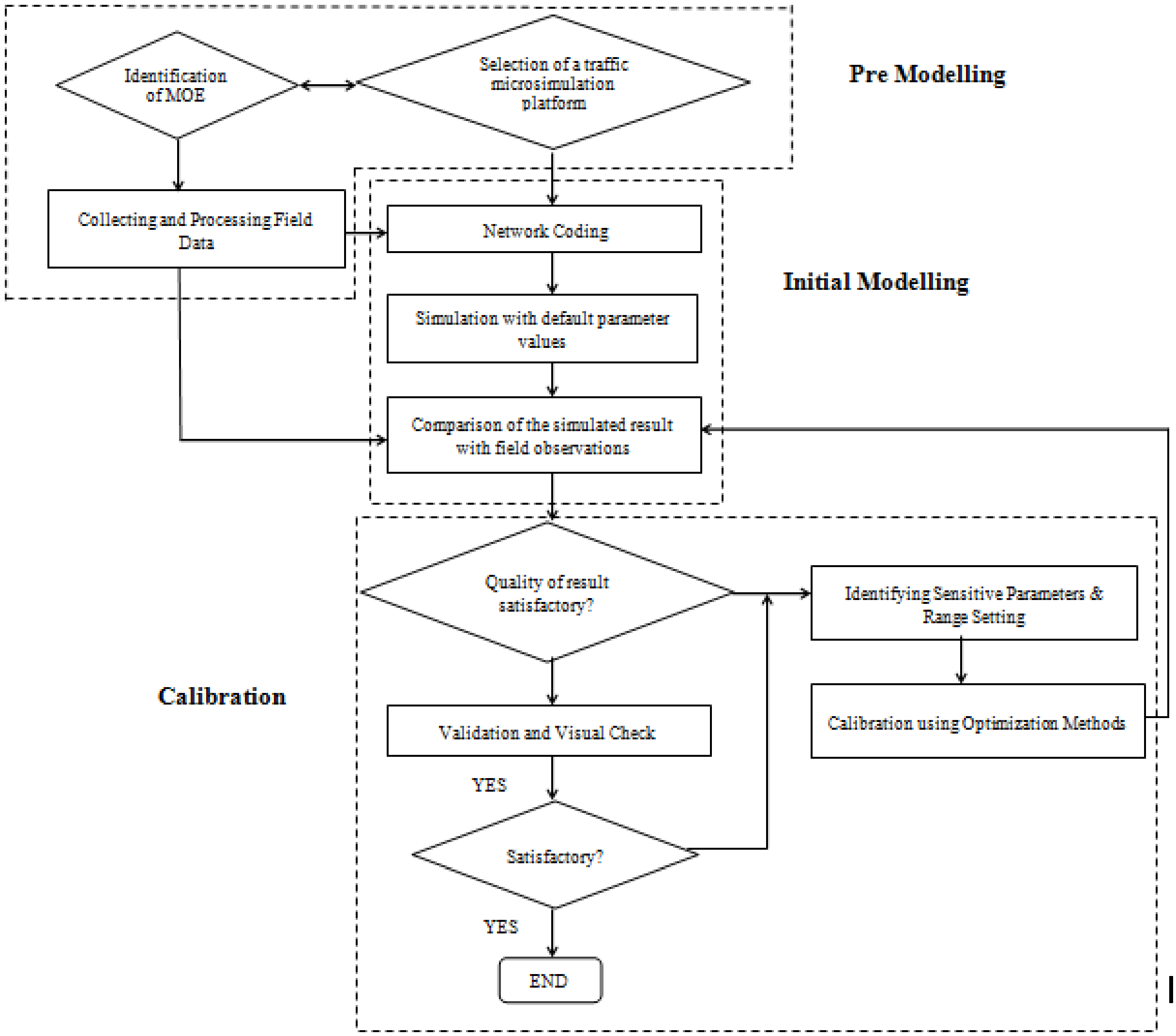


Figure 1. Flowchart for proposed methodology

3.3.1. Identifying sensitive parameters & range setting

The parameters sensitive to the MOE may be identified manually by varying each parameter by small amounts of 10% and keeping all others at their defaults and observing the effect on the MOE. The parameters giving a major change in the output with small increments in their values may be declared to be sensitive. To cut down the wide range of values these parameters can have, a suitable range needs to be decided within which these parameters can vary. The range is identified in a way that it covers a range of 0.5-2 times of the MOE value observed in the field. Thus, every sensitive parameter may be incremented or decremented individually (by 10%-steps) until the desired lower or upper limit of the MOE is reached.

