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Sensitivity Analysis of VISSIM Parameters for Modeling Heterogeneous Traffic Conditions Using Latin Hypercube Sampling and ANOVA Testing: A Case Study of Singhadurbar Intersection

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Abstract
Most developing countries consists of unsignalized intersections carrying heterogeneous traffic conditions. Microsimulation models and their environment are widely being used for the evaluation of such traffic conditions and development of road networks worldwide. Due to the difficulties in analyzing the complexities of heterogeneous traffic and calibrating the microsimulation, their use in Nepalese context is limited to research studies. This study proposes a methodology to develop microsimulation models at unsignalized intersections with heterogeneous traffic and identify sensitive calibration parameters tailored to local conditions. VISSIM, a microscopic, time step oriented, and behavior-based simulation tool was used to model the intersection which consists of a large number of input parameters making model calibration rather difficult. Sensitivity analysis was performed to identify the sensitive calibration parameters using Latin Hypercube Sampling (LHS) and one way ANOVA testing. Based on the findings of the literature review, 12 calibration parameters were identified. Using traffic flow as a measure of effectiveness, the parameters were reduced to 9 sensitive calibration parameters. It is expected that the use of these sensitive calibration parameters and their ranges would significantly reduce the time and effort consumed during calibration of the VISSIM models.

Keywords
VISSIM, Simulation, Sensitivity Analysis, Latin Hypercube Sampling, ANOVA

1. Introduction

Traffic microsimulation models and their environment are widely used in the evaluation and development of road networks worldwide. VISSIM is a microscopic, time step oriented, and behavior-based simulation tool for modeling urban and rural traffic as well as pedestrian flows [1]. VISSIM software has been highly effective in modeling traffic simulation problems because simulation is safer, less expensive, and faster than field implementation and testing [2]. Developing simulation models using such tools requires several steps which include data collection, model formulation, calibration, and validation of the model. Due to the difficulties in analyzing the complexities of heterogeneous traffic and calibrating the microsimulation, their use in Nepalese context is limited to research studies and they are rarely used for assessment of road networks to aid real-life planning and decision making.

Majority of the Asian countries have heterogeneous traffic conditions which results in a very complex behavior of traffic which is also the case in the majority of our urban intersections. As opposed to homogeneous traffic conditions having good lane discipline, heterogeneous traffic consists of both motorized and non-motorized vehicles whose static and dynamic characteristics are mixed. Other distinguishing factors include traffic composition where motorcycles are abundant in the context of Nepal as opposed to other countries, side-by-side stacking of vehicles, variable lane widths, and the absence of lane marking and lane discipline across the road.

VISSIM models are only successful if the model can accurately represent the field conditions and for such accuracy, the model needs to be calibrated. Calibration is the process of fine-tuning the different parameters in the model such that the error between the actual and simulated measures is less than the acceptable value. Various calibration parameters significantly affect the traffic flow like Wiedemann-74 car following parameters, lane change parameters, lateral behavior parameters, and Wiedemann-99 car following parameters. Calibrating all these parameters is very time-consuming and ineffective for model calibration since all these factors may not affect the model in a significant way depending on local traffic condition. To accurately simulate such systems, the default behavioral parameters should be studied to find out the sensitive behavioral parameters which require modification for calibration and validation of the system model. Therefore, this study focuses on sensitivity analysis to identify the sensitive calibration parameters that have a relevant impact on the results of the simulation model on a case study intersection to reduce the computational time and effort during calibration.

2. Literature Review

VISSIM consists of multiple parameters that can be adjusted to calibrate and customize the simulation. These parameters can be related to vehicle behavior, traffic control devices, driver behavior, lane-changing behavior, network properties, and other simulation settings. It also includes a range of pre-defined parameter sets that can be used for different types of traffic scenarios. Many calibration procedures are unable to calibrate every parameter within the model because of time and resource constraints. As a result, calibration is carried out only for a limited number of input parameters. However, there is usually no formal procedure for selecting these parameters, other than choosing the ones that appear to the model user as most likely to have a significant effect on the result [3].

