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ASSESSMENT OF DRIVING BEHAVIOUR AT TOLL PLAZA UNDER HETEROGENEOUS TRAFFIC CONDITIONS USING VISSIM

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ABSTRACT

Traffic Simulating and Evaluating Traffic Patterns at heterogeneous traffic Situations in the Indian Context is extremely increasing. Many researchers from all over the world are trying to explore driving behavior and simulate traffic flow conditions under heterogeneous traffic environments. Simulating Traffic at a Microscopic Level with VISSIM is used in this study identifying every element that contributes to traffic at various traffic stages. Further, the VISSIM model was calibrated based on the desired safety distance and car-following theory. Traffic metrics including flow volume, speed, acceleration, and deceleration were all input parameters in the VISSIM model for simulation purposes. Furthermore, the analysis part of different cases of driving behavior models, such as the default case, and calibration values based on measurement were compared to find out if there was a significant improvement. Moreover, the linear regression model was proposed to understand the calibrated model versus the default case parameters, and it was identified that it is significant when plotting the data. The proposed study results highlighted driving behavior under heterogeneous traffic conditions using VISSIM at Toll Plaza.

1. INTRODUCTION

In India, there is significant improvement in the highway network, and it is essential to have national highways as long-distance roads for any nation. The improvement of infrastructure will be generally considered based on the toll plazas, which significantly raises the financial requirements for such an improvement of the road network. The driver's behavior abruptly changes at toll plazas, either to minimize their queue length or due to multiple services at toll plaza vehicular movement patterns. Generally, the new highway has advantages like minimizing average travel time on its route; however, the toll plaza’s blockages at tolls. The adverse effects of heavy vehicles include

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environmental damage and fuel loss (Wang, 2017; Mittal & Sharma, 2020; Mittal & Sharma, 2022). Moreover, waiting times and queue length have been widely studied by researchers (Sharma et al., 2010), including queue length at tolls. The driving behavior at tolls is less explored under improved toll operations such as payments by Radio Frequency Identification (RFID) system, which tries to minimize the delay at tolls. Recently, in India, the National Highway Authorities of India (NHAI) have implemented FASTag, an RFID-enabled toll collection system, to streamline traffic flow and reduce waiting times at toll plazas.

Typically, toll plazas are organized into three key zones: merging areas, queuing areas, and toll booths, facilitating a systematic approach to traffic management. Further, in order to minimize the queue length, a growth in the number of toll booths has been observed, and such scenario merging areas are critical, which creates queues in the queuing area (Kim, 2009; Abdelwahab, 2017). There are several contributing factors to effectively manage queue formation during peak hours, a microscopic simulation of toll plaza dynamics is required to explore the contributing factors that influence queue formation. Furthermore, attention to microscopic simulation for traffic analysis has intensified, as simulation models prove adept at scrutinizing traffic patterns, vehicle types, and queuing patterns through a refined calibration process. Moreover, it requires a high-accuracy calibration process that can forecast traffic for various complex conditions with varied driving behavior. Within this framework, the study specifically concentrates on the driving behavior observed at the toll plaza based on Verkehr in Städten – simulation model (VISSIM) simulation software.

2. LITERATURE REVIEW

The study on driving behavior has been considered an essential approach for identifying solutions to improve roadway levels of services by reducing congestion, delays, and accidents. Driving behavior modeling has been developed to measure the effects of individual differences in traffic flow characteristics, driving behavior, and their interaction. Driving behavior parameters are calibrated by micro-simulation and subsequently used to develop driving behavior models. In the recent past, to account for additional traffic situations and driver behaviors, researchers have sought to calibrate several microscopic tools (Al-Deeket al., 1996; Al-Deeket al., 2000; Wang et al., 2018; Mehar et al. 2014).

Researchers have explored the waiting and traffic queues at toll plazas using PTV VISSIM and generating different scenarios for improving the existing congestion of toll plazas (Al-Deek et al., 2000; Dubedi et al., 2012). They have used Electronic Toll Collection (ETC) in toll plazas to increase the efficiency of revenue collection of toll plazas as manual collection is time time-consuming process before using ETC. Lane configuration in mixed traffic approach-based approach has been used. The author found that having lanes more or less than required also leads to traffic congestion in the toll plaza. The result shows that using E-tag in lanes gives an improvement of 75.9 %, 93.6% and 57.7% in throughputs, waiting time and queue length respectively (Dubedi et al., 2012). Researchers have used PTV VISSIM for simulate the existing condition of toll plazas and generate some scenarios for decreasing waiting time and also checking calibration results with existing results (Aycin et al., 2009; Ozbay 2005). From the result, it was found that calibrated parameters like queue length, average service time, etc. are the same as existing parameters with plus or minus 2% error and it was also found that for exempted and fast-tag vehicles average service time that is waiting time is less compared to card or cash payment. Studies have explored the effect of toll booth shape on waiting time and queue length. For this, the PTV VISSIM microsimulation tool was used to represent the Kurnakoy toll booth. It was discovered that this operation was the best since delays caused by barriers and delays caused by bottlenecks were avoided (Neuhold et al., 2019).

