Periodica Polytechnica Transportation Engineering, 51(2), pp. 117–125, 2023

Optimization of VISSIM Driver Behavior Parameter Values Using Genetic Algorithm

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Received: 05 March 2022, Accepted: 09 January 2023, Published online: 19 January 2023

Abstract

Modeling effective vehicular traffic is a highly contested topic, especially in developing countries like Sri Lanka, which has a wide range of driving conditions. VISSIM microsimulation software is currently used by Road Development Authority (RDA) and relevant authorities to perform traffic management solutions in Sri Lanka. However, it is required to do modifications to the existing driver behavior parameter values to effectively reflect the realistic traffic conditions observed in the real-world in the simulated model. The main purpose of this study is to calibrate the VISSIM driver behavior parameter values using a genetic algorithm (GA). The methodology and results of the VISSIM model's sensitivity analysis and calibration, which was developed for the Malabe three-legged signalized intersection, are presented in this study. A sensitivity analysis was used to find the most sensitive driver behavior parameters. Using the multi-objective GA optimization tool in the MATLAB software's optimization toolbox, the optimum driver behavior parameter values for these identified most sensitive driver behavior parameters were determined. The findings revealed that GA optimization is effective in reducing the difference between observed and simulated results.

Keywords

optimization, micro simulation, driver behavior, traffic flow, genetic algorithm

1 Introduction

For developing countries such as Sri Lanka and India it is possible to observe a heterogenous traffic condition. A mixed or heterogeneous traffic flow is one that contains a variety of vehicles, both motorized and non-motorized. A main feature of the heterogeneous traffic conditions is the lack of lane disciplines and lane markings. Microsimulation, also known as microscopic simulation, indicates that each real-world entity (vehicle, train, person) is simulated separately and it is represented in the simulation by a corresponding entity that takes into account all necessary features. The entities have the same relationships.

Several software had been developed to model the real-world traffic scenarios such as VISSIM, PARAMICS and AIMSUN (Hidas, 2005). This micro-simulation software is extensively used for transportation operations and management analysis because doing simulations for traffic operations and management before implementing in the real world is cost-effective and timesaving. The micro-simulation software includes the capabilities needed to represent the real-world traffic and roadway characteristics, as well as other features such as evaluations for improving and replacing existing conditions. For this study, the VISSIM software is used.

PTV VISSIM is a microscopic multi-modal traffic flow simulation software package (Harvey, 2016). Traffic engineering, public transportation, urban planning, fire safety, and 3D visualization for illustrative purposes and public communication are all included in the scope of applications. In 1974, Rainer Wiedemann of Karlsruhe University developed the basic traffic model that guides vehicle movement (Wikiwand, 2022). VISSIM has the capability to change the driver behavior, vehicle behavior, etc. from the origin to destination. VISSIM is applicable for multiple of scenarios and through comparison with the other simulation software, VISSIM is efficient in modelling interactions. VISSIM can simulate and interact with several sorts of traffic, including cars, buses, and trucks, as well as public transportation, cycles, pedestrians, and rickshaws. VISSIM can represent vehicle conflict spots using Priority Rules, Conflict Areas, and Signal Heads.

Cite this article as: Gunarathne, D., Amarasingha, N., Kulathunga, A., Wickramasinghe, V. (2023) "Optimization of VISSIM Driver Behavior Parameter Values Using Genetic Algorithm", Periodica Polytechnica Transportation Engineering, 51(2), pp. 117–125. https://doi.org/10.3311/PPtr.20106

Models developed in VISSIM must be calibrated to reflect the field conditions accurately. During the calibration process the default driver behavior parameter values must be changed until the error between the observed and the simulated results was within the acceptable error margin of 15% (Brockfeld et al., 2005; Raju et al., 2020). The calibration is carried out to ensure that the model outputs are close to the observed data. Out of more than hundreds of available driver behavior parameters there are 10 sensitive driver behavior parameters that could be calibrated which include, additive part of safety distance (APSD), multiplicative part of safety distance (MPSD), average standstill distance (ASD), minimum headway (MH), waiting time before diffusion (WTBD), look ahead distance (LAD), look back distance (LBD), safety distance reduction factor (SDRF), distance standing (DS) and distance driving (DD) (Gunathne et al., 2020; Jayasooriya and Bandara, 2018).