3.3.2. Latin Hypercube Design and ANOVA

This step shall help to select the most sensitive parameters out of the sensitive ones, thus eliminating the less sensitive parameters. The number of combinations for many parameters at a time is enormous making it impossible to examine all possible combinations of a parameter set. Latin Hypercube Design (LHD), a stratified-random sampling procedure, provides an efficient way of sampling variables from their distributions (Iman and Conover, 1980). A LHD algorithm reduces the number of combinations to a reasonable level, still covering the entire parameter surface.

All possible combinations of parameter values obtained from LHD may be provided as input to the model one by one, and the results may be recorded. Multiple runs may be conducted for every combination to address the stochastic variability. Lastly, one-way ANOVA which is a method of determining the statistical significance of the parameters with respect to the output may be performed to further reduce the sensitive parameters to get the 'predictor variables' or the most sensitive parameters.

3.3.3. Multiple Linear Regressions

Once the final set of driver behavior parameters are known, a linear regression model may be developed with driver behavior parameters as independent variables (X) and the desired output as dependent variable (Y) from LHD samples wherein 100 parameter value sets are generated and average of 3 runs is taken for every set. Multiple regressions allow determining the overall fitness of the model and the relative contribution of each of the predictors to the total explained variance. Moreover, the equations obtained will be specific only to the network under consideration and a new regression model must be created in case of other networks.

3.3.4. Optimization using a Genetic Algorithm

This is the final step of calibration where the equations generated will act as inputs to the Genetic Algorithm toolbox in MATLAB. Genetic Algorithm is an extensively used search technique that inherits ideas from natural evolution to effectively find good solutions for combinational parametric optimization problems (Zhizhou et al, 2005). The GA uses a specific number of digits, called a chromosome, which is generated at random. The chromosome's specific digits correspond to parameter values. By generating a single chromosome, values for each parameter are generated and with them a completely randomized simulation run is done. Three basic operators of a GA analysis are the reproduction, crossover, and mutation. The optimization can be done in 2 ways:

- Single criteria - wherein parameter values are obtained in a way that the equation for every vehicle type is optimized individually (one at a time). The objective function is specified in a way that the difference between simulated and observed travel time is less than 15%

$$\%Absolute\ error = \frac{|\ TTobs - TTsim\ |}{TTobs} X100$$

- Multi-criteria - wherein optimized parameter values are obtained for every vehicle type is optimized by a single objective function. The objective function is defined as the weighted % error. The weightage may depend on the share of a vehicle type in the traffic stream.

$$\%weighted\ error = \frac{(\mathrm{W}_1 * error_1) + (\mathrm{W}_2 * error_2) + \cdots + (\mathrm{W}_\mathrm{n} * error_n)}{\mathrm{W}_1\ + \mathrm{W}_2 \ldots . + \mathrm{W}_\mathrm{n}}$$

Where,
W_1, $W_2 \ldots W_n$ is the share [%] of a particular vehicle type in the traffic stream
$error_1$, $error_2 \ldots error_n$ are the absolute errors of output for vehicles 1, 2…n

