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MACHINE LEARNING APPROACH IN CALIBRATING VISSIM MICROSIMULATION MODEL FOR MIXED TRAFFIC CONDITIONS

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ABSTRACT

Traffic Simulation has empowered transportation engineers by providing a means of visual interpretation for real-life traffic conditions. PTV VISSIM is a well-known microsimulation software used to analyze and predict traffic operations and behavior by considering factors such as lane configuration, traffic composition, transit stops, etc. A non-laned-based heterogeneous traffic stream characterizes the urban traffic system of Dhaka. This makes it burdensome to calibrate and validate VISSIM models to reflect field-obtained traffic flow. To calibrate VISSIM-developed simulation models, Weidemann 74 and 99 car-following models are widely adopted. These car-following models and other movement parameters, such as lateral movement and lane-changing behavior parameters, are usually adjusted to calibrate the microsimulation model. This study aims to develop a new approach using sampling and machine learning to calibrate the Weidemann 99 car following model parameters in VISSIM microsimulation software for mixed traffic conditions. A portion of Abdul Gani Road, which represents the typical characteristics of the traffic system of Dhaka, was chosen to be the epicenter of this study. Latin Hypercube Sampling has been used to generate the number of combinations required to properly explore the effects of the ten calibration parameters of the Weidemann 99 car following model on the validation accuracy. The validation accuracy has been measured by using the GEH statistic. A total number of 500 simulations were generated, and from these 500 simulations, 37 combinations were obtained to have acceptable GEH values, which is generally considered to be less than 5%. These combinations were further analyzed using a k-means clustering algorithm to generate the centroid line of the acceptable parameter combinations. A sensitivity analysis was conducted using the obtained simulation dataset to determine the impact of changing values of the parameters on traffic flow. The findings of this study will aid future traffic simulation researchers by providing them with a guiding framework in calibrating VISSIM simulation models for mixed traffic conditions similar to Dhaka.

Keywords: *PTV VISSIM, Latin Hypercube Sampling, Cluster analysis, Calibration, Wiedemann 99*

1. INTRODUCTION

In recent decades, computational technology has led to the widespread adoption of microscopic traffic simulation models as the primary method for evaluating and enhancing road traffic management and control systems worldwide. These models have gained popularity among researchers as a valuable tool for assessing various alternative design and management strategies for road networks before their real-world implementation. Among those, VISSIM is one of the most widely used microscopic traffic simulation tools known for its versatility and capabilities in modeling complex traffic scenarios and practical applications in transportation planning and traffic management. However, the effectiveness of a traffic simulation model in evaluating scenarios hinges on its ability to accurately mirror the local area's network, infrastructure, and driver characteristics. Model calibration can be described as the systematic process of aligning the model's initial assumptions with the real-world conditions observed in a specific local context. This involves carefully selecting and adjusting the model's input parameters to match better the actual traffic conditions measured in the field. The goal is to ensure that the model accurately represents the specific local traffic conditions by refining default values and incorporating field-measured data. (Park & Schneeberger, 2003).

The traffic condition of Dhaka city is characterized by non-lane-based heterogeneous traffic. Heterogeneous traffic is defined as a mix of vehicles having diverse static (length, width, etc.) and dynamic (acceleration/deceleration, speed, etc.) properties. These vehicles include nonconventional and nonmotorized vehicles, and their composition is highly transient. Another distinguishing aspect of such traffic is the absence of lane marking and lane discipline, resulting in a complex movement of vehicles, especially at intersections. The proportion of NMVs can vary widely, and they significantly impact traffic conditions, especially at signalized intersections. NMVs reduce road capacity and motorized vehicle speed, contribute to congestion at intersections during discharge, and influence queue length and delay times in traffic operations. (Manjunatha *et al*., 2013;

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Mashrur & Hoque, 2016). Although studies have found success in somewhat replicating traffic movement of Dhaka in simulation models particularly in comparative analysis on the oversaturated signalized intersections (Hoque and Naz, 2023), many challenges are yet to be overcome.