Before the calibration process it is necessary to conduct a sensitivity analysis to identify the most sensitive driver behavior parameters which has a significant effect on the simulated results. There are more than hundreds of available parameters which affect the driver behavior, but not all of them affect the simulated results in a significant way (Jayasooriya and Bandara, 2018).

The GA is genetics- and natural-selection-based search-based optimization technique (Tutorialspoint, online). It is frequently employed in the search for ideal or near-optimal solutions to complicated problems that would otherwise take a long time to solve. It's commonly utilized in science and machine learning, as well as to address optimization problems. John Holland and his students and colleagues, most notably David E. Goldberg, devised GAs at the University of Michigan, and have subsequently tried on a number of optimization problems with considerable success (Tutorialspoint, online). In GAs, there is a population or pool of potential solutions to a problem. GA optimizations are sufficiently randomized in nature. GA optimizations outperform random local search as it additionally employs historical data.

The objective of this study is to conduct a sensitivity analysis to identify the most sensitive VISSIM driver behavior parameters and optimize the identified sensitive VISSIM driver behavior parameters using GA for the Sri Lankan context. A sensitivity analysis is important as it gives an in-depth study of all the parameters which eventually helps in identifying the most suitable parameters that should be used for optimization (Kenton, 2022). Due to the variation of the driver behavior from country to country, it is required to calibrate the driver behavior parameter values to the local context to ensure the model reflects the real-world traffic conditions. To determine the optimal driver behavior parameters, it is difficult to individually change the driver behavior parameter values to identify the most suitable set of driver behavior parameter values. Therefore, through a GA optimization algorithm it will help in identifying the most optimal driver behavior parameter values quickly.

2 Literature review

Maheshwary et al. (2020) investigated a methodology for calibrating a traffic micro-simulation model in an Indian urban scenario for a midblock section and an intersection approach in Kolkata, taking vehicle-class specific driver behavior into account. The goal of their research was to develop a well-defined methodology for calibrating driver behavior parameters for diverse traffic using a step-by-step approach. Latin Hypercube design was used to identify the most sensitive elements affecting driver behavior for each vehicle type, utilizing travel time as a performance measure. The relevant driver behavior factors were found by altering each parameter by 10% and evaluating the effect on the Measure of Effectiveness (MOE) while leaving all others at their settings. For each vehicle class, linear regression models were created with the sensitive driver behavior factors in mind. GA optimization was applied to find the best parameter sets for different vehicle classes. GA toolbox in MATLAB was used for the optimization of the sensitive driver behavior characteristics. Single and multi-criteria calibration methodologies were used to get considerably more realistic results, reducing weighted error across all vehicle classes. Through the study it was discovered that these vehicle classes maintain different safety distances, with the smallest being for the bikes.

Muhan et al. (2013) investigated the use of a GA to calibrate four driver behavior factors and proposed a set of calibration procedures based on VISSIM. Maximum queue length and travel time were used at the MOE. The research was conducted at a single signalized intersection in Beijing's Yizhuang Zone. Sensitivity analysis was performed by changing the value of one unknown parameter while leaving the others unchanged. Maximum LAD, ASD, APSD, MPSD, WTBD, MH, maximum deceleration (MD), and allowed deceleration (AD) were the eight model parameters chosen for the sensitivity analysis. The most sensitive driver behavior parameters were determined to be the ASD, APSD, MPSD, and maximum deceleration. A GA-based calibration approach was developed to optimize the sensitive driver behavior parameters. The Average Absolute Relative Error (AARE) for the maximum queue length was 31.3% before calibration and 9.8% after calibration. Before calibration, the Mean Absolute Percentage Error (MAPE) for the travel time was 15.2%, and after calibration, it was 7.3%. Through the study it was found that this calibrating procedure is both practical and effective. The simulation results had acceptable errors, and this method accurately reproduced the operating state while also providing a solid foundation for the creation of a later optimization scheme.