Sensitivity analysis is an important method used to assess the impact of changes due to the calibration parameters on the model's performance. Multiple methods are available and have been used to conduct sensitivity analysis in VISSIM models which include Pearson correlation coefficient, one-way ANOVA, two-way ANOVA, elementary effects method, quasi-optimized trajectory in elementary effects, Latin Hypercube Sampling (LHS), multiparameter sensitivity analysis, etc.

LHS is a statistical sampling technique that ensures that the sampled values are representative of the full range of parameter values and that they are evenly distributed across the parameter space. So, it reduces the number of samples required to perform computation while covering the entire representative space which makes it a powerful tool for exploring multi-dimensional parameter spaces. Performing sensitivity analysis helps in identifying the most impactful parameters on the model's performance, which informs the calibration process and enhances the accuracy and reliability of the model saving a considerable amount of computational time and effort.

Sensitivity analysis was performed on 9 identified calibration parameters referring to studies on similar countries which resulted in 5 sensitive parameters based on the results of Pearson correlation coefficient and 10 percent significant level [4]. One-At-a-Time (OAT) method has been used to determine the parameters influencing capacity during congestions [5]. A study was performed in 3 similar signalized intersections for non-lane-based mixed traffic conditions in India. The intersections were simulated in VISSIM by changing each parameter value by a fixed amount (10 percent) while keeping the default value for other parameters, and evaluated the sensitivity of the output for each change. This resulted in the identification of 13 sensitive parameters [6].

Analysis of Variance (ANOVA) and elementary effects method were compared during a study which showed that both methods are effective in finding the sensitive parameters. During the first level sensitivity analysis, the same 5 calibration parameters were found to be sensitive among the 11 parameters chosen for testing from both methods. Second-level sensitivity analysis was performed on the remaining 6 parameters which resulted in further 4 sensitive calibration parameters using the same methods in the first-level sensitivity analysis. The study was performed at a part of an IT corridor [7]. Another study performed at three unsignalized three-legged intersections resulted in the identification of 8 sensitive calibration parameters out of 10 considered parameters for analysis using one-way ANOVA [8].

Multi-parameter sensitivity analysis and two-way ANOVA were performed using link capacity as the measure of sensitivity which resulted in the identification of 5 sensitive parameters among the 13 tested parameters. The study was performed at two signalized intersections in Mumbai [9]. ANOVA and LHS were used to find the sensitive parameters at an actuated signalized intersection from a set of eight parameters that were to be calibrated. 200 sample sets were generated using LHS for the eight parameters which were simulated in VISSIM. Finally, one-way ANOVA was performed using average travel time as the measure of effectiveness [10]. The Elementary Effects (EE) method was improved upon by performing a Quasi-optimized trajectory in elementary effects resulting in higher performance and lower computational time for sensitivity analysis. The study was performed in a case study involving a network in the City of Zurich [3].

In the case of the Nepalese context, 7 calibration parameters were altered at the New Baneshwor intersection simulation model for calibration and validation of the model. Sensitivity analysis was not performed and optimization was done based on a trial and error approach [11]. Another study performed sensitivity analysis and optimization on 9 selected calibration parameters by varying the values of the parameters adopted from different literature similar to a trial and error approach. The simulation run was conducted by changing one parameter value while keeping the other parameters unchanged from the VISSIM default values [12].

3. Methodology

The methodology involved in this study consists of several distinct steps. The first step involves site selection and the collection of data using the video graphic recordings and field survey at the selected intersection. The second step was to develop and simulate the VISSIM model by incorporating the various geometric, vehicular and traffic behavior characteristics prevalent in the study area. Finally, sensitivity analysis was performed in the simulation model using traffic flow as the measure of effectiveness (MOE). The steps involved in this study are discussed in the following sub-sections.