The suggested approach by researchers involves the integration of queuing theory and VISSIM for traffic simulation, aiming to estimate traffic flow conditions at toll plazas (Ceballos & Curtis, 2004). Studies have analyzed traffic at toll plazas based on the AIMSUN simulation model to figure out the complete financial yield from toll collections (Poon & Dia,2005). The time taken for tax collection at toll booths has been a focal point in research studies, serving as a crucial metric for evaluating traffic flow (Poon & Dia,2005). Researchers have estimated driver behavior based on toll plaza traffic and driver behavior analyzed based on the number of lanes and vehicle types (Klodzinski et al.2002, 2007). Studies have focused on understanding the dynamics of vehicle lane selection patterns at toll booths through the implementation of microsimulation-based traffic simulation models (Dubedi et al., 2012). Researchers have explored the effect of vehicle speeds on capacity on multilane highways (Velmurugan et al. 2010).

Researchers have engineered a simulation framework for toll plazas for varied lane configurations and vehicle characteristics (Al-Deek et al. 1996; 2000). The study incorporated multiple factors, namely vehicle speed, acceleration, and deceleration, with a focus on analyzing traffic flow and delays as the output variables. The exploration of driving behavior in this study centered on lane choice, with a specific emphasis on minimizing the queue length at the toll booth. Further, researchers have used the VISSIM to analyze the delays at tolls and queuing analysis was carried out (Ceballos & Curtis, 2004). Researchers have developed a traffic simulation model corresponding to a lane-changing model (Mahdi et al., 2019). These existing studies have proven that micro-simulation is an effective tool for analyzing driver behaviour in heterogeneous traffic conditions. Researchers have studied vehicle speed-flow relationships on the multilane highway to analyze the effect of speed on the capacity of various roadways using micro-simulation tools (Velmurugan et al., 2010). Researchers have estimated the passenger equivalency factor based on the traffic flow models based on various categories of vehicles using micro-simulation tools (Coelho et al., 2005). In contrast to earlier studies conducted in developing countries, this research focused on analyzing driving behavior in lane selection utilizing PTV VISSIM. Additionally, driver behavior parameters were calibrated within the VISSIM model at the toll plaza.

3. METHODOLOGY

The proposed procedure for the measurement of driving behavior parameters and calibration of different driving behavior values is based on microscopic traffic flow simulation. The proposed study methodology is shown in Figure 1. The study methodology involves selecting the study area, conducting field data collection, and extracting relevant data. Further development of model calibration, including network building, introducing input parameters to the model, appropriate driving behavior model selection, calibration, and validation process using VISSIM PTV.