The efficiency of microsimulation depends on how accurately the parameters can be calibrated. Calibrating a large set of parameters manually is burdensome work. Various approaches have been taken to produce the optimal set of parameters for calibration. Manjunatha *et al.* (2013) conducted a case study in signalized intersections with different traffic characteristics in Mumbai using the Latin Hypercube method to generate scenarios and the solution parameter set was determined by using a genetic algorithm (GA). A sensitivity analysis of the parameters was conducted, and optimization was introduced to identify a parameter set that minimizes intersection delay. The Wiedemann 74 and 99 models were calibrated at three intersections for this study. A two-way analysis of variance (ANOVA) was utilized for the calibration process, focusing on five parameters, with the metric of delay serving as the measure of effectiveness (MOE) for calibration. The calibration can be repeated at the network and corridor levels, and the effectiveness metrics and methodology can be appropriately adjusted. To calibrate the parameters of the microscopic simulation, Siam *et al.* (2018) used an application tool called VISCAL, which is based on three heuristic optimization algorithms: genetic algorithm (GA), simultaneous perturbation stochastic approximation (SPSA), and simulated annealing (SA). Three objective functions—speed, flow, and speed-flow were utilized to test the VISCAL calibration procedures on a 3.26 km freeway in Dhaka, Bangladesh. Dey *et al.* (2018) proposed a procedure that recognized this lack, and that can be used effectively to calibrate and validate the VISSIM model for signalized intersections. Another study done by Azam *et al.* (2019) considered the maximum queue length as MOE. Their approach was divided into two stages: system calibration and operational calibration. System calibration considered the actual geometry of the roads and the control conditions, whereas operational calibration utilized Sensitivity Analysis (SA). This study showed that SA can help determine the most significant parameters and their values. Unfortunately, the authors did not mention any specific methodology to calibrate the parameters. Mer *et al.* (2021) developed a methodology to calibrate the parameters in the context of India. They developed a VISSIM model, which included 7 intersections. Later, they conducted a one-way ANOVA sensitivity analysis using the SPSS tool and determined 11 parameters among 19 sensitive items. These 11 parameters were calibrated using Python's Genetic Evolutionary Algorithm Toolbox (GEATPy). This study is only limited to interurban road intersections and appropriate modifications are a must to apply this methodology to different traffic facilities. The authors also suggested using stop delay, fuel consumption, capacity, and so on as MOE. Additionally, Chaudhari *et al.* (2021) presented a Wiedemann-99 model calibration procedure based on optimizing trajectory profiles, acceleration, and speed as microscopic performance measurements to determine appropriate calibration parameters. The procedure was based on root mean square error (RMSE) between simulated and observed trajectories of mixed traffic, primarily consisting of motorized two-wheelers and cars. Budhkar & Maji (2022) proposed a method to calibrate the simulation model of a merging section, which was then used to estimate the capacity of the merging section. They took macroscopic and microscopic parameters to calibrate the model and found 8 parameters to be significant. The authors suggested considering the effect of geometric variation and traffic composition for better output.

Maheshwary *et al.* (2020) attempted to calibrate the VISSIM microstimulator based on the driving behavior concerning different vehicle classes. A case study of a traffic corridor was conducted in Kolkata using the Latin Hypercube method, and a genetic algorithm (GA) was used to obtain optimal parameter sets for different vehicle classes. A one-way analysis of variance (ANOVA) was utilized for the calibration process, with travel time as the measure of effectiveness (MOE) for calibration. The limitation of this study was that the findings were highly dependent on vehicle class; thus, the authors suggested calibrating the model for other vehicle classes to increase its applicability to other non-lane-based heterogeneous traffic scenarios. Bhattacharyya *et al.* (2020) used a Genetic Algorithm (GA) to optimize the parameters considering every mode of a multi-modal traffic network. Their proposed methodology performed well when validated against a typical Kolkata city, India road network representing non-lane based heterogeneous traffic conditions. Sashank *et al.* (2020) used a Simulation of Urban Mobility (SUMO) instead of VISSIM for model development. They tried to calibrate the model for Indian lane-less mixed traffic. Using the ANOVA test, they found 14 parameters that can affect the simulation model. These parameters were then optimized on a trial-and-error basis and using Genetic Algorithm methods. Prabhash & Amarasingha (2021) also took queue length as a performance measure. They used Genetic Algorithms tools in MATLAB to select 6 out of 10 parameters and then determined the optimal values. The limitation of this study is that the calibrated parameters would perform well in similar sub-urban conditions. Still, it would require more calibration to be used in different traffic conditions.

Significant research gaps have been identified in calibrating the VISSIM model for metropolitan cities like Dhaka, where mixed traffic conditions characterize traffic conditions. This mix includes motorized vehicles such as cars, buses, trucks, auto-rickshaws, motorbikes, and non-motorized vehicles like rickshaws, bicycles, and vans. Although a few researchers have contributed to calibration methodologies for similar conditions, based on the research gap, to increase the efficiency as well as the accuracy of calibration of microsimulation models, a new method, including a machine learning approach has been proposed in this study to investigate VISSIM parameters and establish a framework for guiding future research in this area in this study.

2. METHODOLOGY

2.1 Data Collection

An urban site with significant transportation mode and flow volume variation was chosen. For this study, Abdul Gani Road, with two signalized intersections, was selected considering all the requirements for the calibration process. A screenshot from Google Maps is shown in Figure 1. The eastern intersection is marked as 01, and the eastern intersection as 02 in Figure 1.

