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Calibration of Car-following Parameters in VISSIM for Traffic in Kathmandu

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Abstract
Traffic simulation is widely used to perform analysis of traffic operations. Traffic in Nepal is non-lane based, heterogeneous and mixed while car-following models are developed for lane based and homogeneous traffic condition.Traffic simulation software needs to be calibrated to represent local conditions. The main objective of this study was to calibrate Car-following parameters in VISSIM. The parameters for calibration were selected based on past studies on VISSIM calibration in heterogeneous traffic condition. Eleven parameters were selected for analysis. Latin hypercube sampling technique was used to create the sample set of parameters for simulation. One way ANOVA was used to determine the sensitive parameters. Linear equations were developed using sample set prepared by Latin hypercube sampling technique. Multi objective Genetic algorithm tool available in MATLAB was used to perform optimization of linear equations to minimize the difference between field delay and simulated delay. Three car-following parameters of Widemann-74 model were found sensitive which were calibrated using genetic algorithm to obtain optimal values.

Keywords
VISSIM, Genetic algorithm, LHS, ANOVA

1. Introduction

Microscopic simulation model provides a quicker, cheaper, and safer environment for conducting studies than field installation and testing, so it is extensively utilized in both transportation operations and management analysis [1]. The use of microscopic traffic simulation tools enables the introduction and assessment of various situations without affecting the flow of traffic on the road. These traffic simulation tools are based on different theories of microscopic traffic behavior, such as car following and lane changing [2].

The traffic in Nepal is non-lane based, heterogeneous, and mixed while car following models are developed for lane based and homogeneous traffic environment. Analytical modeling of non-lane-based and mixed traffic is in its developing stage. For the purpose of analyzing and modeling heterogeneous traffic, microscopic simulation is preferred [3].

Previous studies suggest that microscopic simulation model need to be calibrated to represent the local traffic. This can be accomplished through model calibration, which is a process of choosing the optimal set of model input parameters by changing or fine-tuning their default values to accurately reflect the field-measured and simulated local traffic conditions. [1].

2. Literature Review

A comprehensive calibration process should be performed before any further study or evaluation is done in order to ensure that the simulation models are sufficiently reliable [4]. In the early stages of traffic flow micro-simulation, researchers adopted the trial-and-error method and opted for default parameters for representing diverse traffic scenarios, resulting in substantial errors in the model outputs [1]. Recently, researchers have developed procedures to calibrate car-following parameters to increase the reliability of the simulation model.

Park and Schneeberger proposed a nine step method to calibrate VISSIM, a micro-simulation software. A linear equation was developed and optimized by excel solver to match the field travel time value [1].

Park and Qi devised a methodology where calibration of VISSIM was done by selecting a measure of effectiveness(MOE) as performance measure for calibration. Travel time of south bound approach of intersection located in Virginia, U.S.A was used as measure of effectiveness. The parameters which were significant to the study was found by ANOVA test. The sampling plan for ANOVA test was created by Latin Hypercube Sampling (LHS) technique. Genetic Algorithm was used as optimization technique to calibrate 8 sensitive parameters [4].

Mathew and Radhakrishnan studied three intersection in India to calibrate VISSIM in heterogeneous traffic condition. Delay was used as the MOE for calibration. Field delay was measured by procedure recommended by HCM[5]. The sensitive parameters were identified utilising trial and error approach in which each parameter was increased and decreased by 10% individually. The sensitive parameters were then calibrated by using genetic algorithm, the minimization of difference between field delay and simulated delay was used as tuning parameter for genetic algorithm. Seven parameters were calibrated which included three Widemann-74 and four Widemann-99 parameters [3].