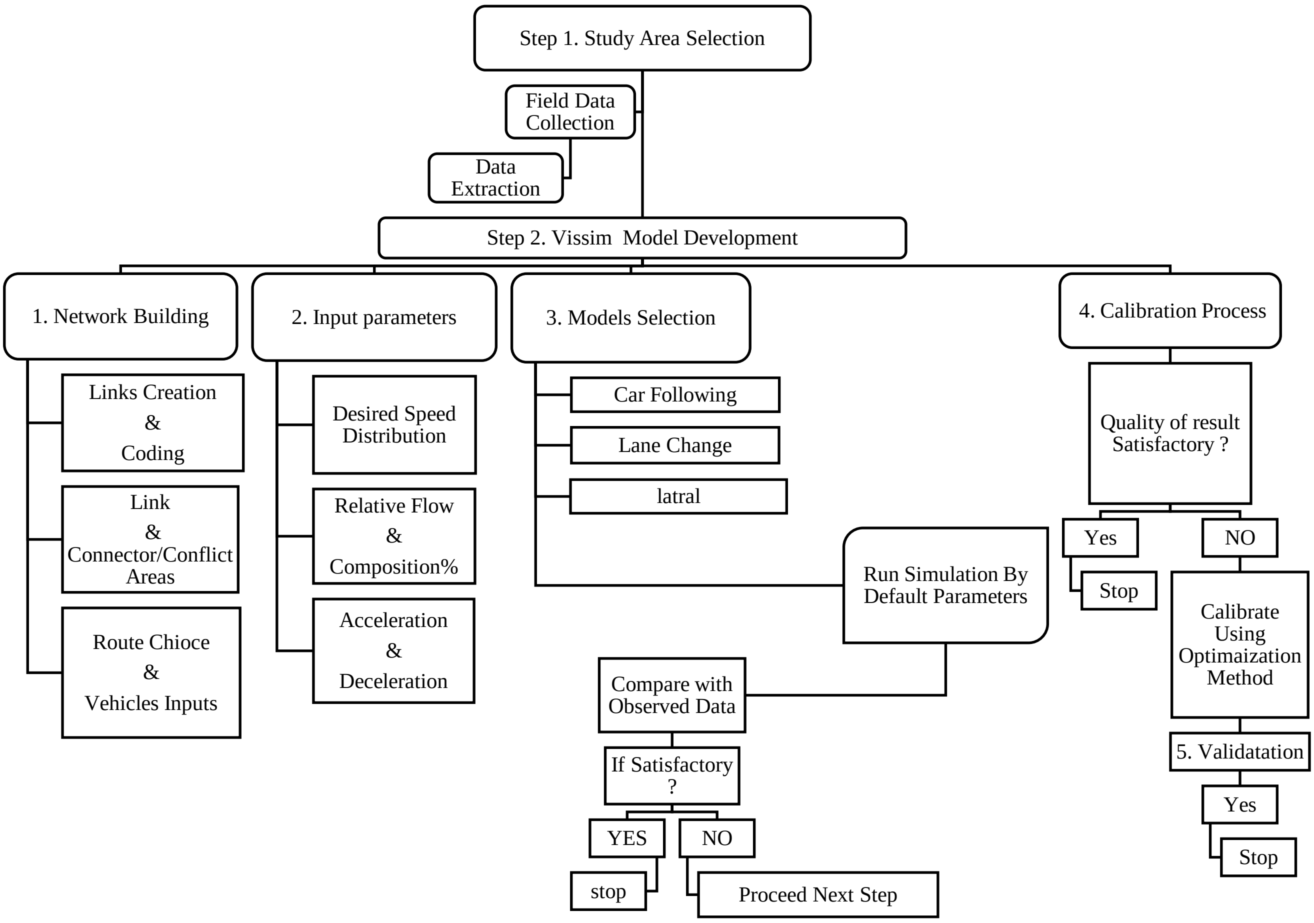


Figure 1. The envisioned research methodology

4. STUDY AREA AND DATA COLLECTION

Traffic data collection took place at the Panthangi toll plaza located on NH-65, 70 kilometres from Hyderabad, India, and a satellite image (bird view) is shown in Figure 2. Data was gathered from morning to evening, encompassing peak hours (7:00 AM to 8:00 PM). The overall count of four cameras was used; two were at the entrance and two were at the exit points of Toll Plaza to capture a video graphic image of all lanes of Toll Plaza. The traffic extractor software was used to extract the following data: vehicular traffic, speed, acceleration, and deceleration at entry, as well as exit points of the toll plaza.