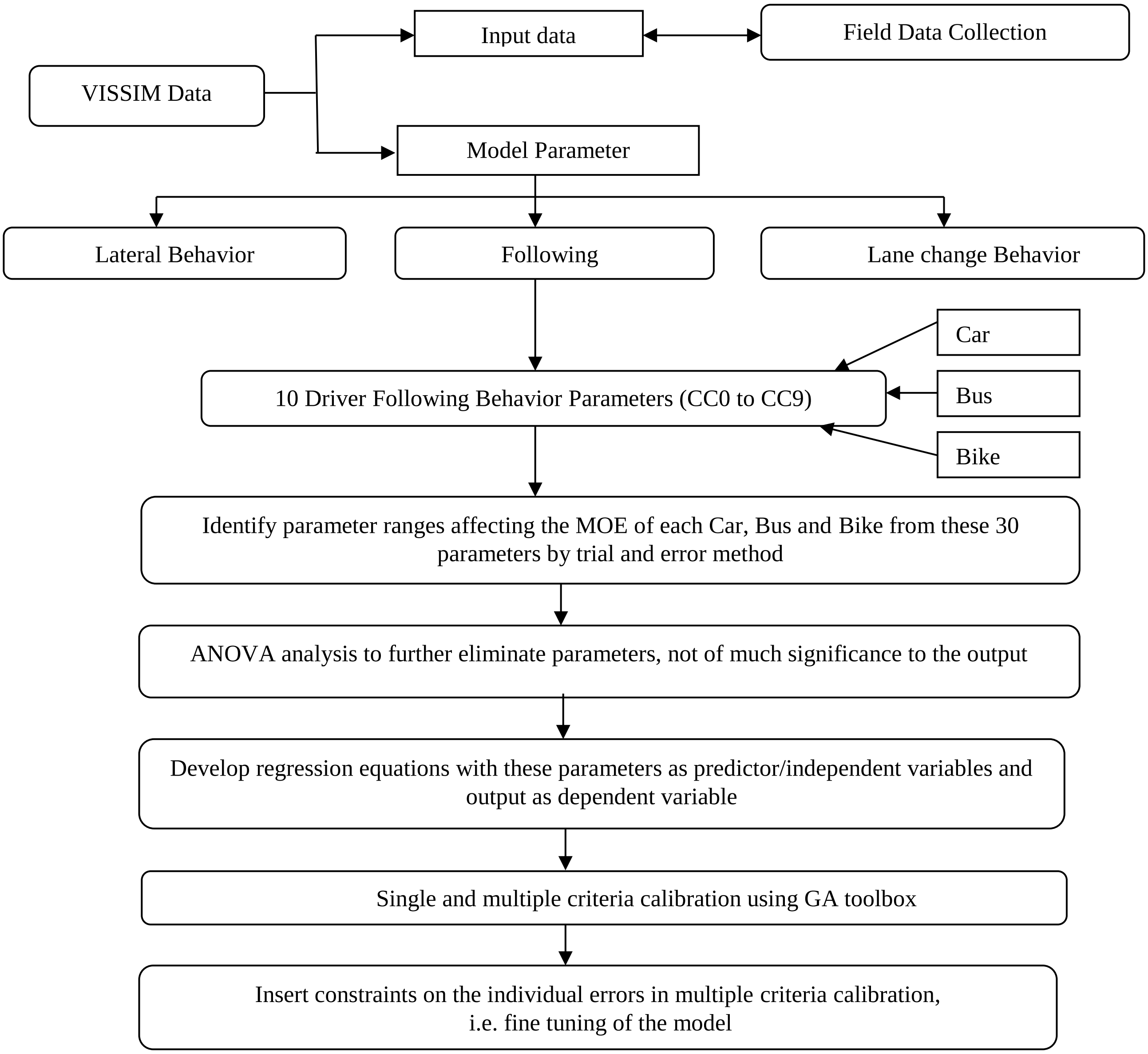


Figure 2. Detailed structure of the calibration procedure

3.3.5. Constraint Insertion

Reducing the objective function to less than 15% does not necessarily guarantee the minimization of individual vehicle errors. This necessitates moving a step further in the process of calibration by putting constraints on individual errors in addition to the weighted % error. This will ensure a high degree of accuracy and robustness of the calibrated model.

3.3.6. Validation and Visual Check

To perform validation of the microscopic simulation model, a new set of field data for different hours of the day or different sections of the corridor may be collected and tested against the calibrated model. It is also important to check the visual proximity of the simulation to the traffic flow observed in the field thus ensuring the plausibility of the calibrated parameter set.

4. Study Area and Database development

The study area as shown in figure 3 is a part of the 3 km long stretch called Dr.Meghnad Saha Sarani in South Kolkata, connecting Golpark with Deshapriya Park. The study area covers about 500 m with an intersection approach, and the road network is coded in VISSIM 7.0. It majorly comprises of three vehicle types i.e. Car, Bus and Bike. The data collected on the field forms a part of the input data given to VISSIM while modelling the network.