3.1 Study Area

The study area is selected considering the manual regulation of traffic by the traffic police officers during peak hour. Singhadurbar intersection was found to be suitable for the

Figure 1: Singhadurbar Intersection (Source:Google Earth)

study which is one of the major intersections of Kathmandu. It has a cross configuration connecting Padmodaya followed by Putalisadak to the north, Sahidgate to the west and Maitighar to the south. There is a small central island at this intersection which makes the junction appear like a mini-roundabout but the right turning traffic from Putalisadak are not enforced to comply with the rotary movement through the central island. The traffic going towards the Singhadurbar access way is found to be insignificant and thus, the effects of the access way were neglected. Figure 1 shows the general layout of the intersection.

3.2 Data Collection and Model Development

3.2.1 Video Graphic Recordings

A microscopic simulation model gives intricate details about the individual vehicle movements and their interactions within the system and such models require an abundant amount of input data. Congestion is relevant in almost all of the intersections within Kathmandu which can often extend beyond one hour peak in heavily congested areas. To analyze such behavior detailed data is required. A study was carried out by the Department of Roads to collect 72 hours traffic volume count of major 20 intersections inside Kathmandu Valley for signal time design at peak hour volume based on the collected data [13]. This study uses the collected data of the 72 hour video graphic recordings.

3.2.2 Data Extraction

Different types of vehicles take up differing amounts of road space and have different speeds and impose differing loads on the road structure. It is, therefore, necessary to adopt a standard traffic unit to which other types of vehicles may be related. For the geometric design of roads, this standard is the 'Passenger Car Unit (PCU)' which is that of a normal car (passenger car), light van, or pick-up [14].

Vietnamese standards recommends the PCU for motorcycles and bicycles as 0.3 and 0.2, respectively for Vietnam, having similar mixed traffic conditions like in Kathmandu. There is no PCU for tempos and microbuses in the Nepal Road Standard. The JICA Survey Team adopted 1.0 as the PCU of tempos, and 1.5 as the PCU of microbuses based on the size of each vehicle [15]. Based on the combination of [14] and [15], the vehicle types and PCU values adopted in this study are shown in Table 1. The vehicle types (multi axle truck, tractor, power trailer, non-motorized cart, rickshaw, and auto rickshaw) have not been considered for the vehicle count as they have comparatively low frequency to the other vehicle types.

Table 1: Adopted Passenger Car Unit

S.N.	Vehicle Type	Equivalency Factor
1	Heavy Truck	3.0
2	Light Truck	1.5
3	Big Bus	3.0
4	Mini Bus	3.0
5	Micro Bus	1.5
6	Car	1.0
7	Motorcycle	0.3
8	Utility Vehicles	1.0
9	4 Wheel Drive	1.0
10	3 Wheeler (Tempo)	1.0
11	Bicycle	0.2

3.2.3 Development of VISSIM Model

The latest version of PTV VISSIM 2023 (SP 06) Academic License has been used for the development of the model which was provided for six months for this research study [16].

3.2.4 Geometric Data Representation

The first step in the model development involves representing the intersection accurately which was done using the primary source field observation data and satellite imagery data from Google Earth. The intersection layout includes the number of approaches, width of each approach, length of each approach, turning space and so on. A satellite image was saved using Google Earth Pro and was imported as a background image in VISSIM. The scale was adjusted in the image and the intersection geometry was constructed using links and connectors. The road widths were given as per the field data and the background image was used to ensure that the intersection layout was precisely drawn.

3.2.5 Vehicle Representation

Standard vehicle types such as car, bus, truck, motorcycle, bicycles, etc. are available in VISSIM but these models may not perform well under heterogeneous traffic conditions. Nonstandard vehicle types such as tempo and microbus also exist in our intersections.

VISSIM has the ability to define vehicle types and change its static and dynamic characteristics. Therefore the next step in the model development involves defining the characteristics of the vehicles in terms of length, width, and speed ranges. The adopted size of the different vehicle types used in this study are shown in Table 2.