Siddhartha and Ramadurai used flow as MoE to calibrate VISSIM, LHS was used for sampling plan and first level sensitivity analysis was done by ANOVA, second level sensitivity analysis was done by elementary effects method on parameters which were not found significant from Anova test. Genetic algorithm was used to find the optimal values of sensitive parameters during calibration. A total of nine parameters were calibrated, which included minimum headway, average standstill distance, additive part of safety distance, multiplicative part of safety distance, minimum lateral distance of bike at 0 kmph, look ahead distance minimum, look back distance minimum, desired acceleration for bike and HMV at 0 kmph [6].

Maheshwary et al. used travel time as MOE to calibrate VISSIM, initial sensitivity analysis was done by individually varying each parameter by 10 % and measuring its effects. Further LHS was used to create sampling plan and ANOVA was used to find significant parameters. The LHS was used to develop regression equations; travel time was used as dependent variable and sensitive parameters as independent variables. The regression equations were input to genetic algorithm mechanism to obtain the optimal values of the parameters. The genetic algorithm toolbox in MATLAB was utilised for the optimization of the obtained sensitive car-following parameters for each vehicle class [7].

Gunarathne et al. selected a three legged intersection to calibrate VISSIM in Srilanka. Queue length was selected as MoE. Initially ten parameters were selected by reviewing past studies. The sensitive parameters for calibration was determined by trial and error method in which each parameter was altered individually without changing other parameters. Six parameters were found sensitive which was optimized using genetic algorithm. Genetic algorithm optimization tool available in the optimization toolbox of the MATLAB was used as genetic algorithm framework for optimization. Minimum absolute percentage error (MAPE) between observed and simulated queue length obtained below acceptable range was used to obtain optimal value of parameters [8].

Acharya and Marsani altered driving behavior parameters so as to match the traffic volumes obtained from VISSIM with the field data [9].

Shrestha and Pradhananga used volume as key performance measure and queue length as additional calibration measure, the parameters used for calibration was based on review of literature related to VISSIM calibration under heterogeneous and non-lane-based traffic, trial and error method was used to find the optimal values of the parameters [10].

Considering the literature above VISSIM was used by many researchers for simulation [1, 4, 8, 7, 6, 3, 9, 10]. Delay, flow, travel time, and queue length were among the likely MoEs used for calibration. For sensitivity analysis ANOVA and for sampling plan LHS were frequently used. Finally genetic algorithm was used as optimization algorithm [3, 4, 6, 8]. Hence, for this study field delay was used as MoE, ANOVA was used for sensitivity analysis, LHS was used to create sampling plan and genetic algorithm for optimization. Brockfield et al. stated that "the acceptable range for the MAPE is 15%–22% or lesser error, such that the model would be considered as a calibrated model" [11]. For this study, the MAPE range from 0% to 15 % was selected for validation.

3. Objective of Study

The main objective of this study is to calibrate car-following parameters in VISSIM. The specific objectives are:

- To perform sensitivity analysis of driving behaviour parameters in VISSIM
- To calibrate sensitive parameters using genetic algorithm

4. Methodology

4.1 Study Area

A map of Kathmandu was analyzed to find the suitable network for simulation in VISSIM 2023 (SP08). The considered criteria for site selection were that the site should have simple geometry, a wide range of vehicle composition, and be signalized. The Putalisadak intersection was selected for this study as it met all the criteria for site selection.

Figure 1: Putalisadak Intersection

4.2 Overview of Methodology

The proposed framework for the research is shown in Figure 2.