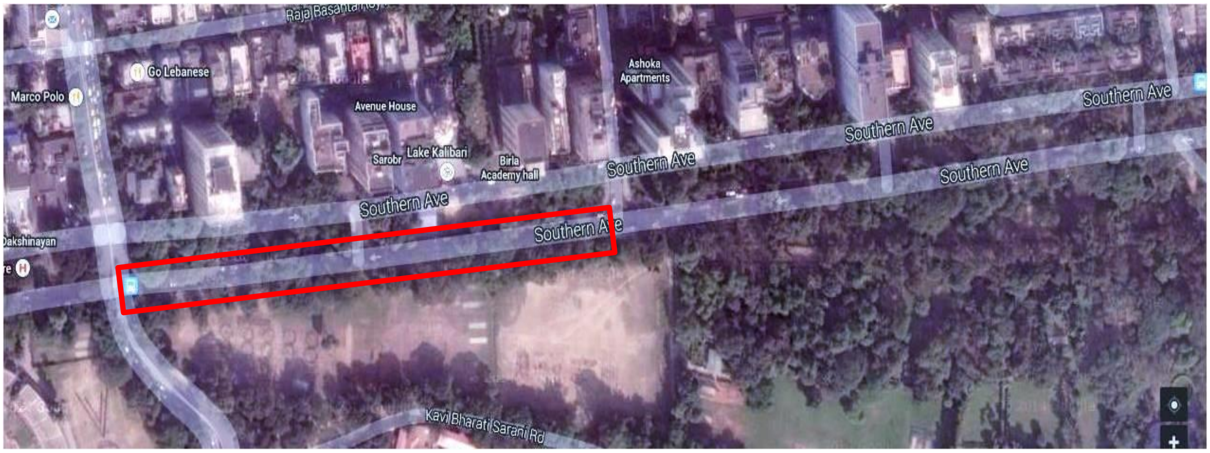


Figure 3. Study Area

The data comprises of geometrical measurements, free flow speed, vehicle compositions, travel time, dwell time, turning movement, parking, and signal timing studies. Also, longitudinal and lateral distances are measured for all possible combinations of vehicles at intersections. Travel time is chosen as the MOE for the study. The parameters are calibrated for Peak Hour and then validated for Non-Peak Hour for the same study area. Additionally, a calibration is done for a midblock section and an intersection approach to see if there is any statistically significant difference in the optimized parameter value set.

4.1. Data Analysis

The extracted data reveals that the traffic stream constitutes 70% cars, 23% bikes and 7% buses. Also, apart from driver behavior parameters, lateral distances and speed-acceleration profiles of the vehicle types contribute towards the simulation of heterogeneous traffic (Jie et al, 2011). These data have also been extracted from the field data collected as shown in table 2 and table 3 and given as input in the form of speed distribution graphs, acceleration distribution graphs and lateral distances between vehicles at 0 km/h into the model. As it may be seen from table 3, the lateral and longitudinal distances vary with respect to the participating vehicles. In general, at zero speed, buses maintain higher distances and bikes maintain lower distances with reference to cars.

Table 2. Observed vehicle speed and acceleration characteristics

Type of Vehicle	Length (m)	Width (m)	Acceleration(m/s^2) at speed ranges* (kmph)				85th Percentile Free Flow Speed** (kmph)	
			0-20	20-40	40-60	60-80	Near intersection	Away
Car	4	1.6	1.5	1.2	0.9	0.7	51	62
Bus	9.8	2.2	0.8	0.7	0.4	0.3	40	48
Bike	1.6	0.55	1.3	1	0.6	0.5	50	60

** Source: Manjunatha et al, 2013*
*** Source: Primary traffic studies by the authors*

Table 3. Lateral and longitudinal distance between vehicles at intersection.

Vehicle Type	Car			Bus			Bike		
	Car	Bus	Bike	Car	Bus	Bike	Car	Bus	Bike
Avg. Lateral gap** (m)	0.60	0.90	0.40	0.90	1.1	0.60	0.40	0.60	0.30
Avg. Longitudinal gap** (m)	1.2	1.6	0.70	1.92	1.59	0.36	0.92	0.80	0.49

*** Source: Primary traffic studies by the authors*

5. Application

The following section presents the stepwise application of the calibration procedure on the selected study corridor. The methodology was carried out with reference to the VISSIM traffic flow simulator. The car following model in VISSIM is based on the continued works of Wiedemann (VISSIM 7 User Manual) with the assumption that a driver can be in one of four driving modes: Free Driving, Approaching, Following, and Braking.Wiedemann-99 model is used in the present study given that it offers more flexibility over Wiedemann-74 model. The following section presents the stepwise application of the proposed procedure on the study area taken.

5.1. Initial Modelling

5.1.1. Network Coding

With the data gathered from the field, the study area is modelled in VISSIM. The geometrics of the area are first coded with the help of Google maps, and then the data analysed is given as input into the model.

5.1.2. Simulation with Default Parameter Values

Once the study area is modelled, ten simulation runs are carried out keeping the driver behavior parameters at their default values.

5.1.3. Comparison of the simulated result with field observations

The average difference between simulated and observed travel times for all vehicle types is then calculated for both, intersection and midblock section. The difference being significant, calibration was necessary and the following steps were adopted.

5.2. Calibration

5.2.1. Identifying sensitive parameters & Range setting

The process starts with 30 parameters in total, i.e.*CC0* to *CC9* for car, bus and bike each. These parameters are subjected to 10% increment/decrement, reducing the number of parameters to eight as shown in Table 4. Their ranges are obtained such that the lower and upper bound values cover an interval of 0.5-2 times the observed value of travel times on field.

Table 4. Sensitive parameter ranges for car, bus and bike

Vehicle type	Parameter	Default value	Lower bound	Upper bound
Car	CC0	1.5	0	2
	CC1	0.9	0.9	4.2
	CC3	-8	-13	-8
Bus	CC0	1.5	0	1.6
	CC1	0.9	0.85	3.85
Bike	CC0	1.5	0	0.8
	CC1	0.9	0.8	2.5
	CC7	0.25	0.25	2

5.2.2. Latin Hypercube Design and ANOVA

The eight parameters obtained, further go through ANOVA analysis where six parameters are finalized as predictor variables for intersection approach as shown in table4. ANOVA analysis is conducted at 95% confidence interval based on the samples obtained from Latin Hypercube Design and the parameters having p value less than 0.05 are the ones sensitive to the travel time.