Table 2: Adopted Average Vehicular Dimensions

S.N.	Vehicle Type	Length (m)	Width (m)
1	Heavy Truck	8.6	2.5
2	Light Truck	7.5	2.35
3	Big Bus	11	2.5
4	Mini Bus	6.1	2.2
5	Micro Bus	5	1.9
6	Car	3.44	1.45
7	Motorcycle	1.85	0.74
8	Utility Vehicles	4.4	1.5
9	4 Wheel Drive	4.4	1.5
10	3 Wheeler (Tempo)	3.4	1.4
11	Bicycle	1.9	0.45

3.2.6 Traffic Representation

The next step involves achieving the actual heterogeneous traffic movement and behavior such as aggressive driving, lack of lane discipline, lane changes, overtaking, seepage of smaller vehicles like motorcycles and bicycles to reach the front of a queue, etc. in VISSIM. The available parameters in the simulation model may not be sufficient to replicate certain special movements by the vehicles in mixed traffic, but depending on the flexibility of the network modeling, one can try to bring the behavior in the simulation as close as possible to reality [9]. To emulate the unique behavior in mixed traffic the following features can be incorporated in VISSIM.

- Vehicle behavior was set to "left hand traffic" regulations.
- General behavior was set to "free lane selection" in lane change driving behavior.
- Desired position at free flow was set to "Any" in lateral driving behavior.
- Diamond queuing was enabled to take into account the realistic shape of the vehicles.
- Overtaking was allowed from both left and right side in lateral driving behavior.
- The simulation resolution was set to 10 time steps per simulation second.

3.2.7 Vehicle Inputs, Compositions and Vehicle Routing

The vehicle inputs were given in each approach link of the model. Peak hour traffic volume data was fed into the simulation model in 15 minute intervals relative to the simulation period of 1 hour. A warm up period of 5 minutes was provided at the beginning of each simulation run so that the initial empty network was filled with vehicles to allow the simulation model to reach equilibrium. The classified volume counts were used to input vehicle compositions and the directional movements were also differentiated from the analyzed data to input the vehicle routing decisions.

3.2.8 Signal Control

Pre-timed traffic signal devices have been installed in the intersection but traffic control is still being done manually by the traffic police officers especially during peak hours. So, primary source of data collection for signal timing was required. The collected signal phase and timing data was classified as red time, amber time and green time. Amber time was difficult to pinpoint during the field observations so it was averaged as three seconds preceded by green time. The phase sequence and timings were then input into the signal program and signal heads were inserted at the stop line of each approach.

3.2.9 Desired Speed Distribution

The speed of vehicles was obtained by marking a 50 m strip. The time taken by the vehicle to cross the 50 m marked segment was noted in the field. Speed was calculated as the ratio of distance travelled (50 m) by the vehicle to the time taken to travel that distance. 20 samples in each approach leg were taken for random vehicle categories. Since the amount of data samples was small, it was also verified with the speed distribution in similar literatures [6, 8, 12]. The collected data is found to be in the average speed range provided by [12]. The desired speed range used in this study is as shown in Table 3.

Table 3: Adopted Minimum and Maximum Speed of Different Vehicle Categories

S.N.	Vehicle Category	Min Speed (km/h)	Max Speed (km/h)
1	Two - Wheeler	15	60
2	Three - Wheeler	15	35
3	Four - Wheeler	30	50
4	Buses and Truck	30	45
5	Bicycle	5	15

3.3 Initial Evaluation

Once the simulation model was set up, the model was run using the default parameter settings and the output were compared to the input data. The output flow was measured by placing data collection points on the simulation model. They were set up at the exit points of the three approach legs of the intersection.

3.4 Sensitivity Analysis

Sensitivity analysis is a statistical technique that studies the effects of varying various parameter assumptions to the outcome of the process. VISSIM provides multiple parameters that can be adjusted to influence the simulation. There are around 40 parameters which can be changed for modeling the driver behavior patterns [4]. Performing analysis on all the parameters offered by VISSIM will consume a considerable amount of time and effort. A proper sensitivity analysis, including the initial screening of the parameters, can be very valuable for the subsequent calibration process.

It involves the process of incrementing the value of the identified calibration parameters in small units and analyzing the effect on the simulation output. Multiple simulation runs are performed with different random seeds to reduce the effect of stochasticity. The steps involved are discussed in the following sub-sections.