Tettamanti et al. (2015) investigated the possibility of using a calibration method to construct realistic VISSIM simulations. The major goal of the study was to suggest a calibration technique based on floating car speed data that used GA optimization to simulate actual traffic on a network. The research was carried out on the Oktogon Square in Budapest. Floating car data (FCD) was primarily acquired from fleet automobiles equipped with a GPS receiver that provided accurate speed data and GPS position logs in the real world. A combination of different demand flows was examined in the event of a larger traffic network. It was proposed to use an online and iterative optimization method to solve the problem. An integrated VISSIM-MATLAB traffic simulation platform-based interface was used for advanced simulations. FCD-based average speeds were gathered in a road segment between two signalized intersections, as well as average junction turning rates and signal timings. As the objective function has no derivative, formalizing and solving the optimization problem as a GA problem was a possible approach. The fluctuation in the fitness function value was less than 22%, which was regarded as an acceptable calibration accuracy. The proposed calibration procedure was validated under various traffic conditions using real-world floating automobile traffic data and a traffic simulator. It was emphasized that the method can be used to create any form of traffic simulator.

At work zone sites, Mahmood and Kianfar (2019) investigated providing different calibration parameters for heavy vehicles and passenger vehicles. The main goal of their research was to come up with a set of model calibration parameters in the simulation model that would reflect the real-world traffic conditions in St. Louis, Missouri, USA. Portable traffic sensors were used to collect data on speed, flow, and occupancy in the eastbound work zone taper. AARE was used as measure of dissimilarity between simulation and observed data. A particle swarm optimization (PSO) framework was implemented to improve the effectiveness of the calibration process. MATLAB was used to construct a VISSIM-COM script that automatically updates the vehicle input volumes and runs the PSO optimization algorithm for each day. It was discovered that for heavy trucks, the desired time headway was 2.31 s and for passenger cars, 1.53 s, and that the longitudinal following threshold for large vehicles and passenger cars was 17.64 meters and 11.70 meters, respectively. According to validation, the AARE for flow rate at the taper was 10%, and the Mean Absolute Error (MAE) was 54 veh/h/ln. It was found that the PSO framework was more computationally effective than brute-force search methodologies used in previous studies, and that it can determine optimal driver behavior features.

Wu et al. (2005) investigated how the GA, an optimal optimization method, was used to identify an appropriate combination of VISSIM parameters. Field data from Shanghai's Traffic Information Collecting System (TICS) was used to explore and simulate the North-South Expressway on the VISSIM platform. Inner City Information Collecting Systems (ICICS) was used to collect real-time data for the "Yan'an" elevated expressway, including volume, speed, vehicle type, occupancy, and headway for each lane at a 20-second interval. One week data was used for the study. TongJi Video Information Collecting Systems (TJVICS) was used to save a day's worth of video data from the "N-S" elevated expressway during rush hour. For model calibration and validation, manual traffic counts of the license plate at on and off ramps were done to obtain the N-S trip OD. The tests site was modeled with VISSIM, and the calibration parameters were determined based on expressway traffic flow characteristics and past experience. The GA optimization approach was used to optimize the calibration parameters. The software that performed the calibration included the VISSIM, GA, and control modules. Through optimization the perfect driver behavior parameters were identified. When the optimized driver behavior parameters were used it was found that, the VISSIM predicted average speeds were pretty similar to the field findings. The MAPE between actual and simulated speeds before calibration was 1.86%, with a 3.88% Root Mean Square Error (RMSE). With an RMSE of 2.09, the MAPE after calibration was 0.84%. The VISSIM model, which had been calibrated, replicated and recured observed traffic operations on the field road.

Yu et al. (2004) investigated the possibility of using a GA-based strategy to calibrate the driver behavior parameters of VISSIM microsimulation software. The goal of their research was to create a GA-based approach for calibrating driver behavior parameters of VISSIM using GPS data, and then apply it to the road networks surrounding the terminals of Houston's Intercontinental Airport (IAH). Traffic counters were used to collect data, a test vehicle equipped with GPS looped around IAH to obtain the instantaneous speed data of the vehicle. Ten driver behavior parameters were considered for the proposed approach. The performance metric was defined as the sum of squared error (SSE) of observed vs simulated vehicle speeds at cross sections along the route. AUTOSIM simulation approach was used to express the link between the SSE and the 10 driver behavior factors in an indirect manner. To minimize the SSE, GA optimization was used to discover the ideal driver behavior parameter values. The proposed GA-based calibration approach was implemented using the GA toolbox in the MATLAB platform. After comparing the data, it was found that the SSE had fallen by over half after the calibration, demonstrating that the proposed GA-based technique was very efficient and feasible.