Firstly, ANOVA analysis is considered for the intersection. CC0 i.e. the standstill distance between vehicles is a major contributing parameter to the travel time as vehicles are stacked closely at intersections. However, these CC0 values are not of much significance to the midblock section because vehicles don't normally stop there. So, fixing the CC0 values obtained for intersection, ANOVA is done for midblock with the assumption that the CC0 for car, bus and bike is invariant throughout the road stretch being modelled. Table 5 demonstrates the most significant parameters for the intersection and the midblock section that are further used in the subsequent steps.

Here, CC0 is the average standstill distance between 2 vehicles. It has no variation.CC1 is the Following Distance. It is the distance that a driver wants to maintain at a certain speed. Higher the speed, more cautious the driver is.CC3 Controls the deceleration process i.e. how much time before safe distance, driver recognizes a preceding slower vehicle.CC7 is the Oscillation during acceleration (VISSIM 7 User Manual**).**

5.2.3. Multiple Linear Regressions

With the help of Latin Hypercube Samples, three regression equations are developed for intersection and midblock each. The travel time for every vehicle type is the dependent variable and the driver behavior parameters are the independent variables or predictor variables.

Initially, three equations are developed (for Car, Bus and Bike) for Peak Hour at the intersection. Once the optimized values for driver behavior parameters are obtained using the Genetic Algorithm procedure, only then calibration may be carried out for the midblock as it requires a fixed value for CC0. The optimal CC0 values obtained for car, bus and bike are changed from default to those obtained from the intersection calibration. Keeping these values as fixed, ANOVA analysis is repeated for the remaining parameters. Additionally, Latin Hypercube samples are generated for these sensitive parameters to develop separate regression models for midblock travel times. Equations 1, 2 and 3 are for intersection, and equations 4, 5 and 6 are for midblock section. From the equations, it may be observed that, in several cases, the travel time of a particular mode is not only dependent on driver behavior of that mode but also on the driver behavior of the other modes.

Table5. ANOVA analysis for intersection and midblock section

Vehicle Type	**Parameters**	**Intersection**		**Midblock**	
		P-Value	**Significant Parameters**	**P-Value**	**Significant Parameters**
Car	CC0 Car	0.00	CC0 Car, CC1 Car, CC1 Bus, CC1 Bike	fixed	CC1 Car, CC1 Bus, CC1 Bike
	CC1 Car	0.00		0.00	
	CC3 Car	0.37		0.08	
	CC0 Bus	0.27		fixed	
	CC1 Bus	0.05		0.05	
	CC0 Bike	0.59		fixed	
	CC1 Bike	0.05		0.03	
	CC7 Bike	0.17		0.54	
Bus	CC0 Car	0.00	CC0 Car, CC1 Car,CC0 Bus, CC1 Bus, CC1 Bike	fixed	CC1 Car, CC3 Car, CC1 Bus
	CC1 Car	0.00		0.00	
	CC3 Car	0.43		0.02	
	CC0 Bus	0.00		fixed	
	CC1 Bus	0.00		0.02	
	CC0 Bike	0.52		fixed	
	CC1 Bike	0.00		0.24	
	CC7 Bike	0.21		0.54	
Bike	CC0 Car	0.00	CC0 Car, CC1 Car,CC0 Bus, CC1 Bus, CC0 Bike, CC1 Bike	fixed	CC1 Car
	CC1 Car	0.00		0.00	
	CC3 Car	0.42		0.25	
	CC0 Bus	0.02		fixed	
	CC1 Bus	0.01		0.84	
	CC0 Bike	0.05		fixed	
	CC1 Bike	0.00		0.62	
	CC7 Bike	0.54		0.32	

TT car $(Y_1) = 28.48 + 3.96\ CC0_{Car} + 3.49\ CC1_{Car} + 0.44\ CC1_{bus} + 0.73\ CC1_{bike}$ (1)

TT bus $(Y_2) = 32.23 + 2.92\ CC0_{Car} + 2.85\ CC1_{Car} + 0.76\ CC1_{bus} + 1.08\ CC1_{bike} + 1.25\ CC0_{bus}$ (2)

TT bike $(Y_3) = 25.57 + 2.82 CC0_{Car} + 1.77\ CC1_{Car} + 0.58 CC1_{bus} + 1.08\ CC1_{bike} + 0.96\ CC0_{bus} + 1.18\ CC0_{bike}$ (3)

TT car $(Y_1) = 0.075 + 4.64\ CC1_{Car} + 0.52\ CC1_{bus} + 1.425\ CC1_{bike}$ (4)

TT bus $(Y_2) = -4.79 + 5.22\ CC1_{Car} + 0.86\ CC1_{bus} - 0.66\ CC3_{Car}$ (5)