Figure 2. Satellite Image of Study Area

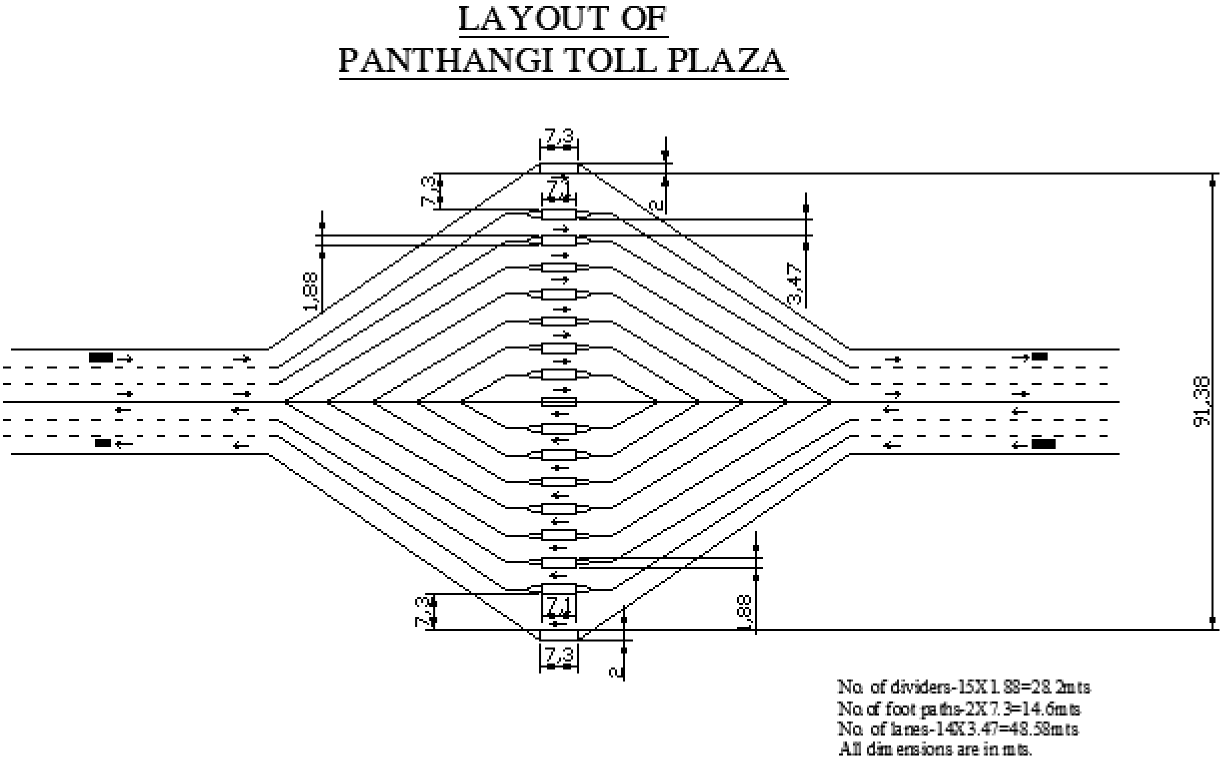


Figure 3. Layout Image of Study Area

From the video survey data, the gathered data includes details such as the quantity of traffic flow, types of traffic composition, parameters related to velocity, dynamics of acceleration, patterns of deceleration, specifications of vehicles, characteristics of road structure, attributes of roadway geometry, and configuration of the transportation network were extracted. The extracted traffic volume data as well as average vehicle speed are presented in Table 1, and the traffic composition is presented in Figure 4. From the survey results, it is observed that 40% of the traffic composition is small cars that pass through the toll plaza, followed by big cars with 22%. The residual vehicular movement is constituted by heavy-duty vehicle categories, incorporating light commercial vehicles, buses, heavy commercial vehicles, mixed-axle vehicles and trailer-type vehicles.

Table 1. Traffic Flow and Speed Data observed at Panthangi Toll Plaza

	Traffic Flow				**Speed**	
S.NO	**Traffic Flow**	**NO**	**PCU**	**Traffic Composition%**	**Average (m/s)**	**KMPH**
1	Small Car	525	525	40	13.2	48
2	Big Car	294	294	22.4	11.25	41
3	LCV	168	168	12.8	13.5	49
4	HCV	189	567	14.4	9.8	35
5	Bus	60	210	4.6	10	36
6	MAV	63	189	4.8	8	29
7	Trailer	12	36	1	7.5	27
	Total	1311	1989	100		

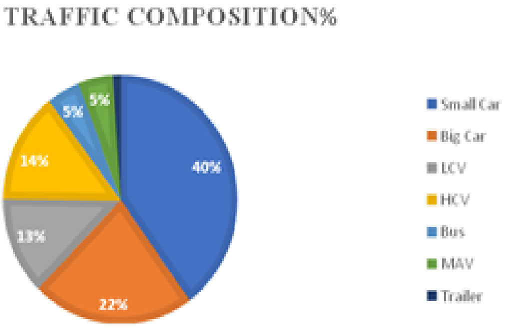


Figure 4. Traffic Composition at Panthangi Toll Plaza

From the video survey results, it is observed that the maximum acceleration 4.73 m/sec^2 on extreme toll booth and the minimum acceleration is observed in inner lanes as shown in Table 2. From the deceleration data, it is observed that the highest deceleration is observed in inner lanes as compared to the extreme lanes maybe when the driver decelerates their vehicles and changes lanes to reduce the queuing.

Table 2. Traffic Acceleration and Deceleration Data Observed at Panthangi Toll Plaza

Acceleration			**Deceleration**		
Mean Acceleration (m/sec^2)	**Minimum**	**Maximum**	**Mean Deceleration (m/sec^2)**	**Minimum**	**Maximum**
0.056	0	4.73	-0.6	-4.36	0
0.056	0	4.73	-0.605	-4.37	0
0.0019	0	3.9	-0.63	-4.34	0
0.0069	0	3.5	-0.63	-4.208	0
0.0059	0	3.5	-0.47	-4.659	0
0.0088	0	3	-0.437	-4.65	0
0.0088	0	3	-0.42	-4.012	0

5. MICRO SIMULATION MODEL DEVELOPMENT

The VISSIM micro-simulation model was developed and calibrated based on the selected parameters of vehicular movement and speed. The network of the simulated model of the toll plaza is shown in Figure 5. In the initial step, the model is simulated with default parameters, and from the simulated model, the traffic comparison as well as speed are observed and contrasted with the field data. Executing the calibration process for the simulation model, route choice, car following model of Wideman74, and safety additive distances were considered, and the vehicle composition and relative flow were observed as well as compared with field observed data.