Liu et al. (2006) investigated the use of a hybrid empirical algorithm as an optimization strategy for determining the best micro-simulation parameter combination. The research was carried out in Hefei, China, on an urban downtown road network. License Plate Survey and a loop detector were used to collect traffic data. The utilized hybrid algorithm which was referred to as the GSA Algorithm and comprised of a combination of GA and Simulated Annealing (SA) Algorithm. Eight sensitive driver behavior parameters were identified; Emergency Stop Distance (ESD), Lane Change Distance (LCD), WTBD, MH, Number of Observed Vehicles (NOV), ASD, APSD, and MPSD and their respective values through a series of simulation tests. Travel time was used as the performance measure. Optimizations were done until a percentage error of less than 15% between the simulated and observed outcomes were obtained. It was identified that using calibrated driver behavior characteristics and the GSA algorithm, it is possible to duplicate real traffic flow on the VISSIM model. It was found that the GSA algorithm could effectively limit the likelihood of early convergence and converge to a local optimum.

Manjunatha et al. (2013) investigated the feasibility of developing a methodology for calibrating a micro simulation model for mixed traffic circumstances. The research was carried out in Mumbai on two signalized crossings with varying traffic characteristics. The goal of the study was to examine the effectiveness of the calibrating process. VISSIM was used to model the vehicle, geometry, and traffic representations, and then a multi parameter sensitivity analysis was used to discover the calibration parameters, using link capacity as the sensitivity measure. A genetic approach was used to find the best calibration parameter values by minimizing the difference between observed and simulated outcomes. For the study, the control delay was used as the MOE. A new data set was used to validate the calibrated parameter values, and the permissible absolute error margin was set at 15%. It was found that the simulated results utilizing the calibrated parameter values reflected the field circumstances through calibration and validation, multi parameter sensitivity analysis was an efficient method for identifying important factors and their interactions and combining the proposed methodology with GA optimization in VISSIM yielded credible results.

The above research studies had been conducted on calibration and optimization of the driver behavior parameter values in various countries which also include sensitivity analysis in determining the most sensitive driver behavior parameters. In the local context, no research studies were found that conducted a sensitivity analysis and only a few studies used the optimization techniques to determine the optimum set of driver behavior parameters. This study mainly focusses on identifying the most sensitive set of driver behavior parameters through a sensitivity analysis and optimization of the identified driver behavior parameters through a GA optimization algorithm to determine the optimum set of driver behavior parameter values which reflect the field conditions in the simulated model.

3 Methodology

3.1 Study area

Malabe intersection (Fig. 1) is a signalized intersection located at Malabe town in Colombo District, Sri Lanka. The intersection consists of three legs and has a heavy traffic volume. All the legs consist of two lanes at each approach as shown in Fig. 2.

3.2 Data collection and analysis

Data collection for the study was conducted on a weekday during the off-peak time from 11:00 am to 12:00 noon at the Malabe intersection. The geometric data were collected through field measurements using a measuring wheel and Google Earth Pro software. The Google Earth measurements were validated by measuring the length of the road segment in the field and comparing with the same

Fig. 1 Malabe intersection

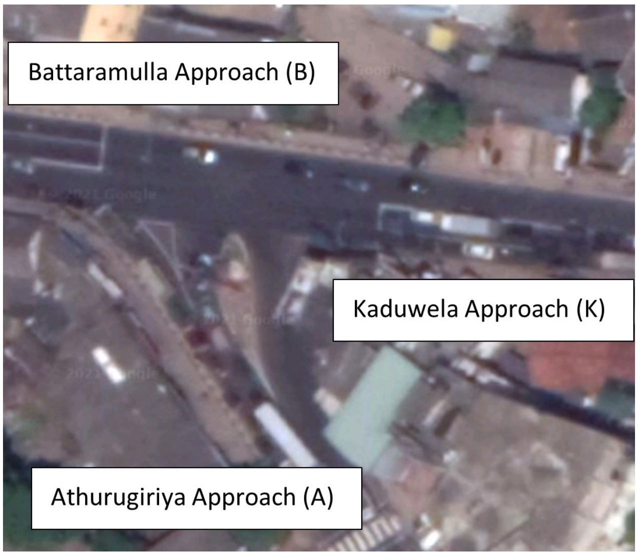

Fig. 2 Malabe intersection (close view)

length of the road segment length obtained through the Google Earth Pro software. Video tape recordings were collected at the intersection using three video recorders for the three legs of the intersection. Vehicle volume data, vehicle turning movement data, and vehicle composition data were obtained by manually analyzing each video tape recording. The signal timing, signal phasing, and signal cycle time data were collected by on-site observations. The queue length of vehicles was obtained by placing masking tapes at 5m intervals at each leg of the intersection and the queue length was recorded at the intersection itself. The vehicle volume data (Fig. 3), vehicle turning movement data (Fig. 3), vehicle composition data (Figs. 4 to 6) and the signal timing data (Table 1) were used as the input for the VISSIM microsimulation software.