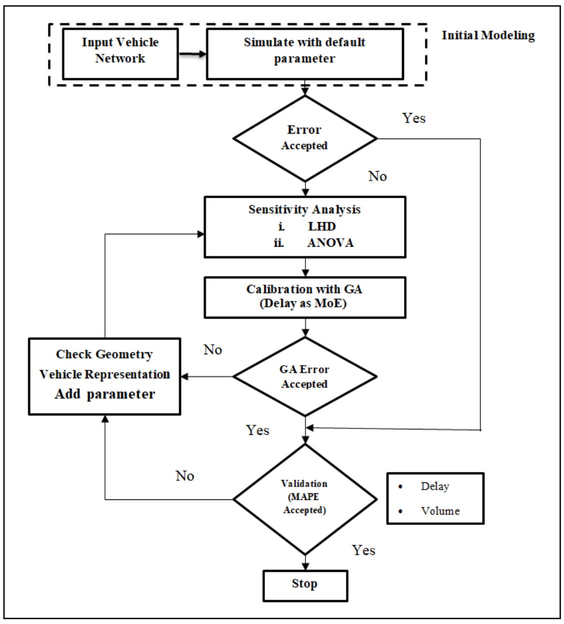

Figure 2: Methodological Framework

4.2.1 Mean Absolute Percentage Error

Mean absolute percentage error (MAPE), is a frequently used metric to assess the accuracy of model predictions. The average absolute percentage difference between expected and actual values is known as MAPE. The equation used was:

$$MAPE = \frac{\frac{ODelay - SDelay}{ODelay} * 100}{N} \tag{1}$$

where,
ODelay = Observed Delay
SDelay = Simulated Delay
N = no. of fitted point

4.3 Initial Modeling

4.3.1 Data Requirement

The data required for this study were intersection geometry, vehicle types, traffic inflow, proportion of turning vehicles, vehicle composition, signal timing and phasing, and delay at intersection. A video graphic survey was performed to obtain the traffic details and signal timing of the intersection. Video graphic survey was conducted for three days from 26-7-2021 to 28-7-2021, a video of one hour was recorded at non-peak hour from 01:00 p.m. to 02:00 p.m. for first two days which was used for calibration and a video of one hour was recorded at evening peak hour form 05:00 p.m. to 06:00 p.m. which was used for validation. Classified volume count of vehicles was obtained from recorded videos by running it multiple times. The vehicle types were considered as per Nepal Road Standard 2070 [12]. Figure 3 shows the directional traffic movement in PCU data from 01:00 p.m. to 02:00 p.m. of date 26-7-2021. Figure 4,5,6,7 shows the vehicle composition of respective direction.

Field delay was quantified using the technique mentioned in the highway capacity manual [5]. In this technique, the vehicles in queue are counted from the start of red until the last vehicle in the queue clears the stop line. The counting of vehicles is done for a fixed interval (sec). The cumulative vehicle-in-queue count is obtained and averaged over the total number of vehicles passing through the intersection during the observation period to get the delay. Field delay of through vehicle from Singhadurbar to Kamaladi was calculated and used for calibration.