According to field observations, the state of conflict areas is determined. As shown in Figure 6, there are four different types of conflict areas in the VISSIM model: one waits for 2, two holds for 1, undecided, and passive. The first two states imply that vehicles on major and minor routes are given preference when entering a conflict zone. When the major street crosses the minor street, these should be utilized. Use either indeterminate or passive when two major highways intersect. Undetermined means that traffic on both crossing roads behaves as though it were a single link. The modeling of traffic movement at merging and diverging portions considered this situation of conflicting regions. A passive state assumes that no priority is allocated at all, which will lead to vehicle collisions during the simulation run. As soon as the simulation model notices the conflict zones where traffic from intersecting roadways collides, it automatically assigns itself this classification. This status must also be determined based on the observations made in the field and may differ from one road facility to another.

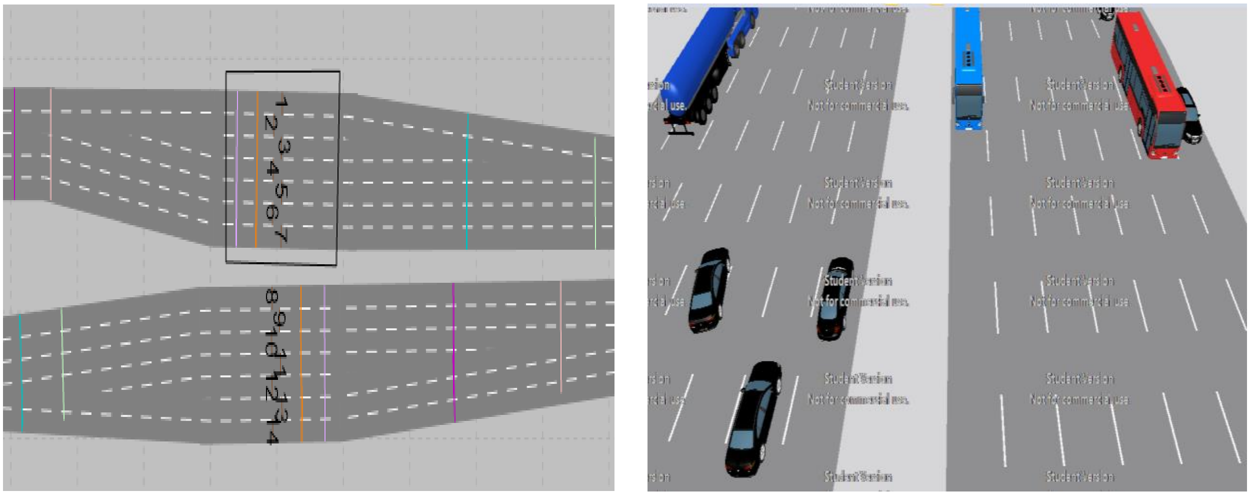
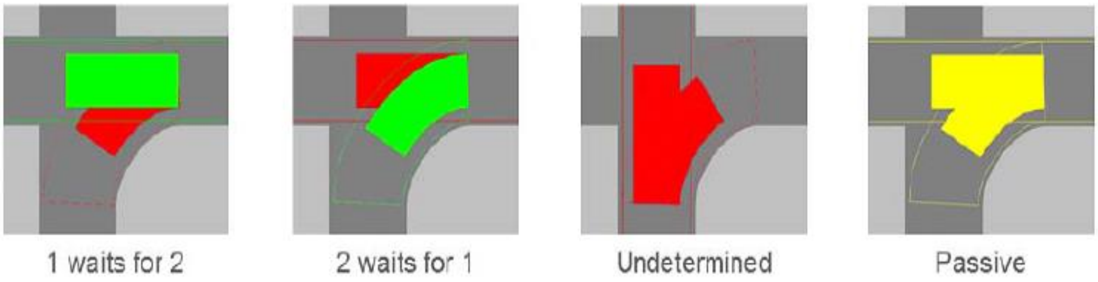


Figure 5. The VISSIM Network of the Simulated Toll Plaza


1 waits for 2

2 waits for 1

Undetermined

Passive

Figure 6. Sates of Conflict Aeras in Simulated Model

For the study according to Indian traffic conditions, the traffic composition based on the Indian scenario was introduced and applied to the model. Vehicle composition in the model, relative flow, and speed measures were calibrated according to the field-observed data. The driving behavior and link behavior models were calibrated using default values. Also, data collection points at the link sections and link evaluation parameters were introduced for the model. The result obtained from the micro-simulation was configured and evaluated using default parameters. Urban motorized vehicle driving behaviors were introduced for each link (see Table 3).

Table 3. Default Parameter for Driving Behaviour (Wiedemann 74).