3.4.1 Identification of Relevant Calibration Parameters

Based on similar studies in Kathmandu and other Asian countries with heterogeneous traffic conditions and personal engineering judgment, 12 driving behavior parameters were considered important and selected for the study. The acceptable range for these parameters were also fixed based on the data from studied literatures [4, 6, 7, 8, 9, 10, 11, 12, 17, 18] including the VISSIM user manual [1]. The studied parameters, their symbols, and the adopted ranges used in the study are shown in Table 6.

3.4.2 Latin Hypercube Sampling

Latin Hypercube Sampling (LHS) is a powerful and widely-used statistical technique for sampling from multi-dimensional parameter spaces in a systematic and efficient manner. Unlike traditional random sampling methods, LHS ensures a more representative and evenly spaced coverage of the input variables, making it particularly valuable when dealing with complex systems and computationally expensive simulations or experiments [19]. The fundamental idea behind LHS is to create a stratified and space filling sampling design that ensures even and representative coverage of the input parameter space while reducing sampling variance. The resulting samples form a "Latin hypercube," which refers to the Latin square-like structure of the data points.

The amount of time to consider all the possibilities for testing the 12 identified parameters will be extremely large. For e.g., if 5 values were provided to each studied calibration parameters, it would generate 5^{12} = 244140625 possible combinations. The amount of time to conduct simulation runs for each possible combination along with multiple runs with different random seeds would have been immense. Hence, LHS was used to reduce the number of combinations for the study.

Two hundred scenarios with five random seeds were deemed to be adequate to cover the entire parameter surface based on similar literatures [7, 10, 18]. Hence, in this study 12 calibration parameters each with three to five different values inside the range defined in Table 6 were used to generate 200 scenarios. 5 random seeded runs of the 200 scenarios were performed in VISSIM, for a total of 1000 runs and the error between the actual and simulated traffic volume was collected. The 5 random seeded runs were then averaged to represent the results of each of the 200 parameter sets.

VISSIM has a COM interface which can be accessed to call and simulate VISSIM externally through a code. To reduce time and effort, a Python programming language code was written through COM interface of VISSIM to create parameter sets from LHS, run the simulation, and collect the output in a separate Excel file. The randomly created samples from LHS were then made discrete, grouped and indexed.

3.4.3 First Level ANOVA Testing

Analysis of variance is being widely employed for obtaining the optimal set of parameters [5, 10]. The effectiveness of using ANOVA in finding the parameters that are sensitive in a significant way has been shown in [7]. Hence, one way ANOVA was used in this study for sensitivity analysis. SPSS, a statistical package was used for this analysis. ANOVA tests the null hypothesis that the means for several groups in the population are equal by comparing the sample variance estimated from the group means with that estimated within the groups [20]. It is used to draw conclusion about population means when the means are affected by different factors and shows whether the particular parameter affects the output of the simulation.

The discrete values of the parameter from the LHS samples and the change in error with respect to the default parameter set values are input into SPSS to perform one way ANOVA testing. The change in error was calculated by comparing the traffic volume obtained using default parameter values as shown in Table 4 with those obtained by changing the parameter values. Trials were carried out on the three approach legs of the intersection. When the significance value of the F-test (p-value) is smaller than the user defined confidence level, the null hypothesis is rejected, thereby indicating that the group means are statistically different. The parameters with small p-values less than 0.2 were identified as sensitive parameters [7, 8].

3.4.4 Second Level ANOVA Testing

After performing first level sensitivity analysis, a second level sensitivity analysis was performed for the parameters which were not found to be sensitive. The reason for doing so is the possibility of highly significant parameters dominating the effect of marginally significant parameters. Similar to the first level testing, the same code with some minor adjustments was run by removing the sensitive parameters identified from the first level of testing.

3.4.5 Measure of Effectiveness (MOE)

Measure of effectiveness provides a basis for evaluating the performance of a system. The choice of an effective measure influences the calibration process. Traffic volume has been widely implemented by various researchers as a basic MOE for calibration and validation in signalized intersections [7, 11, 12], roundabouts [21], and unsignalized intersections [8, 22]. In this study, traffic volume has been selected as the key measure of effectiveness.