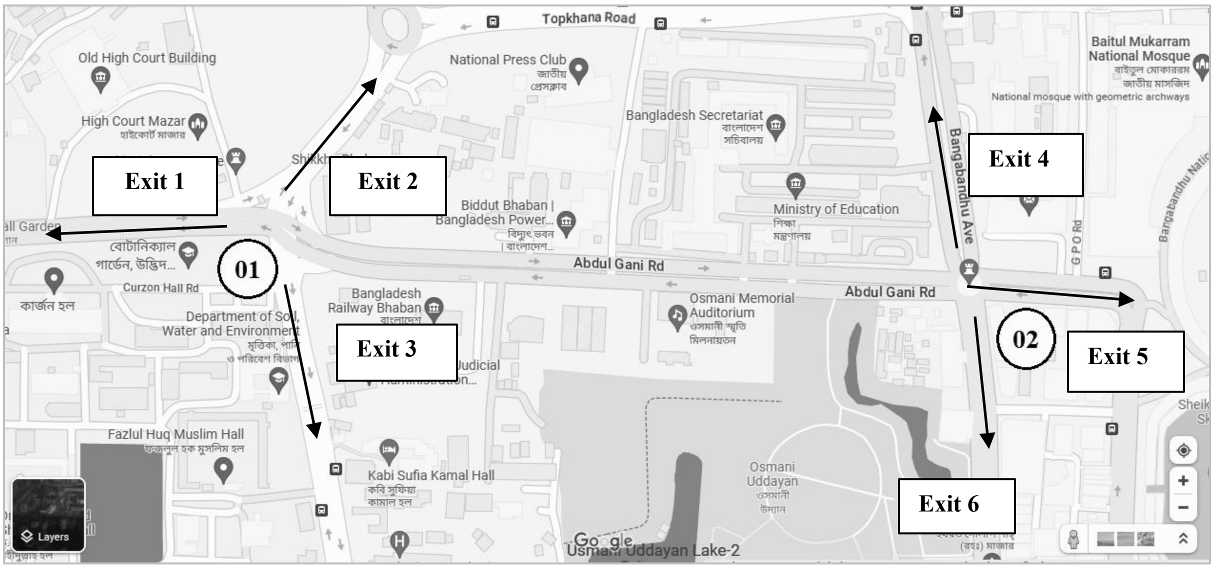


Figure 1: Study Area

Two types of data were collected from the study site. The first set of data was related to road geometry, such as the number and width of the lanes, the number of approaches at each intersection, channelization, and turning facilities. This data was collected by field survey. Another type of data related to traffic operation was collected by video survey, which also included traffic count data. 2 cameras at each intersection were placed to conduct a video survey. Traffic count at intersections, routes, and vehicle composition were found from the video survey. After analyzing 24 hours of data, a peak of two hours of data was used for modeling. A few local roads between the selected two intersections are mostly used for parking cars of officials or as the entrance of a park. These roads do not generate a significant amount of traffic compared to the selected roads. Hence, these roads were not considered during modeling. The data obtained from the video survey is presented in Table 1. In the future, using Intelligent Transportation Systems (ITS) technologies can significantly improve the quality of collected data (Naz and Hoque, 2023).

Table 1 Traffic Survey Data

Intersection	Exit No.	Number of Lanes	Width of Lanes (m)	Total Vehicles (All Types)
	1	2	3.2	656
1	2	3	3.5	718
	3	2	3.5	707
	4	2	3.3	667
2	5	2	3.3	583
	6	2	3.3	614

2.2 Network Coding

To develop the microsimulation model, the Graphical User Interface (GUI) of VISSIM was utilized to draw the whole network of the study area. An appropriate number of links and connectors were used to represent the roads; signal heads were used to implement the signal control system. Vehicle inputs, relative percentage flow, and vehicle routes were adequately added to the simulation model. Intermediate points were added to adjust the curves of the streets, and data collection points were added to all the exit points of the road network for the calibration process. The smaller connecting roads beside the Bangladesh Secretariat were ignored, as very little traffic from those roads was approaching the study network. The built-up simulation model is showcased in Figure 2.

Figure 2: VISSIM Simulation Model

2.3 Latin Hypercube Sampling

The Latin hypercube sampling (LHS) was first proposed by McKay *et al.* (1979) and has been further developed for different purposes by several researchers, e.g., Iman & Conover (1982) and Olsson *et al.* (2003). It is a technique recommended to make various important sampling methods more efficient when analyzing the reliability of structures. In a basic form of importance sampling, where we shift the sampling focus from the starting point to the design target, LHS can be used instead of the standard Monte Carlo sampling method for better results (Olsson & Sandberg, 2002). LHS optimizes computer processing time in Monte Carlo simulations and provides an efficient way of sampling variables from their distributions (Iman and Conover, 1982). It becomes particularly valuable when working with slower operating systems and software, as it can significantly enhance efficiency. While some argue that advancements in modern computing technology have diminished the importance of LHS, it remains a widely used and beneficial approach. This study incorporates a simulation model based on Wiedemann 99 car-following model parameters. LHS is used here to create sample sets of all the 10 parameters associated with this model. Table 2 (PTV VISSIM 2022 User Manual) provides a brief description of the parameters (CC0 to CC9).