Wiedemann 74 Parameters		Description	Value
Following	Look head distance	Minimum	0.00 m
		Maximum	250.00 m
		No interaction objects	4
		No interaction vehicles	99
	Look back distance	Minimum	0.00 m
		Maximum	150.00 m
	Behavior during recovery from speed breakdown (Slow recovery)	Speed	60.0%
		Acceleration	40.0%
		Safety distance	110.0%
		Distance	2000.00 m
	Standstill distance for static obstacles	0.50 m	
	Model Parameter	Range	
Car Following Model	(AX)Average Standstill Distance	2.00 m	
	Additive Part of a Safety distance	2.00 m	
	Multiplicative Part of safety Distance	3.00 m	

Lane Change	Necessary lane changes (route)	Parameter	Following Vehicle	Trailing Vehicle
		Maximum Deceleration	-4.00m/s^2	-3.00 m/s^2
		-1 m/s^2 per distance	100.00m	100.00m
		Accepted Deceleration	-1.00 m/s^2	-1.00 m/s^2
	Waiting Time before diffusion	60.00 sec		
	Min clearance (front/rear)	0.50 m		
	To the slower lane, if the collision time is above	11.00 sec		
	Safety Distance reduction factor	0.60		
	Maximum Deceleration for cooperative breaking	-3.00 m/s^2		
	Cooperative lane change	Maximum speed difference	10.80 Km/h	
		Maximum Collision time	10.00 sec	
	Rear Correction of lateral positions	Max speed	3.00 Km/h	
		Active during a time period from	1.00 sec	10.00 sec

6. CALIBRATIONS AND VALIDATIONS

This study incorporates the Weidman-74 driving behavior model in the context of varied traffic conditions. The car-following model's safety distance is established by referencing prior research, which considers parameters such as the average standstill distance, the additive element of the safety distance, and the multiplicative component of the safety distance (Matthew and Radhakrishnan, 2010). These values were chosen by the results of the trial-and-error procedure and the traffic patterns in the chosen research region. The calibrated results of additive safety distance are presented in Table 4. The AX additive and BX multiplicative distances were computed based on equations 1 to 8.

Table 4. Calibrated Safety Distance Parameters for Different Vehicular Categories

Vehicles Type	**AX**	**BX Additive**	**BX Multiplicative**
Small Car	0.90	0.70	0.50
Big Car	0.90	0.50	0.40
MAV	1	0.5	1
Bus	1.00	0.50	1.00
HCV	1.00	0.50	1.00
LCV	1.00	0.50	1.00
Trailer	1	0.5	1

The calculated safety margin, identified as d, is computed as:

$$d = ax + bx \tag{1}$$

Where $bx = (bx_{add} + bx_{mult} * z) * \sqrt{v}$ (2)

In this context, v represents the speed of the vehicle in meters per second, while z is a value within the range of 0 to 1. This value follows a normal distribution centered around 0.5, with a standard deviation of 0.15..

$$\begin{aligned} Ax(mixed) = {} & Ax.Car * \%car + \mathrm{Ax.Big\ car} * \%\mathrm{Big\ Car} + AxLCV * \%\ \mathrm{LCV} + Ax\mathrm{HCV} * \%HCV + AxBus \\ & * \%Bus + AxMAV * \%MAV + Ax\ Trailer * \%\ Trailer \end{aligned} \tag{3}$$

$$\begin{aligned} bxadd(mixed) = {} & Bx.Car * \%car + \mathrm{Bx.Big\ car} * \%\ \mathrm{Big\ car} + BxLCV * \%\ \mathrm{LCV} + Bx\mathrm{HCV} * \%HCV \\ & + BxBus * \%Bus + BxMAV * \%MAV + Bx\ Trailer * \%\ Trailer \end{aligned} \tag{4}$$

$$\begin{aligned} & Bxmulti(mixed) \\ & = Bx.Car * \%car + Bx.Big\ Car * \%Big\ Car + BxLCV * \%\ \mathrm{LCV} + Bx\mathrm{HCV} * \%HCV \\ & + BxBus * \%Bus + BxMAV * \%MAV + Bx\ Trailer * \%\ Trailer \end{aligned} \tag{5}$$

By substituting the values, we get,

$$Ax(mixed) = 0.9(0.4) + 0.9(0.22) + 1(0.012) + 1(0.015) + 1(0.046) + 1(0.048) + 1(0.01) = 0.691 \tag{6}$$

$$\begin{aligned} Bxadd(mixed) = {} & 0.7(0.4) + 0.7(0.22) + 0.5(0.012) + 0.6(0.015) + 0.5(0.046) + 0.5(0.048) + 0.5(0.01) \\ & = 0.494 \end{aligned} \tag{7}$$

$$BxMult(mixed) = 0.5(0.4) + 0.4(0.22) + 1(0.012) + 1(0.015) + 1(0.046) + 1(0.048) + 1(0.01) = 0.42 \tag{8}$$

From the calibrated VISSIM model, the look head distance, look back distance, behavior during recovery, and standstill distance were computed for the following model (see Table 5). The calibrated values pertaining to the average distance during standstill, the additive portion of safety distance, and the multiplicative segment of safety distance are 0.7, 0.5, and 0.42, respectively. From the lane changing case, it is observed that the minimum clearance (front and rear) and safety distance reduction factor were observed at 0.45m and 0.4 m, respectively.