3.4.6 Statistical Checks

The error between the simulation output and observed measurements were found using mean absolute percentage error (MAPE). MAPE is a measure of prediction accuracy of a forecasting method in statistics. It has been widely used for testing the goodness of fit by various researchers [4, 7, 8, 21]. It usually expresses the accuracy as a ratio defined by the formula as given in Equation 1 below.

$$\text{MAPE} = \frac{1}{N} \times \sum_{i=1}^{N} E_i \tag{1}$$

where,

$$E_i = \frac{|\text{Actual } Q_i - \text{Simulated } Q_i|}{\text{Actual } Q_i} \times 100\% \tag{2}$$

4. Results and Discussion

4.1 Peak Hour, Vehicle Inputs and Compositions

The simulation model was created as explained in the section 3.2. Using the adopted PCU factor, the video graphic recording data was analyzed to find the peak hour period and the peak hour volume in vehicles/hr and PCU/hr. The peak hour was identified as 10:00 AM – 11:00 AM. The data shows that the maximum traffic occurred in the approach leg connecting Sahidgate and Maitighar. This may have occurred due to the location of major business and commercial centers around Maitighar and Sahidgate area. The peak hour data from the first and second days were used as vehicle inputs in the simulation as shown in Table 5.

The vehicle compositions for each approach leg of the intersection were computed from the data and assigned in the VISSIM model. The data shows that motorcycle contributes the most to the total traffic volume followed by car. The vehicle composition of the entire network is shown in Figure 2.

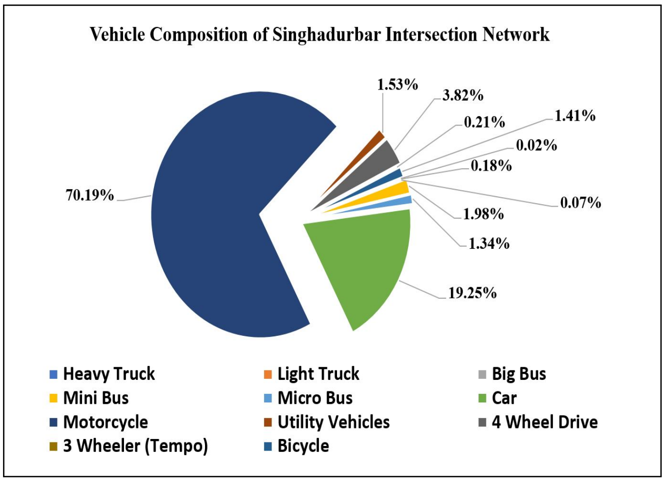

Figure 2: Vehicle Composition of the Singhadurbar Intersection Network

4.2 Signal Timing

It was observed that there were 3 phases of movement in the intersection. The Red – Green - Amber signal state sequence has been used in the VISSIM input as shown in Figure 3.