Table 2 Car Following Model Parameters

Parameters	Unit	Description
CC0	m	**Standstill distance:** It is the desired standstill distance between two vehicles. It has no stochastic variation.
CC1	s	**Gap time distribution:** It refers to the distribution of time in seconds from which a driver selects the desired time gap to maintain, in addition to the standstill distance between vehicles.
CC2	m	**'Following' distance oscillation:** It refers to the maximum extra distance beyond the preferred safety distance that a driver tolerates when following another vehicle
CC3	s	**Threshold for triggering 'BrakeBX':** It is the period before reaching the maximum safe distance (assuming a constant speed) to a slower-moving leading vehicle.
CC4	m/s	**Negative speed difference:** This represents the minimum relative speed threshold compared to the slower leading vehicle during the following process (expressed as a negative value).
CC5	m/s	**Positive speed difference:** This denotes the relative speed limit compared to the faster leading vehicle during the following process (expressed as a positive value). Negative values, on the other hand, lead to the adoption of a deceleration speed that is more closely resembling that of the leading vehicle.
CC6	1/(m*s)	**Distance impact on oscillation**: This refers to the influence of distance on the boundaries of relative speed limits during the following process: (i) When the value is 0, distance does not affect these limits. (ii) For larger values, the limits expand as the distance increases.
CC7	m/s^2	**Oscillation acceleration:** Acceleration oscillation during the following process.
CC8	m/s^2	**Acceleration from standstill:** The rate of acceleration experienced when a vehicle begins moving from a standstill position.
CC9	m/s^2	**Acceleration at 80 km/h:** The rate of acceleration exhibited when the vehicle is traveling at a speed of 80 km/h.

During this study, an exploration of traffic dynamics was conducted through the generation and examination of 500 unique combinations. The parameters were given a large range for the LHS to generate samples of a large variation. These combinations were executed in simulation scenarios with two distinct intersections, each featuring three exit points. Subsequently, the simulation runs yielded valuable output data in the form of traffic counts. The model accuracy gained from each combination was calculated using the GEH statistic that compared the simulated traffic flow and the real-life traffic flow.

2.4 GEH Statistic

The GEH statistic establishes the connection between observed and simulated traffic flow. Through calibration and validation results, GEH statistics reveal a robust correlation between experimental and simulated flow. This statistic effectively tackles the potential challenge posed by a network containing various roadway functional classes by determining percentage errors relative to the mean values of both observed and simulated counts (Balakrishna *et al*., 2007). Typically, the GEH statistic is recommended for comparing hourly traffic volumes exclusively. It is defined by the equation specified by Dowling (2004):

$$\sqrt{\frac{2(M-C)^2}{M+C}} \tag{1}$$

Where, M indicates simulated traffic volume, and C indicates the observed traffic count.

Different GEH values provide insights into the goodness of fit, as explained below:

- GEH < 5: Flows are deemed a good fit.
- 5 < GEH < 10: Flows may necessitate additional investigation.
- 10 < GEH: Flows are not a good fit.

Dowling (2004) recommends that a minimum of 85% of the observed links in a traffic model should exhibit a GEH of less than 5.0.

In our analysis, which encompassed 500 combinations, only 37 yielded Generalized Exponential Holt-Winters (GEH) values below the threshold of 5. The study focuses on two intersections, each featuring three exit points, resulting in six GEH values—one for each exit point. Notably, in all 37 validated combinations, the GEH values for all six exit points remained below 5. This rigorous validation process enhances the reliability and credibility of our findings.

2.5 Cluster Analysis

Two terms are associated here - Clustering and Analysis. Clustering is a method of partitioning data sets into different groups based on dissimilarities or differences among the data set. These groups are called clusters. Cluster analysis is a tool that helps determine each cluster's characteristics and then focuses on a specific cluster for in-depth analysis.

In our study, the K-mean algorithm has been used as a partitioning method. Here, the mean value of a data set represents that cluster. In this method, a set of n objects is partitioned into k clusters so that two clusters have low similarity or high dissimilarity. In clustering, dissimilarity between data sets is observed by calculating the distance between each pair of data sets. The K-mean method utilizes Euclidean distance to calculate the distance. Euclidean distance is defined as

$$\boldsymbol{(x, y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2}} \tag{2}$$

Where, x, y = two n-dimensional data set

The k-mean algorithm has two steps. In the 1st step, a k centroid is selected randomly, where the k value is fixed before selection. Later, each data in the data set is correlated with the nearest centroid. The output is an input-specified cluster set containing a k cluster (Yadav & Sharma, 2013; Koshti *et al*., 2022).

In our study, cluster analysis determines a centroid value of 37 different combinations (Table 2) that met the GEH condition.