3.3 Model development

The model was developed using the tools available in the VISSIM microsimulation software with the collected and

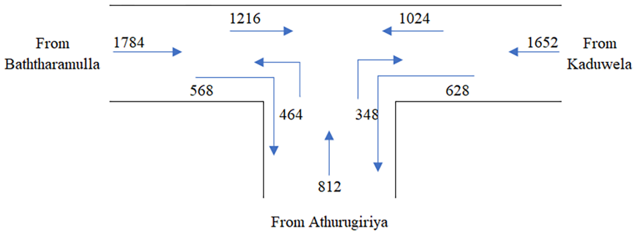

Fig. 3 Vehicle volume data at the Malabe intersection

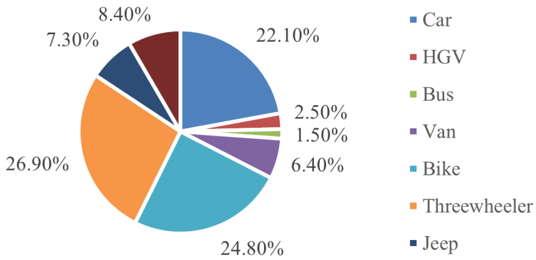

Fig. 4 Vehicle composition from Kaduwela direction

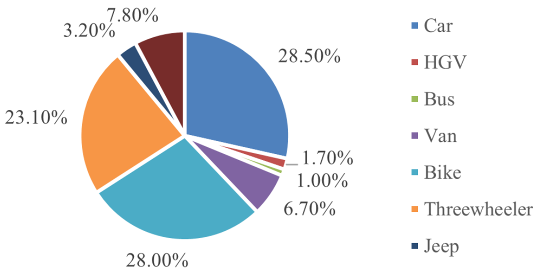

Fig. 5 Vehicle composition from Baththaramulla direction

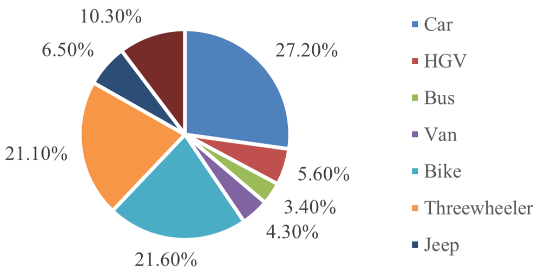

Fig. 6 Vehicle composition from Athurugiriya direction

analyzed data. The average queue length was considered as the MOE. The developed model was simulated and the percentage error between the simulated data and the field observed data for each leg of the intersection was calculated using Eq. (1) (Stephanie, 2016).

$$\%\ \text{Error} = (\text{OAQL} - \text{SAQL})/\text{OAQL}, \tag{1}$$

where:

- OAQL: Observed Average Queue Length;
- SAQL: Simulated Average Queue Length.

Afterwards, the MAPE for the entire intersection was calculated using the Eq. (2) (Stephanie, 2021):

Table 1 Signal timing data at Malabe intersection

Direction	Signal timing (s)			
	Red	Yellow	Green	Yellow
A to K	90	1	20	3
A to B	50	1	60	3
B to A	80	1	35	3
B to K	30	1	90	3
K to A	40	1	75	3
K to B	65	1	50	3

$$\mathrm{MAPE} = \mathrm{SEI}/\mathrm{N}, \quad (2)$$

where:

- SEI: sum of all the % errors at each leg of the intersection;
- N: number of legs at the intersection;

The acceptable range for the MAPE is 15%–22% or lesser error (Brockfeld et al., 2005) such that the model would be considered as a calibrated model. For this study, the MAPE range was considered as 0%–15%. If the MAPE was greater than ±15% the most sensitive driver behavior parameters were identified, and the identified driver behavior parameters were optimized.