TT bike $(Y_3) = 10.52 + 2.93\ CC1_{Car}$ (6)

5.2.4. Optimization using Genetic Algorithm

The equations are used in the GA process to get the optimal values of the driver behavior parameters such that the objective function is reduced down to a minimum possible value. The GA parameters like crossover and mutation probabilities are chosen heuristically. A general roulette wheel technique is used in the selection of parameter values. The calibration principle may be of two types: (i) Single criteria where travel time of car, bus and bike are calibrated separately taking only those parameters that are sensitive to a particular vehicle type under consideration, and, (ii) Multi criteria where all three travel times are considered together and weighted error is minimized. Single criteria calibration focuses only on the absolute error in the output for a particular vehicle type. In that process, the weighted error or the other vehicle types are not taken care of. Multi criteria calibration proves to be much more realistic and should be preferred. Table 6 demonstrates the optimum value of parameters, weighted error and individual error after calibration considering the midblock section during the peak hour. It may be observed that although the weighted error was within acceptable limits, the individual errors for buses and bikes were really high.

Table 6. Individual and weighted error for midblock in the peak hour

Type of Calibration	Parameter	Default Value	Vehicle Type	Optimized Value	% Individual Error	% Weighted Error
Multi Criteria	CC0 Car	1.5	Car, Bus, Bike	1.7	Car-0.04, Bus- 18.26, Bike- 23.07	6.61
	CC1 Car	0.9		3.10		
	CC3 Car	-8		12.25		
	CC0 Bus	1.5		1.35		
	CC1 Bus	0.9		3.21		
	CC0 Bike	1.5		0.45		
	CC1 Bike	0.9		1.88		

5.2.5. Constraint Insertion

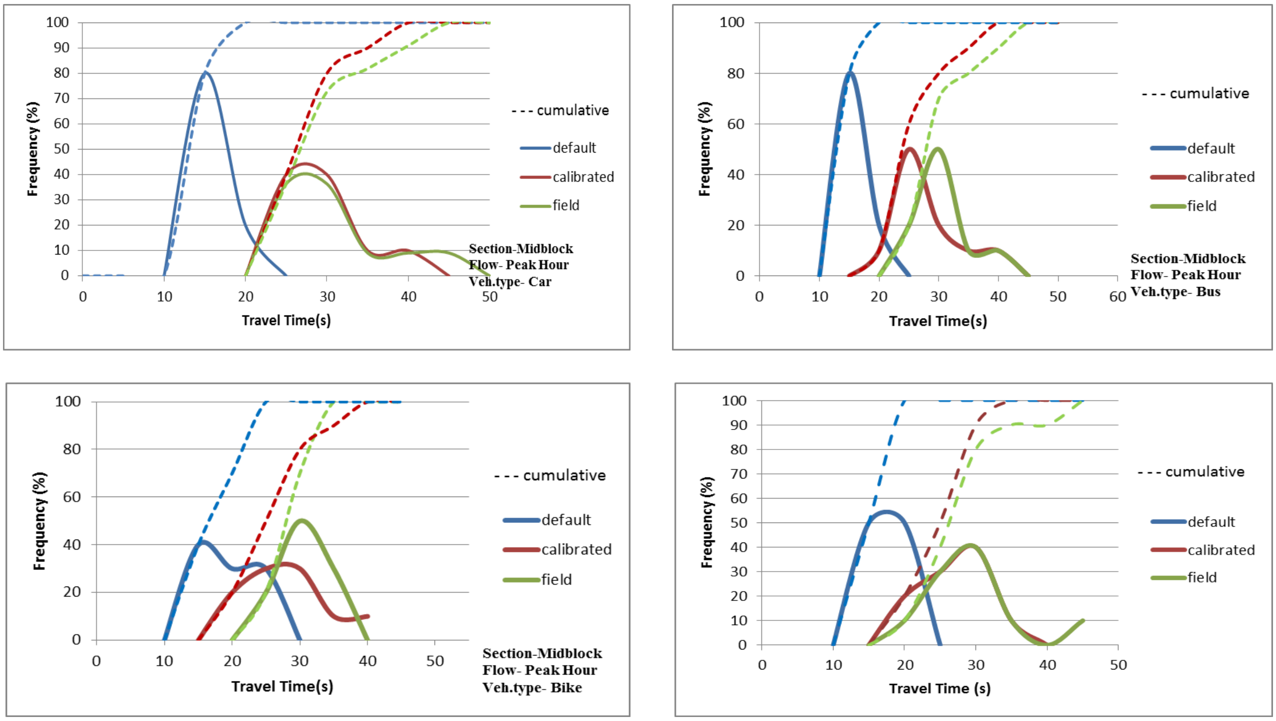
Only Multi criteria calibration will not provide an optimal set of parameters, as the objective to get the weighted error<15% maybe achieved even if the individual vehicle errors (esp. bus and bike) continue to have larger values. For example, the weighted errors as demonstrated in table 6 lie well within limits even though the error in travel time of bus and bike are on a higher side as the weightage factor for bus and bike is comparatively small. To avoid such a situation and get more realistic results, insertion of constraints on individual travel time error of vehicles is necessary with simultaneous minimization of weighted error. Thus, an improved optimized parameter set may be obtained by putting an additional constraint that the individual errors are also within specified limits. The required changes are made to the algorithm and the final set of optimal parameters is obtained as shown in table7. From the table, it may be highlighted that on inserting constraints in the algorithm, the parameter search space becomes much more restricted thus giving more realistic estimates of the parameter values. It also reduces the weighted error in addition to the individual errors.