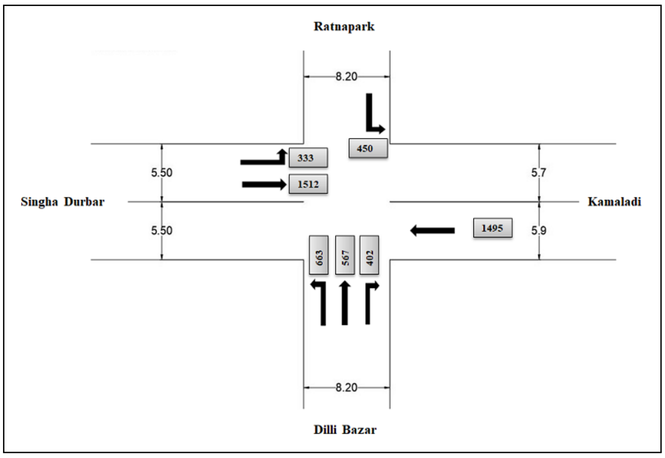

Figure 3: Direction movement in PCU 1:00 PM - 2:00 PM

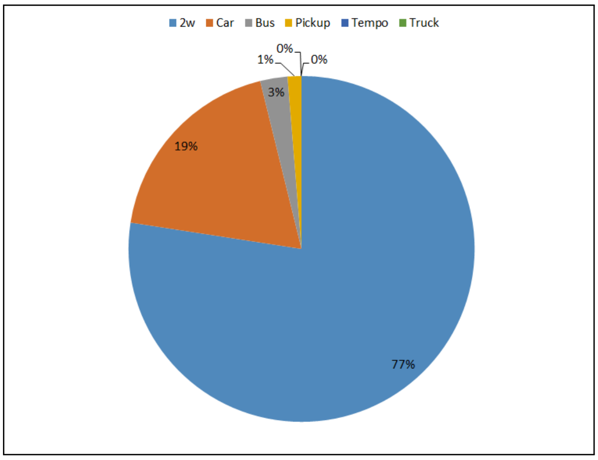

Figure 4: Vehicle composition of incoming traffic from Singhadurbar Lane

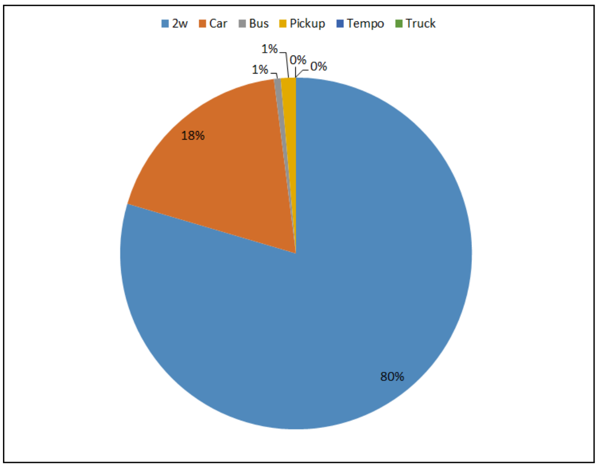

Figure 5: Vehicle composition of incoming traffic from Kamaladi Lane

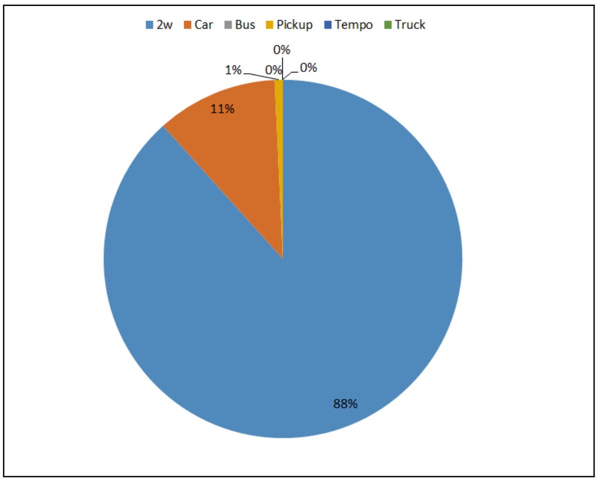

Figure 6: Vehicle composition of incoming traffic from Ratnapark Lane

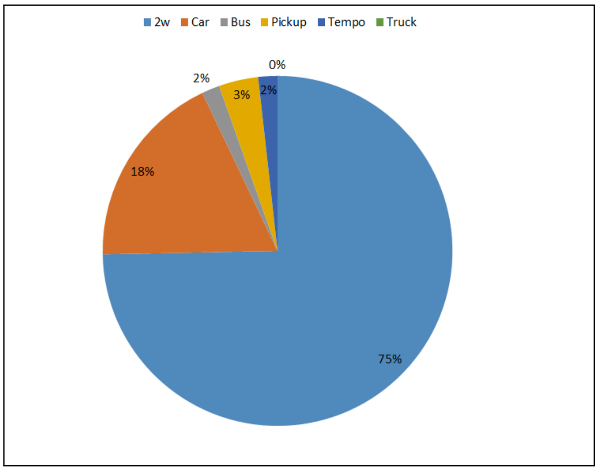

Figure 7: Vehicle composition of incoming traffic from Dillibazar Lane

4.3.2 Network Coding

The data gathered from field were used to generate model in VISSIM. Figure 8 shows a typical representation of intersection in VISSIM.