3.3.1 Sensitivity analysis

Out of more than hundreds of available driver behavior parameters there are 10 sensitive driver behavior parameters that could affect the simulated results which include, APSD, MPSD, ASD, MH, WTBD, LAD, LBD, SDRF, DS and DD (Jayasooriya and Bandara, 2018; Park et al., 2006; Siddharth and Ramadurai, 2013). A sensitivity analysis was performed to determine which of these parameters affect the simulation results significantly. The sensitivity analysis was done by changing a single driver behavior parameter value individually, while keeping the rest of the driver behavior parameters with their default values and by observing how it affected the simulated results. If the driver behavior parameter led to a significant change in the simulated results, it was considered as one of the most sensitive driver behavior parameters for the study. Similarly, the same process was done for all the ten driver behavior parameters and the most sensitive driver behavior parameters were identified.

3.3.2 Optimization through genetic algorithm

Polynomial equations were developed for each of the identified sensitive driver behavior parameters by varying the value of each parameter individually and keeping the rest of the parameters in their default values. Fitness function was developed as a linear equation and optimized to determine the optimal values of the sensitive driver behavior parameters which reduced the MAPE within the acceptable range. Optimization was done using the multi-objective GA optimization tool available in the optimization toolbox of the MATLAB software. The optimization program was run with a population size of 20 and the number of generations were set to 1000. Each optimization run provided with different set of optimum driver behavior parameter values which could reduce the MAPE. The results provided by the optimization program were entered into the identified sensitive driver behavior parameters in the VISSIM software. The developed model was run with each of the results provided by the optimization program and the MAPE was observed until the most suitable set of optimal values for the sensitive driver behavior parameters to reduce the MAPE were identified. The most suitable set of optimum values for the sensitive driver behavior parameters were considered as the calibrated driver behavior parameter values for the developed model.

4 Results and discussion

The model simulation for the Malabe intersection was done using VISSIM after developing the model of the intersection. The simulated average queue length provided by the VISSIM software was compared with the data of the average queue length obtained through observations and the percentage error in each leg of the intersection and the MAPE of the entire intersection were found. The results showed that the MAPE was greater than 15% as shown in Table 2.

As the MAPE was greater than 15% the sensitivity analysis was done to determine the most sensitive driver behavior parameters which affected the simulation results. Out of the 10 sensitive driver behavior parameters that could affect the simulated results which include, APSD, MPSD, ASD, MH, WTBD, LAD, LBD, SDRF, DS and DD, the 6 most significant sensitive driver behavior parameters were identified. The identified sensitive driver behavior parameters are APSD, MPSD, ASD, LAD, DS and DD.

Polynomial equations were developed for each of the identified sensitive driver behavior parameters by varying

Table 2 Simulation results with default driver behavior parameter values at Malabe intersection

Direction	OAQL	SAQL	% error	MAPE
From Kaduwela	67.72 m	90.14 m	−33.10%	
From Battaramulla	49.33 m	65.53 m	−32.83%	29.05%
From Athurugiriya	67.86 m	82.25 m	−21.21%	

the value of each parameter individually and keeping the rest of the parameters in their default values (Table 3). Each of the identified sensitive driver behavior parameters were allowed to vary within its minimum and maximum value range (Table 3) during the optimization.

The results from the optimization done using the multi-objective GA optimization tool available in the optimization toolbox of the MATLAB provided with different set of optimum driver behavior parameter values (Table 4) which could reduce the MAPE and were fed to the VISSIM software to obtain the MAPE.

The optimization trial number 43 (Table 4) provided with the most optimal driver behavior parameter values which reduced the MAPE from 29.05% to 7.82% (Table 5). As the MAPE was within the acceptable range, the most optimal driver behavior parameter values from the optimization trial number 43 were considered as the calibrated driver behavior parameter values for the Malabe intersection.

VISSIM calibration studies have been conducted by previous researchers. Jaysooriya and Bandara (2018) had calibrated the VISSIM software by manually modifying the driver behavior parameters which also provided with a reliable error percentage of 5.67% for Katubedda intersection. However, by using the GA optimization in this study provided a faster result compared to the method of modifying the parameters individually. Siddharth and Ramadurai (2013) had calibrated VISSIM for Indian heterogeneous traffic conditions, where Analysis of Variance (ANOVA) was used to identify the most sensitive driver behavior parameters which provided with nine sensitive driver behavior parameters and after calibration it provided with a reliable error percentage of 7.47%. In this study the most sensitive calibration parameters were identified by changing a single driver behavior parameter value individually while keeping the rest of the driver behavior parameters with their default values and by observing how it affected the simulated results. In this study six most sensitive calibration parameters were identified and after calibration this study also provided with a reliable error percentage of 7.82%.