Table 5. Calibrated Wiedemann – 74 Parameters for Different Vehicular Categories

Wiedemann 74 Parameters		**Parameter**	**Default Value**	**Calibrated Value**
Following	Look head distance	Minimum	0.00 m	30 m
		Maximum	250.00 m	150 m
		No. of interaction objects	4	4
		No. of interaction vehicles	99	25
	Look back distance	Minimum	0.00 m	30
		Maximum	150.00 m	150 m
	Behavior during recovery from speed breakdown (Slow recovery)	Speed	60.0%	
		Acceleration	40.0%	
		Safety distance	110.0%	
		Distance	2000.00 m	
	Standstill distance for static obstacles	0.50 m		
	Model Parameter	Default Value	Calibrated Value	
Car Following Model	(AX)Average Standstill Distance	2.00 m	0.7	
	Additive Part of Safety distance	2.00 m	0.5	
	Multiplicative Part of safety Distance	3.00 m	0.42	
Lane Change	Necessary lane changes (route)		Own	Trailing Vehicle
		Maximum deceleration	-4.65 m/s^2	-3.00 m/s^2
		-1 m/s^2 per distance	100.00m	100.00m
		Accepted deceleration	-1.00 m/s^2	-1.00 m/s^2
	Waiting Time before diffusion	60.00 sec	Calibrated value	
	Min clearance (front/rear)	0.50 m	0.45 m	
	To slower lane, if collision time is above	11.00sec		
	Safety Distance reduction factor	0.60	0.40	
	Maximum Deceleration for cooperative breaking	-3.00 m/s^2	-4.65	
	Cooperative lane change	Maximum speed difference	10.80 Km/h	
		Maximum Collision time	10.00 sec	
	Rear Correction of lateral positions	Maximum speed	3.00 Km/h	
		Active during time period from	1.00 sec.	10.00 sec.

Table 6. Simulation Result of Predicted and Observed Traffic Volume at Panthangi Toll Plaza based on Default Case and Calibrated Values of Driving Behaviour Parameters using VISSIM

	NO	**Vehicles**	**Traffic Volume (Veh/hr)**		**No**	**Vehicles**	**Traffic Volume (Veh/hr)**	
			Observed	**Simulated**			**Observed**	**Simulated**
Simulation 600 second	1	Small Car	525	434	1	Small Car	525	490
	2	Big Car	294	100	2	Big Car	294	148
	3	MAV	63	37	3	MAV	63	42
	4	Bus	60	79	4	Bus	60	50
	5	LCV	168	90	5	LCV	168	140
	6	HCV	189	52	6	HCV	189	156
	7	Trailer	12	4	7	Trailer	12	4
	Total		1311	796	Total		1311	1030
Default Parameters					**Calibrated Parameters**			

From the calibrated VISSIM model, the traffic volumes were compared between the observed and simulated cases of default as well as calibrated parameters (see Table 6). The results show that a clear difference is observed between the default parameter and calibrated parameters, and the total volume is observed as 1030 veh/hr, corresponding to the calibrated parameters. From the results, it is also identified that small as well as big cars can be accurately predicted with modified parameters. After the simulation of the model using the default parameters for the car-tracking mechanism and the lane-changing algorithm using Weidman-74 driving behavior options under heterogeneous traffic conditions, a linear regression analysis line was fitted between the observed and simulated values of the calibrated parameters.

Figure 7 indicates the correct predicted accuracy of the calibrated model of the VISSIM simulation. Whereas, the default case of the observed versus simulated result indicates R^2 as 0.82, which is not adequate and further needs the parameters to be calibrated. Further, the calibrated value for the driving behavior model was entered into VISSIM, and after running simulation with calibrated values, it was observed that the model line fit with the data analysis using the regression trend line, and it was observed that the R^2 value was 0.93, which is an acceptable value and indicates significant improvement in the model.