Table7. Optimal parameter values for intersection and midblock in the peak hour

Flow condition	Parameters	Default values	Optimized value Intersection	Optimized value Midblock	Weighted error Intersection (%)	Weighted error Midblock (%)
Peak Hour	CC0 Car	1.5	1.09	1.09	**3.87** With individual constraints<15 %	**2.24** With individual constraints<10%
	CC1 Car	0.9	2.85	3.75		
	CC3 Car	-8	-8	-9.37		
	CC0 Bus	1.5	1.25	1.25		
	CC1 Bus	0.9	2.45	2.72		
	CC0 Bike	1.5	0.5	0.5		
	CC1 Bike	0.9	1.22	2.3		

5.2.6. Plots

Normal and cumulative frequency distribution graphs are plotted for travel time of cars, buses, bikes showing how calibration is effective when compared to field distribution of travel time rather than default. The calibrated travel time distributions shift very close to field distributions leaving behind the default distributions as can be seen in figure 4a-4d.



Figures 4a, 4b, 4c, 4d. Travel time plots for midblock section after calibration

5.3. Validation and Visual Check

The calibrated model has been successfully validated for a different flow levels (Non-Peak conditions) with a weighted error of 10.3% at intersection and 3.8% at midblock.

5.3.1. Statistical Significance Tests

Obtaining an optimal parameter set is not enough until and unless the values have been compared and justified by the user. Hence, statistical significance tests are necessary. To carry out these tests, five different parameter set solutions are derived from the GA, satisfying the constraint conditions. With the help of these values statistical significance is tested for:

Intersection and midblock section – For peak as well as off peak, there are statistically significant ($p<0.05$) differences in the values of parameters CC1 (headway time), CC3 car (deceleration process controller) when calibrated for intersection and then for midblock as shown in table 8. This is because vehicles stack more closely near the intersection as compared to the midblock sections. Moreover, due to the influence of traffic signals, the deceleration behavior is also different at intersections as compared to the midblock sections.

Table 8. Statistical significance test results for intersection and midblock

Section of Corridor		**p-Value**	**Remark**
Intersection	**Midblock Section**		
CC1 Car =2.73	CC1 Car =3.85	0.000	Null Hypothesis Rejected
CC3 Car =-8	CC3 Car =-10.48	0.005	Null Hypothesis Rejected
CC1 Bus =2.56	CC1 Bus =3.15	0.050	Null Hypothesis Rejected
CC1 Bike=1.53	CC1 Bike= 2.05	0.011	Null Hypothesis Rejected

Vehicle-wise driver behavior parameters – These parameter values are the same for every vehicle type by default in VISSIM. However, that is not the case in the real traffic conditions observed in India. In the present study, the values of CC0 (Stopping distance) and CC1 (headway time) are observed to be statistically significant in most of the cases when compared between car, bus and bike.

Table 9. Statistical significance test results for vehicle-wise driver behavior parameters

Vehicle Type			**p-Value**	**Remark**
Car	**Bus**	**Bike**		
CC0 Car=1.06	CC0 Bus=1.16	-	0.368	Null Hypothesis Accepted
-	CC0 Bus=1.16	CC0 Bike=0.384	0.000	Null Hypothesis Rejected
CC0 Car=1.06	-	CC0 Bike=0.384	0.000	Null Hypothesis Rejected
	CC1 Bike=1.53	CC1 Bike= 2.05	0.011	Null Hypothesis Rejected
CC1 Car =2.73	CC1 Bus =2.56	-	0.452	Null Hypothesis Accepted
CC1 Car =2.73	-	CC1 Bike=1.53	0.000	Null Hypothesis Rejected
-	CC1 Bus =2.56	CC1 Bike=1.53	0.000	Null Hypothesis Rejected

6. Conclusions

The study presents a four-step methodology to calibrate vehicle specific driver behavior in heterogeneous traffic conditions. The vehicle specific travel time at different flow levels is taken as the performance measure. The calibrated parameter sets prove to give much better results when compared to the initial simulation with default parameter values as inferred from frequency distribution plots.