Table 3 Maximum and minimum values range of the identified sensitive driver behavior parameters

Parameter	Default	Min	Max
Average Standstill Distance (ASD)	2 m	1 m	2.5 m
Additive Part of Safety Distance (APSD)	2	1	2.5
Multiplicative Part of Safety Distance (MPSD)	3	1	4
Look Ahead Distance (min) (LAD)	0 m	0 m	30 m
Distance Standing (0 km/h) (DS)	0.2 m	0.2 m	1 m
Distance Driving (50 km/h) (DD)	1 m	0.5 m	2 m

Table 4 Optimized sets of driver behavior parameter values and the respective MAPE values

Trial No.	ASD (m)	APSD	MPSD	LAD (m)	DS (m)	DD (m)	MAPE
1	2.274	1.572	3.254	14.199	0.210	0.988	33.99%
3	1.014	1.185	1.074	14.598	0.225	0.299	39.21%
10	1.567	1.237	2.262	10.177	0.203	0.389	24.99%
12	1.792	2.020	1.379	6.823	0.238	0.671	27.09%
20	1.880	1.857	2.664	7.512	0.503	0.525	26.96%
22	1.828	2.009	1.000	0.420	0.200	0.200	26.27%
24	1.568	1.960	1.587	12.553	0.364	0.463	26.38%
29	1.704	1.221	1.389	6.549	0.558	0.644	12.30%
33	1.826	1.240	1.102	14.995	0.231	0.519	18.55%
38	1.757	1.272	2.670	14.938	0.333	0.448	23.31%
40	1.890	1.357	2.002	9.016	0.321	0.484	24.64%
43	1.177	1.283	1.720	14.485	0.727	0.815	7.82%
44	1.175	1.283	1.720	14.485	0.727	0.815	8.37%

Table 5 Simulation results with optimized driver behavior parameter values at Malabe intersection

Direction	OAQL	SAQL	% Error	MAPE
From Kaduwela	67.72 m	68.94 m	−1.80%	
From Battaramulla	49.33 m	47.55 m	−3.61%	7.82%
From Athurugiriya	67.86 m	80.10 m	18.04%	

Through the results obtained from the optimization, it could be concluded that the optimization of the VISSIM driver behavior parameters using the GA is an efficient, reliable, and fast method to identify the optimum driver behavior parameter values for calibrating the VISSIM software into local traffic conditions. It could be concluded that the sensitivity analysis will help in identifying the most sensitive driver behavior parameters which affect the simulated results from the VISSIM software.

5 Conclusion and recommendations

In this study, the VISSIM driver behavior parameter values were optimized using a GA. The study was conducted at the Malabe three-legged signalized intersection. Model simulation of the Malabe intersection showed a MAPE of 29.05% with the default driver behavior parameter values which was above the acceptable range. Therefore, a sensitivity analysis was done to find the driver behavior parameters affecting the results of the simulation. Through the sensitivity analysis done it was found that out of the 10 driver behavior parameters that affect the results of the simulation only six driver behavior parameters affected the simulated results of significantly. Sensitivity analysis was efficient in identifying the driver behavior parameters which have a significant effect on the simulated results. The identified sensitive driver behavior parameters were optimized through a GA. The optimization trial number 43 provided with the best set of optimized driver behavior parameter values which reduced the error to 7.82%. Therefore, it could be concluded that the VISSIM driver behavior parameter optimization by using a GA is an efficient, reliable, and fast method to identify the optimum driver behavior parameters values for calibrating the VISSIM software into local traffic conditions. In order to improve the accuracy of queue length data, vehicle composition, vehicle turning movement, and vehicle volume data more accurate, it is recommended to use a drone to collect the video data and to process the video data using an aerial traffic data analysis software to collect the necessary information.

As the GA optimization provides with efficient, reliable, and fast results, it is recommended to use the GA in identifying the optimum driver behavior parameter values while calibrating the VISSIM software at any circumstance.

Acknowledgement

Authors wish to thank the VISSIM Company for providing the Thesis version of software for this research. This research was supported by the Accelerating Higher Education Expansion and Development (AHEAD) Operation of the Ministry of Higher Education, Sri Lanka, funded by the World Bank.

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