Table 3 Cluster Analysis Input Data

CC0	CC1	CC2	CC3 (- ve)	CC4 (- ve)	CC5	CC6	CC7	CC8	CC9	GEH Range
1.4	0.9	2.73	1.69	1.05	2.05	7.34	0.38	3.53	0.76	0.88-4.82
1.49	0.5	3.98	10.3	2.36	0.9	11.23	0.25	3.08	1.05	3.46-4.91
1.07	1.5	2.23	13.8	1.31	2.25	8.09	0.32	4.37	2.03	2.42-3.96
1.67	0.5	2.8	8.26	0.23	1.34	13.81	0.27	2.54	4.78	0.65-4.91
1.92	0.5	2.28	3.88	0.44	1.2	17.64	0.48	3.82	4.9	1.58-5.00
1.06	0.9	3	12.3	0.85	0.3	19.42	0.21	1.3	4.21	0.12-4.35
1.77	0.5	2.4	0.88	1.18	1.13	8.81	0.3	4.24	4.03	1.72-4.91
1.7	0.6	3.81	1.24	0.87	1.75	18.02	0.23	4.22	0.73	1.09-4.75
1.85	0.6	2.26	7.58	0.79	2.48	10.85	0.25	2.09	4.33	3.63-5.00
1.41	0.5	2.69	3.68	2.2	1.61	8.7	0.47	3.39	3.08	3.43-4.91
1.32	0.5	3.4	13.2	2.11	2.22	17.36	0.43	2.65	1.95	0.48-4.95
1.68	0.5	2.24	8.58	0.24	1.55	11.25	0.38	1.61	4.42	1.92-4.87
1.68	0.6	3.2	2.64	1.34	0.28	8.53	0.33	4.51	1.4	3.01-5.00
1.78	0.6	3.66	9.89	0.74	1.26	6.66	0.25	4.83	0.9	1.71-4.95
1.14	0.6	3.91	8.53	2.47	2.32	14.19	0.41	4.85	4.18	1.78-4.87
1.35	0.6	3.1	10	1.63	2.48	9.41	0.22	2.5	4.23	0.95-4.22
1.29	0.9	3.29	6.32	0.66	2.59	5.98	0.34	1.57	4.16	3.87-4.95
1.5	0.5	2.15	6.96	1.21	1.97	5.8	0.31	3.25	4.57	0.96-4.91
1.26	1.5	2.38	5.76	0.75	1.56	12.67	0.29	2.43	2.43	2.17-4.65
1.51	0.6	2.4	11.7	2.46	1.32	8.34	0.39	4.27	1.32	3.91-4.95
1.42	0.9	3.07	14.1	2.24	0.47	17.28	0.24	2.92	3.49	2.14-4.91
1.56	0.6	2.53	3.38	0.8	1.21	7.63	0.32	3.18	4.45	1.84-4.52
1.53	0.9	2.84	2.3	0.3	1.43	17.23	0.4	4.28	2.7	0.36-4.95
1.89	0.5	2.81	11.5	1.15	1.73	13.37	0.22	3.49	3.64	4.10-5.00
1.74	0.5	3.2	12	0.3	2.09	8.16	0.45	3.89	0.37	1.39-4.84
1.75	0.9	2.74	4.91	0.38	0.26	10.45	0.33	4.39	3.02	1.09-5.00
1.57	0.5	3.25	5.45	1.73	0.43	19.91	0.34	3.84	2.8	3.91-5.00
1.87	0.9	2.62	0.51	1.03	0.8	12.99	0.25	3.95	4.06	2.04-4.91
1.63	0.9	3.99	1.41	0.22	1.58	11.78	0.26	3.97	3.2	2.14-5.00
1.54	0.9	2.55	9.46	1.41	1.21	6.45	0.36	4.07	2.73	0.99-4.70
1.59	0.5	3.08	8.78	0.97	2.52	18.86	0.47	4.08	3.96	4.02-4.87
1.22	0.9	2.81	1.03	2.76	1.57	10.48	0.39	3.85	1.47	1.77-4.82
1.31	0.9	3.89	13.5	2.54	0.64	11.43	0.38	4.05	2.68	3.98-4.95
1.42	0.6	3.28	10.6	0.33	1.59	19.29	0.39	1.6	2.12	0.91-4.62
1.58	0.6	2.25	1.47	0.33	0.44	14.43	0.37	2.89	4.31	0.45-4.82
1.16	0.6	2.31	12	1.49	1.05	6.34	0.45	0.67	0.71	2.21-5.00
1.84	0.5	2.11	12.9	1.39	1.29	13.19	0.21	3.65	0.41	1.44-4.82

The result of the cluster analysis is one single combination that represents the centroid line of the parameters in the aforementioned 37 combinations. These values can be estimated to be the starting point for the calibration process of VISSIM for mixed traffic conditions.