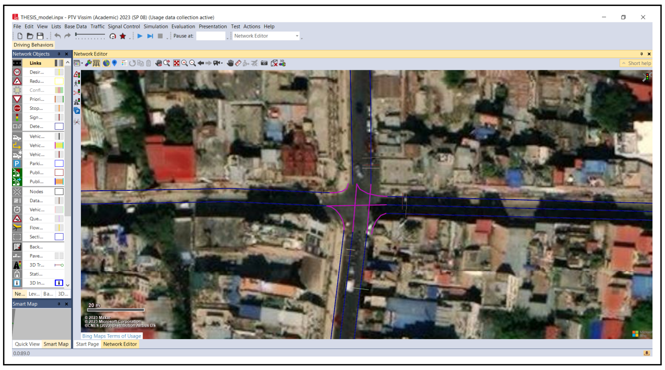

Figure 8: Lane and Connector Configuration

4.3.3 Simulation Run and Comparison

The model was run with default parameters with five different random seeds and the average value of simulated delay was compared with field delay. Table 1 shows that MAPE is 106% which is more than accepted range. Hence, calibration of VISSIM is necessary.

Table 1: Comparison of Field delay with observed delay

SN	Avg Field Delay	Avg Simulated Delay	MAPE
1	37.51	77.43	106%

4.4 Sensitivity Analysis

4.4.1 Identifying Parameters and their Range Setting

VISSIM provides many driving parameters majority of which include car-following, lane changing and lateral movement. Considering the past studies done on heterogeneous traffic simulation calibration in VISSIM [3, 6, 7, 8, 9, 10]. Eleven parameters and their range were selected by reviewing those study. The parameters and their range are shown by Table 2.

Table 2: Selected Parameters and their Range

S.N.	Parameters	Range
1	Look ahead Distance (min) (LAD_min)	10-30
2	Look ahead Distance (max) (LAD_max)	100-140
3	Look back Distance (min) (LBD_min)	6-24
4	Look back Distance (max) (LBD_max)	80-120
5	Average Standstill Distance (AX_still)	0-2.5
6	Additive part of Safety Distance (BX_add)	0-2.5
7	Multiplicative part of Safety Distance (BX_mult)	0-4
8	Minimum Clearance Front and Rear (Min_clc)	0.25-0.8
9	Safety Distance Reduction Factor	0.3-0.7
10	Minimum Lateral Distance Standing (Lat_0)	0-1
11	Minimum Lateral Distance Driving (Lat_50)	0-1

4.4.2 Latin Hypercube and ANOVA

Latin hypercube sampling (LHS) is a type of random sampling method. This method generates random samples, which effectively cover the sample space, reducing the number of samples required as compared to other random sampling methods. In this method, the range of each variable is divided into smaller ranges of values, and one sample is chosen for each combination of variables and ranges.

Analysis of Variance (ANOVA) was used to perform sensitivity analysis. LHS was used to obtain a sampling plan which reduced the number of samples to be tested. ANOVA is a technique that is used to obtain inferences about population means when different factors affect mean values. For identifying whether a specific factor affects the response variable, one-way ANOVA is effective [6]. The response of the samples on delay was input to ANOVA to determine the sensitive parameters.

LHS was used to create 50 scenarios for the parameters with their range selected for study. VISSIM was run for each parameter by keeping other parameters as default. The delay value obtained for each parameter was input in ANOVA to perform sensitivity analysis. ANOVA was conducted at 95% confidence interval. The parameters having p-value less than 0.05 were considered as significant parameters for the delay. Table 3 shows that only three parameters had p-value less than 0.05. The parameters which were found sensitive were widemann-74 car-following parameters average stand still distance (AX_still), additive part of safety distance (BX_add) and multiplicative part of safety distance (BX_mult).