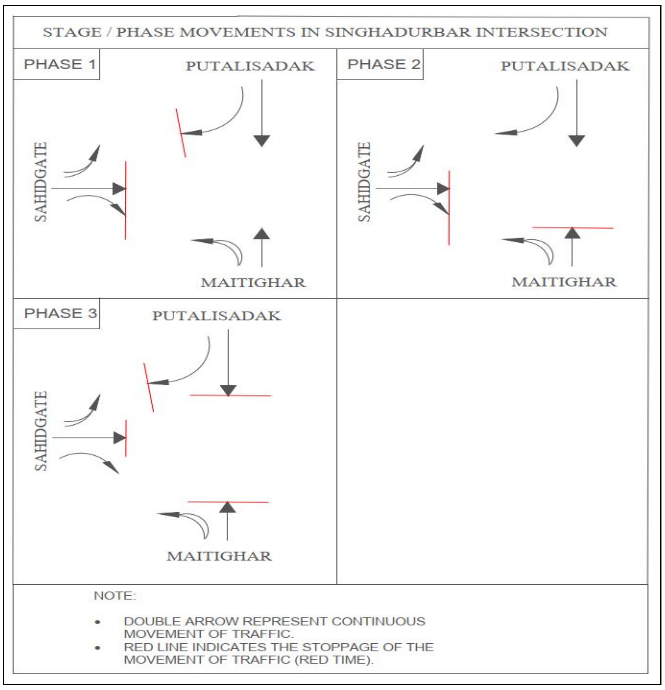

Figure 3: Signal Phase Movement Diagram of Singhadurbar Intersection

4.3 Sensitivity Analysis

4.3.1 Initial Run on Default Parameters

The VISSIM model was run on default parameter settings with 5 different random seed value. The VISSIM output and the MAPE values have been shown in Table 4 for the Sahidgate, Maitighar, and Putalisadak approach legs of the intersection.

4.3.2 First Level ANOVA Testing

Sensitivity analysis was performed as explained in section 3.4 using a Python programming code to execute the 1000 simulation runs. The whole process took 37 hours and 43 minutes. The p – values of the first level one way ANOVA have been shown in Table 7 for the approach legs of the intersection. The results showed that six driving behavior parameters are sensitive with p-values less than 0.2.

4.3.3 Second Level ANOVA Testing

Second level ANOVA testing was performed as explained in section 3.4.4 using an adjusted Python programming code by removing the 6 identified sensitive parameters from the first level of testing to execute another 1000 runs. The whole process took 45 hours and 39 minutes. The p – values of the Second Level one way ANOVA have been shown in Table 8 for the approach legs of the intersection. The results showed that three driving behavior parameters which were not considered to be sensitive in the first level testing are now found to be sensitive with p-values less than 0.2. Thus, nine driving behavior parameters were found to be sensitive for VISSIM models at intersections for heterogeneous traffic conditions which are listed below.

1. Minimum Look Ahead Distance
2. Minimum Look Back Distance
3. Maximum Look Back Distance
4. Average Standstill Distance
5. Additive Part of Safety Distance
6. Multiplicative Part of Safety Distance
7. Minimum Clearance (Front/Rear)
8. Minimum Lateral Distance (Standing) at 0 km/h
9. Minimum Lateral Distance (Driving) at 50 km/h

5. Conclusion

A methodology to model heterogeneous traffic conditions has been presented in this study which was performed in VISSIM. During the study, nine driving behavior parameters listed above out of the twelve studied parameters are found to be sensitive for VISSIM models under heterogeneous traffic conditions. This study is expected to help future practitioners in developing simulation models during calibration of VISSIM models. The use of these sensitive calibration parameters would significantly reduce the time and effort consumed during calibration.

6. Recommendations

Addressing each and every facet of a subject within a restricted timeframe proves to be a difficult task. The subsequent tasks are suggested for further academic investigation:

1. Conducting similar research at corridor or network level is suggested.
2. Only 12 calibration parameters were studied so further research is recommended using additional calibration parameters such as Wiedemann 99 parameters.

Table 4: Error for Default Parameter Values

Time Period (s)	Sahidgate Approach Leg			Maitighar Approach Leg			Putalisadak Approach Leg		
	Actual Flow	Flow with Default Parameters	MAPE	Actual Flow	Flow with Default Parameters	MAPE	Actual Flow	Flow with Default Parameters	MAPE
0-300	WarmupPeriod								
300-1200	219	176	19.63%	424	391	7.78%	82	91	10.98%
	98	81	17.35%	862	500	42.00%	374	286	23.53%
1200-2100	187	148	20.86%	419	384	8.35%	83	91	9.64%
	102	85	16.67%	845	654	22.60%	386	301	22.02%
2100-3000	186	191	2.69%	413	453	9.69%	97	91	6.19%
	97	107	10.31%	870	493	43.33%	406	357	12.07%
3000-3900	163	126	22.70%	389	374	3.86%	104	272	161.54%
	93	87	6.45%	833	625	24.97%	422	329	22.04%
	Average MAPE		**14.58%**	**Average MAPE**		**20.32%**	**Average MAPE**		**33.50%**