Table 4: Cluster Result

CC0	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9
1.53	0.90	2.90	-7.52	-1.20	1.41	12.11	0.33	3.34	2.91

3. RESULTS AND DISCUSSION

The traffic volume of 6 exits was obtained from the VISSIM model simulation. The optimized parameter combination from the cluster analysis has been used as simulation input. The traffic volume from simulation and field reading for each exit, along with their GEH value, is shown in Table 5. The purpose of this study is to develop a methodology that can be used to calibrate VISSIM parameters for non-lane-based heterogeneous traffic. In future studies, researchers can use this method as a standard to calibrate the parameters for similar traffic conditions. During calibration, all the simulations can be run manually, or a fraction of the total number of simulations can be taken to train a machine-learning model. After the training phase, the model would be used to predict the values for the remainder of the combinations. To determine the accuracy of a machine learning model, at first, the model was trained using 70% of the total combination and then the model was used to predict the value of the rest of the 30% combinations. The output obtained from the model was compared to the simulation values by plotting an actual vs predicted plot.

Table 5: Final Model Validation

Exits	Field Value	Simulated Value	GEH
Exit 1	1784	1622	3.93
Exit 2	647	547	4.09
Exit 3	658	522	4.31
Exit 4	617	536	3.37
Exit 5	1411	1278	3.63
Exit 6	537	458	3.54

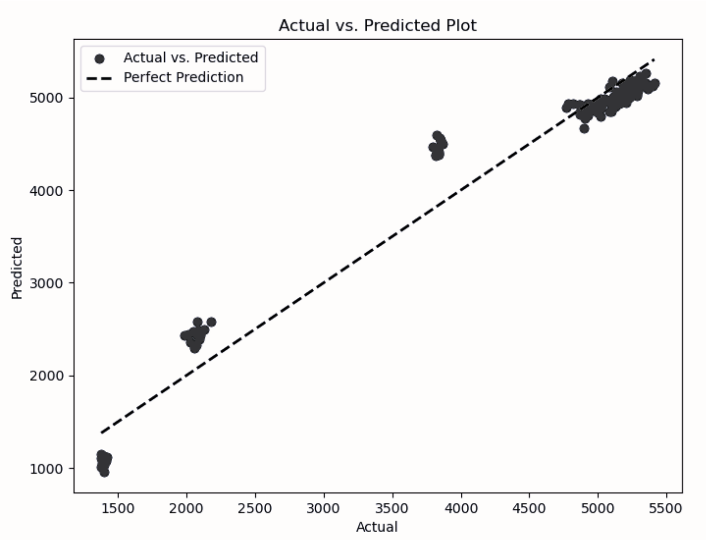


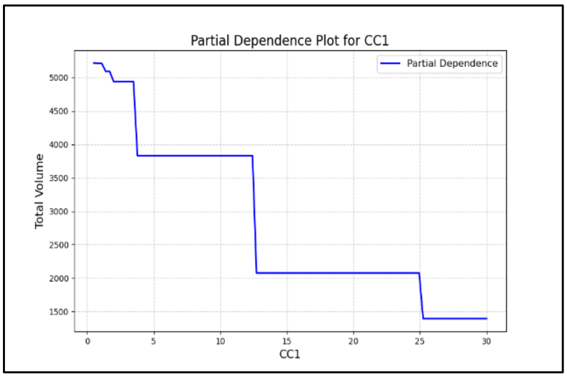
Figure 3: Actual vs. predicted plot

The accuracy of the prediction can be determined from this plot by considering two values: mean absolute error and R2 score. The determined mean absolute error of this plot isfound to be 222.84, which is the average distance between the actual and predicted data. This can be deemed acceptable as the total traffic count is quite large, and this error value is negligible comparatively. On the other hand, our obtained value is 0.958 (near to 1), which shows that the plot is a good fit for the predicted line.

Our obtained values from the cluster analysis can be used directly for future studies. If the given parameter combination proves to be inadequate, then the values of the parameters should be adjusted byfollowing the partial dependence plots showcased in Figure 4. The output should be verified by determining the GEH value for the desired result. If the GEH value exceeds 5%, that particular model should be recalibrated to match the field data.

Figure 4 presents partial dependence plots, showcasing the sensitivity of total traffic volume to variations in the calibration parameters CC0 through CC9. Among these, CC0, CC1, CC2, and CC5 exhibit a decreasing trend in total traffic volume with increased values. This suggests that higher values of these parameters correspond to reduced traffic volume. Conversely, parameters CC3, CC4, and CC8 indicate an increasing trend in total volume as their values rise, suggesting that higher values of these parameters facilitate greater traffic volumes. The clear trends observed in these parameters (both increasing and decreasing) validate their significance in traffic dynamics and suggest their definitions are well-maintained.

However, parameters CC6, CC7, and CC9 do not demonstrate a clear trend and primarily reflect micro-level behaviors in traffic simulation, and they have a limited observable impact on traffic volume. These findings validate the overall calibration approach, confirming the acceptability of the results. Future research should explore the less-defined parameters (CC6, CC7, CC9) to better understand their roles in mixed traffic conditions. Studies using VISSIM microsimulation for such scenarios can adopt the clustered parameter set as an initial calibration point and refine it further using the insights from partial dependence plots.