Table 3: ANOVA Results

S.N.	Parameters	P-value
1	Look ahead Distance(min)	1.000
2	Look ahead Distance(max)	.102
3	Look back Distance(min)	.987
4	Look back Distance(max)	1.000
5	Average Standstill Distance	.000
6	Additive part of Safety Distance	.000
7	Multiplicative part of Safety Distance	.000
8	Minimum Clearance Front and Rear	1.000
9	Safety Distance Reduction Factor	.999
10	Minimum Lateral Distance Standing	.261
11	Minimum Lateral Distance Driving	.990

4.4.3 Multiple Linear Regression

With the help of LHS, three linear equations were developed in which each parameter was altered individually without changing the other parameter's default values. The sample size was determined by using the formula proposed by Khamis and Kepler [13] as n = 20+5k where k is no. of predictors, n is no. of samples. For three predictors sample size is 35, in this study 50 samples were taken to create a regression equation. The linear equations obtained are specific to this particular intersection only. The obtained linear equations to predict delay are shown below.

$$\text{Delay} = 94.964 - 9.66 * AX\_\text{still} \tag{2}$$

$$\text{Delay} = 62.653 + 6.030 * BX\_\text{add} \tag{3}$$

$$\text{Delay} = 66.367 + 2.746 * BX\_\text{mult} \tag{4}$$

4.5 Calibration With Genetic Algorithm

Haupt and Haupt stated that "the genetic algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection." [14]. It works with a population of individuals, each of which represents a possible solution to a given problem. There are three basic operators used in genetic algorithm analysis: reproduction, crossover, and mutation. Multiobjective optimization means optimizing more than one objective simultaneously. In this study, three sensitive parameters need to be optimized simultaneously to minimize the error between the field and the observed delay value. Genetic algorithm was used to perform multiobjective optimization. It can be performed using MATLAB software. The optimization of linear equations was performed by using the multi-objective genetic algorithm optimization tool available in the optimization toolbox of MATLAB. The number of generations was set to 1000 with a population size of 25 in optimization program. For selection, the 3-point tournament method was used; the crossover fraction was kept at 0.90 for reproduction, and a 0.05 value was used for mutation. Different driving behavior parameter values were obtained from each optimization. The parameter values obtained from each optimization trial were input into the VISSIM software's corresponding parameter. The model was run, and MAPE was calculated based on results from VISSIM. The MAPE obtained was compared with the aforementioned acceptable range. The values of the parameters in the trail with the most suitable MAPE were considered calibrated values.

5. Results and Discussions

5.1 Calibration Results

Table 4 shows the results of the optimization performed. The values of sensitive parameters obtained after each trial were provided as input into the VISSIM software to calculate MAPE. Trail No. 27 reduced MAPE from 76.02% initially to 9.7%. The obtained MAPE is less than 15%, which is within the acceptable range. The values obtained from trial 27 were considered calibrated values for driving behavior parameters at the Putalisadak intersection.

Table 4: Optimized Set of Parameters with their repective MAPE

Trail	AX_still	BX_add	BX_mult	Delay	MAPE
1	2.50	2.32	0.74	66.02668	76.02%
2	2.50	0.33	0.03	49.41345	31.73%
3	2.50	2.37	0.03	64.95724	73.17%
4	2.50	0.01	1.03	48.70235	29.84%
5	2.50	0.98	0.00	52.46716	39.88%
6	2.50	0.00	0.00	52.29695	39.42%
7	2.49	0.00	0.28	45.57137	21.49%
8	2.45	0.00	0.00	52.72835	40.57%
9	2.45	0.52	3.98	65.59007	74.86%
10	2.37	0.05	0.00	53.07381	41.49%
11	2.25	1.10	1.47	65.06923	73.47%
12	1.96	0.01	2.12	54.90056	46.36%
13	1.94	2.47	0.04	69.81201	86.12%
14	1.93	2.50	0.01	69.67575	85.75%
15	1.92	1.42	0.00	59.15173	57.70%
16	1.85	0.61	0.00	44.91631	19.74%
17	1.82	0.02	0.71	44.5622	18.80%
18	1.78	0.45	0.00	43.27198	15.36%
19	1.77	0.08	0.20	43.64372	16.35%
20	1.74	1.48	0.00	61.59063	64.20%
21	1.59	0.66	0.11	44.23435	17.93%
22	1.51	0.41	0.83	48.43145	29.12%
23	1.43	0.42	0.11	41.50503	10.65%
24	1.32	0.35	0.02	41.30607	10.12%
25	1.26	0.70	0.63	46.16281	23.07%
26	1.21	0.55	0.45	42.318	12.82%
27	1.15	0.40	0.35	41.1476	9.70%