Table 5: Vehicle Inputs given in 15 minute intervals

Two Day Average Peak Hour Traffic Volume Input (Vehicles)							
Start Time (AM)	**End Time (AM)**	**M-S**	**M-P**	**P-S**	**P-M**	**S-P**	**S-M**
10:00	10:15	219	374	98	424	82	862
10:15	10:30	187	386	102	419	83	845
10:30	10:45	186	406	97	413	97	870
10:45	11:00	163	422	93	389	104	833

M = Maitighar, S = Sahidgate and P = Putalisadak

Table 6: Parameters Considered for Sensitivity Analysis

Driving Behavior	Parameter	Symbol	Range	Unit	Description
Wiedemann-74 Car Following Parameters	Average Standstill Distance	W74ax	(0.3 - 2)	meter	The detailed description of these parameters are provided in the VISSIM user manual [1].
	Additive Part of Safety Distance	W74bxAdd	(0.1 - 2)	-	
	Multiplicative Part of Safety Distance	W74bxMult	(0 - 3)	-	
Following Behavior Parameters	Minimum Look Ahead Distance	Min_lad	(10 - 30)	meter	
	Maximum Look Ahead Distance	Max_lad	(200 - 350)	meter	
	Minimum Look Back Distance	Min_lbd	(5 - 30)	meter	
	Maximum Look Back Distance	Max_lbd	(80 - 180)	meter	
Lane Change Behavior Parameters	Waiting Time Before Diffusion	Wtbd	(30 - 75)	second	
	Minimum Clearance (Front/Rear)	Min_cl_fr	(0.1 - 1)	meter	
	Safety Distance Reduction Factor	Sdrf	(0.2 - 0.7)	-	
Lateral Behavior Parameters	Minimum Lateral Distance (Standing) at 0 km/h	Min_ld_st	(0.1 - 0.5)	meter	
	Minimum Lateral Distance (Driving) at 50 km/h	Min_ld_dr	(0.6 - 1)	meter	

Table 7: First Level ANOVA Results

Parameters	Default Values	p – values			Result
		Sahidgate	Maitighar	Putalisadak	
Min_lad	0	0.257	0.274	0.335	NS
Max_lad	250	0.382	0.896	0.404	NS
Min_lbd	0	0.395	**0.035**	0.275	**S**
Max_lbd	150	0.979	0.94	0.933	NS
W74ax	2	**6.32357E-31**	**3.65783E-15**	**1.56049E-39**	**S**
W74bxAdd	2	**0.000434458**	**2.04711E-11**	**0.000119478**	**S**
W74bxMult	3	**0.001**	**1.68113E-08**	**0.006**	**S**
Wtbd	60	0.43	0.292	0.374	NS
Min_cl_fr	0.5	**0.098**	0.234	**0.038**	**S**
Sdrf	0.6	0.586	0.845	0.706	NS
Min_ld_st	0.2	**0.000005**	**0.000155**	**0.000178**	**S**
Min_ld_dr	1	0.31	0.417	0.287	NS

S = Sensitive and NS = Not Sensitive

Table 8: Second Level ANOVA Results

Parameters	Default Values	p – values			Result
		Sahidgate	Maitighar	Putalisadak	
Min_lad	0	**3.5621E-17**	**2.5833E-10**	**3.7837E-22**	**S**
Max_lad	250	0.799	0.861	0.601	NS
Max_lbd	150	**0.052**	**0.122**	**0.042**	**S**
Wtbd	60	0.613	0.785	0.641	NS
Sdrf	0.6	0.879	0.55	0.555	NS
Min_ld_dr	1	**1.1334E-11**	**1.0267E-20**	**1.0826E-12**	**S**

3. This study uses only traffic volume as a measure of effectiveness so further research is recommended using additional MOEs for the study.
4. Driver behavior may change when it comes to rural areas so further research could be done in such areas.
5. Vehicle characteristics such as axle configuration and turning radius may also be incorporated in further research.
6. Conducting the same research using other traffic flow simulation softwares is suggested.

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