Partial Dependence Plot for CC1
Partial Dependence
Total Volume
CC1
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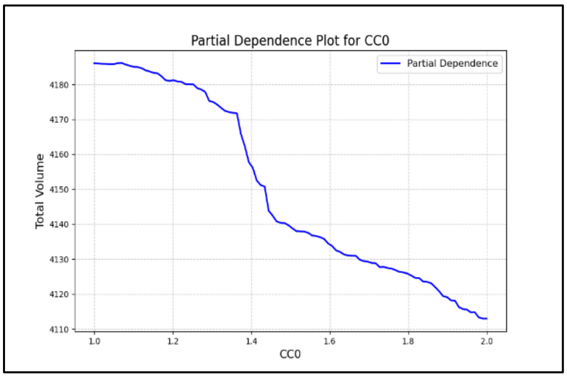
4500
4000
3500
3000
2500
2000
1500
0
5
10
15
20
25
30

(a)


Partial Dependence Plot for CC0
Partial Dependence
Total Volume
CC0
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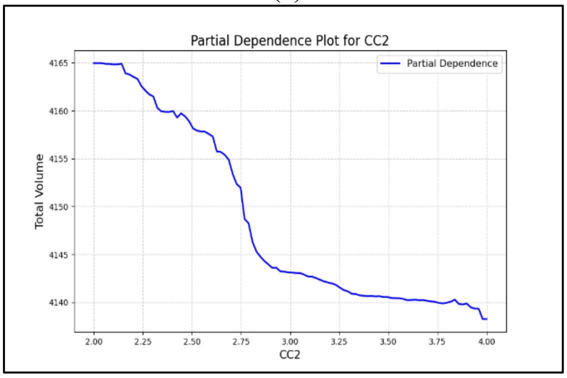
4170
4160
4150
4140
4130
4120
4110
1.0
1.2
1.4
1.6
1.8
2.0

(b)


Partial Dependence Plot for CC2
Partial Dependence
Total Volume
CC2
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4160
4155
4150
4145
4140
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3.00
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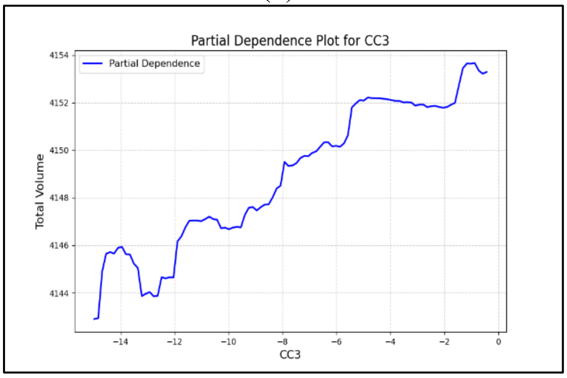
3.50
3.75
4.00

(c)


Partial Dependence Plot for CC3
Partial Dependence
Total Volume
CC3
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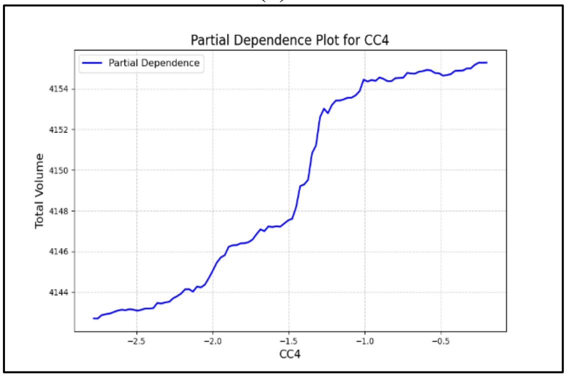
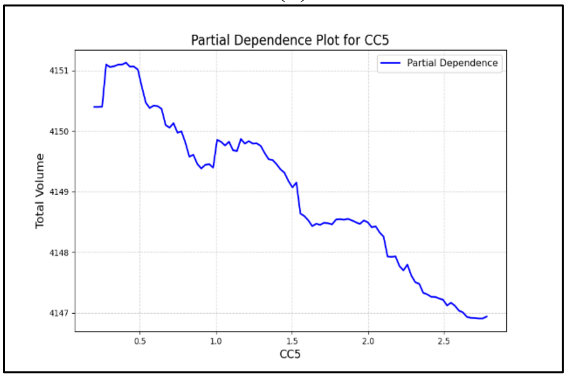
4152
4150
4148
4146
4144
−14
−12
−10
−8
−6
−4
−2
0