The sensitivity analysis is based on a two-step elimination procedure of trial and error coupled with LHD and ANOVA analysis. It has also been found that the travel time of a particular mode depends not only on the parameters of that mode but also of other modes. Such kind of influences have not been investigated or given due attention in the previous studies reported on calibration of driving behavior using VISSIM. A Genetic Algorithm is used for optimization due to its robustness and ability to handle a large number of parameters. Regression equations are generated in SPSS forming the base of the algorithm. All the parameters are calibrated together by formulating an optimization problem in such a way that constraints are imposed on individual travel times as well as weighted travel time of all the vehicle types in the traffic stream which turns out to be an effective way of finding optimal solutions and provides better results.

Approximately five hundred metre stretch of a traffic corridor in the Kolkata City is taken as the area of study. Emphasis is given to calibration of both, intersection and midblock area, because there are statistically significant differences in the calibrated parameter values for both cases. Also, the CC0 and CC1 values separately for car, bus and bike are found to be significantly different. This supports the primary objective of this study to calibrate the driving behavior with respect to different vehicle categories. This finding is extremely relevant in case of heterogeneous traffic operations in developing countries.

The present study demonstrates a methodology to calibrate class-wise driver 'following' behavior with reference to a particular approach of an intersection and a midblock section, and for only three vehicle types. However, the findings encourage further research to investigate and calibrate driving behavior in general for different types of vehicles in different contexts of heterogeneous traffic operations in developing countries.

Acknowledgement
This study was conducted as a project within the Indo-German Master Sandwich Program. The authors would like to express their sincere thanks to the German Academic Exchange Service (DAAD) and Science and Engineering Research Board (SERB, DST) for providing their kind support. They also appreciate a lot that PTV provided a VISSIM license for conducting this study.

References

Iman, R. L., and W. J. Conover. 1980. Small Sample Sensitivity Analysis Techniques for Computer Models, with an Application to Risk Assessment. Communications in Statistics: Theory and Methods A 9: 1749-1874.

Rakha, H., Hellinga, B., Van Aerde, M., Perez, W. 1996. Systematic verification, validation and calibration of traffic simulation models. *75th Annual Meeting of the Transportation Research Board, Washington, DC*. Citeseer.

Hellinga, B.R. 1998. Requirements for the calibration of traffic simulation models. *Proceedings of the Canadian Society for Civil Engineering*, 4, 211-222.

Hourdakis, J., Michalopoulos, P.G., Kottommannil, J. 2003. Practical procedure for calibrating microscopic traffic simulation models. *Transportation Research Record: Journal of the Transportation Research Board*, 1852(1), 130-139.

Park, B.B., Schneeberger, J. 2003. Microscopic Simulation Model Calibration and validation: case study of VISSIM simulation model for a coordinated actuated Signal system. *Transportation Research Record: Journal of the Transportation Research Board*, 1856(1), 185-192.

Dowling, R., Skabardonis, A., Halkias, J., McHale, G., Zammit, G. 2004. Guidelines for calibration of microsimulation models: framework and applications. *Transportation Research Record: Journal of the Transportation Research Board*, 1876(1), 1-9.

Park, B., Qi, H. 2005. Development and Evaluation of a Procedure for the Calibration of Simulation Models. *Transportation Research Record: Journal of the Transportation Research Board*, 1934(1), 208-217.

Wu Zhizhou, Sun Jian, Yang Xiaoguang. 2005. "Calibration OfVissim for Shanghai Expressway using Genetic Algorithm"Department of Traffic Engineering Tongji University, China.

Mathew, T.V., Radhakrishnan, P. 2010. Calibration of microsimulation models for nonlane-based heterogeneous traffic at signalized intersections. *Journal of Urban Planning and Development*, 136(1), 59-66.

Jie, L., Zuylen, H. J., Shoufeng L. Calibration of a Traffic Simulation for a Chinese city, *Proceedings of 2ndInternational Conference on Models and Technologies for Intelligent Transportation Systems*, Leuven, Belgium, 2011.

Manjunatha, P., Vortisch, P., Mathew, T.V. 2013. Methodology for the Calibration of VISSIM in Mixed Traffic. *Transportation Research Board 92nd Annual Meeting*.

Siddharth, S.M.P., Ramadurai, G. 2013. Calibration of VISSIM for Indian Heterogeneous Traffic Conditions. *Procedia - Social and Behavioral Sciences*, 104(0), 380-389.

FHWA.2004 Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modelling Software. Federal Highway Administration Publication No. FHWA-HRT-04-040

PTV, AG 2013. Vissim 7.00 user manual. *PTV Karlsruhe, Germay*.