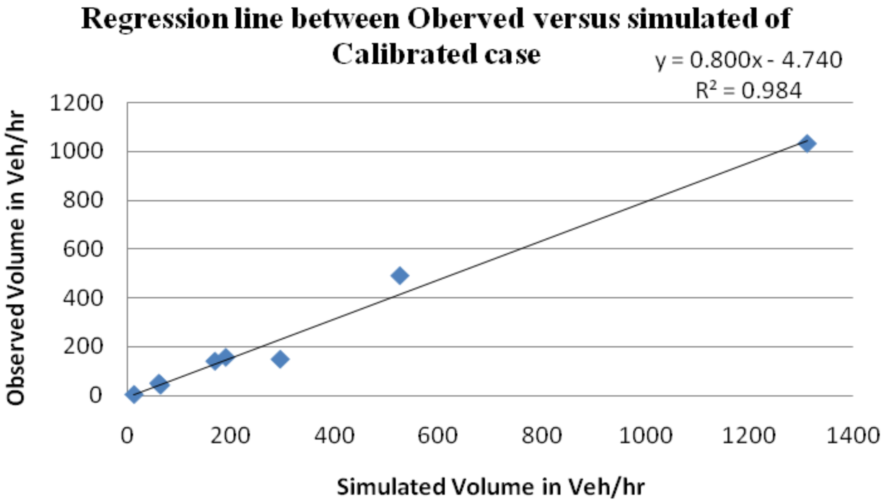


Figure 7. Simulated Fit Plot for Traffic Data using Calibrated Values for Driing Behaviour Parameters

Validation Target

The simulation results were validated using mean absolute percentage error (MAPE), root mean square error (RMSE), and correlation coefficient to ensure that the process of fine - tuning of the driving behavior parameter that was determined in the model achieved the target simulation. This was done to ensure the validity of the calibrating values introduced in the VISSIM model. From the validation results, it was observed that MAPE, RMSE, and correlation coefficient values are 0.25, 0.09, and 0.994, respectively.

Mean absolute percentage error measures the size of the percentage error and is expressed as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{sim}-y_{obs}}{y_{obs}}\right| * 100 = 0.25 < 5\% \quad (9)$$

In this scenario, n denotes the total quantity of observations taken for traffic measurements, y_{sim} and y_{obs} are simulated and observed data points exist within a time-space domain, while, and y_{sim} denotes the average calculated from the entire set of simulated outputs.

$$RMSE = \sqrt{\frac{1}{N}\sum N(X_i - Yy_i)^2} = 0.09 \quad (10)$$

The strength of the linear link between the simulated and observed data was expressed as a correlation coefficient (CC). A perfect and direct association is shown by a correlation coefficient of 1, whereas a perfect and inverse relationship is indicated by a CC of -1. A correlation coefficient of 0.85 is regarded as satisfactory for model calibrations.

$$Correlation\ Coefficient = \frac{1}{N}\sum_{i=1}^{n}\frac{(Yi_{sim}-Yi_{sim})(Yi_{obs}-Yi_{obs})}{\sigma_{sim}*\sigma_{obs}} = 0.994 \quad (11)$$

Where n is the overall number of traffic measurement observations, and Yi_{sim} and Yi_{obs}represent the means of the simulated and observed data, respectively. The standard deviations of the simulated and observed measurements are $\sigma_{sim}$and σ_{obs}, respectively.

7. CONCLUSION

The current research delved into microscopic traffic simulation at a toll plaza to comprehend driving behavior at the toll booth through the utilization of VISSIM. The driving behavior was explored based on the acceleration, and deceleration parameters and modified the driving behavior parameters in VISSIM. In this research paper, a three-phase step methodology is outlined for creating, fine-tuning, and verifying the simulation framework. Parameters that influence the driving behavior at merging and diverging locations.

The required phase-wise procedure indicates the collecting and processing of field data and the creation of a detailed simulative structure at the microscopic level using PTV VISSIM. The field data were assigned to the model and different driving behavior parameters were defined to calibrate and validate using field data. Using the default case parameters, the result of the model output indicates the model fit of (R^2 =0.82) which was in competent to reproduce the observed conditions, although, after multiple simulations running with changing the most influencing attributes such as safety impact factor and headway distance between vehicles, the results showed the higher value of model fit represented as (R^2 = 0.93) which is significantly an acceptable value. From the validation test results, it can be seen that the RMSE for all types of vehicles observed and simulated vehicular movement (0.09<0.2) was found acceptable. The MAPE value shows that the value is in the range of 0.25 which is less than 5% and it is satisfactory. Overall validation results were satisfactory, with minimal error. Therefore, it can be concluded that the model was successfully calibrated and validated.

The study concluded that based on the calibrated model, the driving behavior parameters were observed with as much accuracy with respect to the car following behavior and lane change behavior. Compared to the results of the default model, the statistics of the calibrated model show a significant improvement. It is clear that the MAPE error measurement is less than 5%, which suggests that the observed and simulated traffic statistics are reasonably matched. The RMSE for all simulated and real-world vehicle categories is less than 10%, which is regarded as acceptable for mixed-traffic model validations. In conclusion, all combinations of design characteristics and traffic demand patterns showed good agreement between measured and projected values. In general, the following parameters in Wiedemann 74 are the primary variables that influence the simulation precision. Factors such as AXE, BX additive, and BX multiplicative, and the lane change model parameters, including minimum headway and safety distance reduction factor, were considered, and it was concluded that these factors significantly influence driving behavior.

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