5.2 Validation

The validation was done with a different set of data from the same intersection. Evening peak hour data from 05:00 p.m. to 06:00 p.m. of date 28-7-2021 was used to validate the calibrated parameters. Validation was done using delay and volume in the intersection. The model was run 5 times with different random seed to obtain the delay and volume values. Table 5 and 6 shows the MAPE between simulated and field values.Figure 9 shows comparison of observed and calibrated volume. The MAPE for delay and volume is 3.56% and 2.07% respectively which are within acceptable range. Hence, The model is successfully validated.

Table 5: Comparison of Calibrated delay with observed delay

SN	Avg Field Delay	Avg Calibrated Delay	MAPE
1	18.28	17.63	3.56%

Table 6: Comparison of Calibrated Volume with observed Volume

Time Period(s)	Actual Volume	Simulated Volume	error %	MAPE
0-900	1748	1671	4.41%	
900-1800	1841	1858	0.92%	2.07%
1800-2700	2133	2084	2.30%	
2700-3600	1872	1884	0.64%	

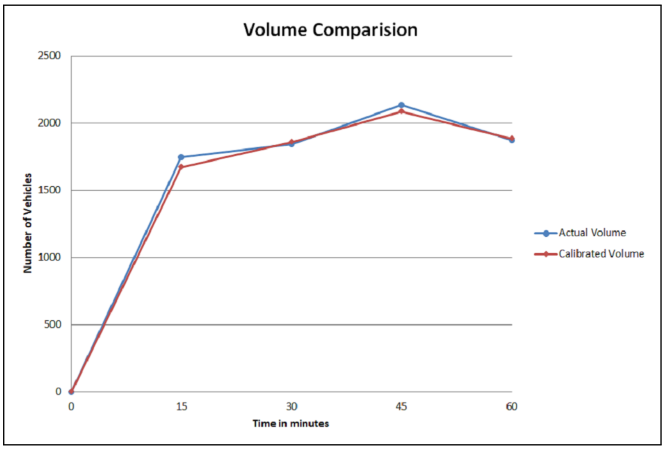

Figure 9: Comparison of Calibrated Volume

6. Conclusions and Recommendation

6.1 Conclusion

From this study it is observed that genetic algorithm can be used to calibrate car-following parameters in VISSIM to lower the error in simulation. Off-peak traffic data recorded for an hour for two days was used to calibrate the model and peak traffic data recorded for an hour for one day was used to validate the model. ANOVA was found as an effective method for finding sensitive parameters which affect the model in significant way. Genetic algorithm provided optimal values for parameters quickly, however manual method was adopted for calibration which resulted to be time consuming. Linear equation obtained for each parameter are intersection specific and can differ for other intersection. The optimal values of widemann-74 car-following parameters average stand still distance (AX_still), additive part of safety distance(BX_add) and multiplicative part of safety distance(BX_mult) for Putalisadak intersection is 1.15 m, 0.4 and 0.35 respectively.

6.2 Recommendation

Following tasks are recommended for further studies

- Pedestrian Interaction with traffic is not considered in this study, which can be done for further study
- One intersection is considered in this study, more intersection can be considered to obtain range of calibrated values
- Automation can be done for optimization of parameters unlike manual method used in this study
- More MoEs can be considered for calibration of parameters.

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