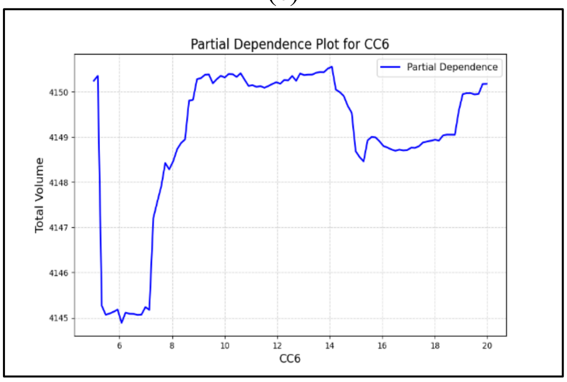
(d)


Partial Dependence Plot for CC4
Partial Dependence
Total Volume
CC4
4154
4152
4150
4148
4146
4144
−2.5
−2.0
−1.5
−1.0
−0.5

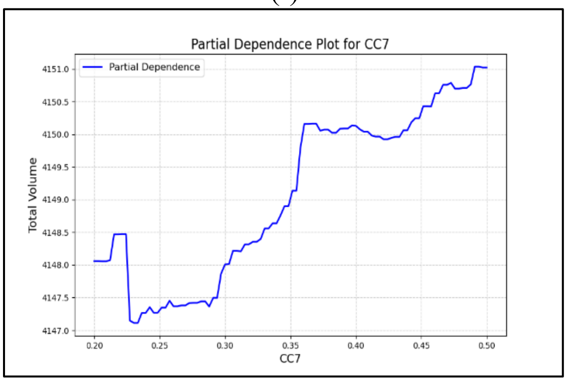
(e)


Partial Dependence Plot for CC5
Partial Dependence
Total Volume
CC5
4151
4150
4149
4148
4147
0.5
1.0
1.5
2.0
2.5

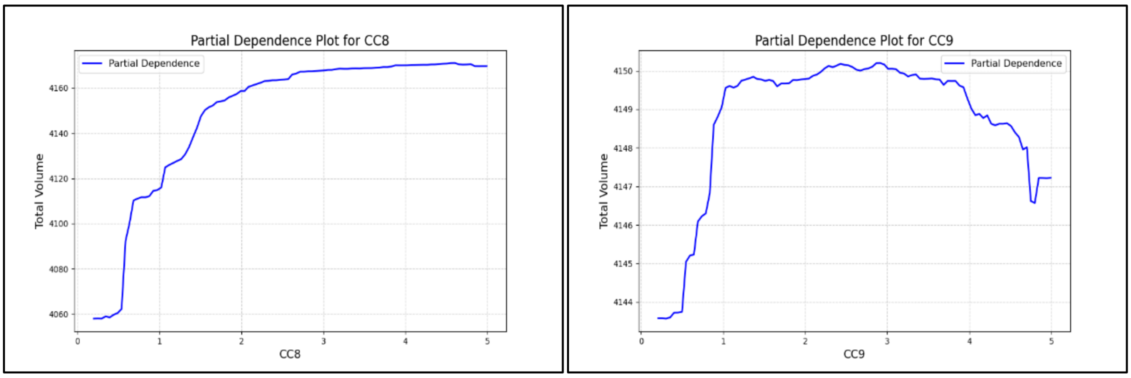
(f)


Partial Dependence Plot for CC6
Partial Dependence
Total Volume
CC6
4150
4149
4148
4147
4146
4145
6
8
10
12
14
16
18
20

(g)


Partial Dependence Plot for CC7
Partial Dependence
Total Volume
CC7
4151.0
4150.5
4150.0
4149.5
4149.0
4148.5
4148.0
4147.5
4147.0
0.20
0.25
0.30
0.35
0.40
0.45
0.50

(h)



(i) (j)

Figure 4: Partial dependence plots of (a) CC0, (b) CC1, (c) CC2, (d) CC3, (e) CC4, (f) CC5, (g) CC6, (h) CC7, (i) CC8, (j) CC9

4. CONCLUSIONS

The primary objective of this study is to propose a methodology for VISSIM microsimulation model calibration for mixed traffic conditions. The proposed methodology can be deemed successful as the output results were able to be recreated, thus proving its validity. The accuracy of the predicted value was also found to be within acceptable limits. The progression of this study included field surveying for data collection. The collected data was then used to create a microsimulation model in the VISSIM simulation software. The calibration parameters were then sampled and put into the simulation to generate output parameters. The acceptable combinations were put into a clustering algorithm to determine the centroid line for the parameters that can be useful for future studies. Although this study included meticulous steps, there were some limitations encountered while constructing the methodology. Pedestrian behavior was not considered at all in the road network, which doesn't reflect the total scenario of the real world inside the simulation model. Besides this, lane-changing behavior. lateral movement parameters and similar variables were kept the default in the model development. Thus, future research should address these issues. Also, signals at the intersections were manually controlled, which may result in different green times, but for this study, a fixed green time was used by averaging the green time for each approach. Since there are some assumptions made to develop this model, it would be better to add more parameters and calibrate this model in different traffic conditions to render more applicability of the model.

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