Identification of Simulation Calibration Parameters Using Urban Freeway Data

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THE UNIVERSITY OF MEMPHIS

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16. Abstract

The reliability of a microsimulation model such as VISSIM depends on proper calibration and validation to accurately represent real-world traffic conditions. However, the VISSIM default values do not apply to local traffic conditions and need to be calibrated for local traffic conditions considering the higher number of car-following parameters. Hence, the present study determines TN-specific calibration parameters for PTV VISSIM microsimulation software using urban freeway data in TN. Field data were collected from the four majorly populated cities of TN namely Memphis, Nashville, Knoxville, and Chattanooga during the peak and off-peak hours of traffic using videography method. Trajectories were extracted using the YOLO-v8 computer vision techniques and the traffic flow variables were obtained from the microscopic trajectories. Wiedmann 99 car-following parameters were selected for the calibration of VISSIM. It was found that considering all the ten car-following parameters in the simulation model significantly reduces the error values between observed and simulated flow rates for the TN urban freeways.

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Executive Summary

The main aim of this research project was to determine Tennessee-specific calibration parameters for PTV VISSIM microsimulation software using urban freeway data in Tennessee. The specific objectives of this study were:

- Identify and determine traffic of urban freeways in Tennessee under different weather and traffic conditions identify and estimate Tennessee-specific calibration parameters for PTV VISSIM microsimulation software using existing ITS data collection infrastructure and additional means if needed.
- Identify the variation in calibration parameters/metrics (e.g., driving behavior, lane-changing behavior, speed distribution during different operating conditions) across urban areas in Tennessee.
- Develop recommendations, user guides, and checklists for PTV VISSIM-based microsimulation analysis for the calibration and validation of VISSIM models.
- Develop recommendations for future ITS infrastructure needs, considering existing data collection gaps; and recommend guidelines.

The methodology included site selection and development of simulation scenarios, field data collection, identification of traffic characteristics, development, and calibration of VISSIM simulation models, and validation of these models. Simulation scenarios were developed to represent the traffic conditions along urban freeways in Tennessee, considering complexity and regional variation in traffic characteristics. Utilizing existing TDOT ITS sources, data such as traffic volume, speed, vehicle class, and weather conditions were collected and analyzed. Detailed VISSIM simulation models were developed for the selected scenarios. Sensitivity analysis was conducted to evaluate the influence of calibration parameters on measures of effectiveness. The simulation models were calibrated using significant calibration parameters identified from field data. Calibrated models were validated using the datasets from the chosen freeway segments.

Our research has significantly advanced the understanding and application of microsimulation in Tennessee by developing locally tailored calibration parameters for the PTV VISSIM software. The study identified critical differences in traffic behavior across urban freeways in Memphis, Nashville, Chattanooga, and Knoxville, leading to more accurate and reliable simulation models. The calibrated models reduced root mean square error (RMSE) values, demonstrating a closer alignment with observed traffic data. Key parameters such as standstill distance (CC0), time gap (CC1), following distance oscillation (CC2), threshold for entering 'Following' (i.e., CC3), distance dependency of Oscillation (i.e., CC6), and acceleration from standstill (CC8) were identified as particularly influential in accurately replicating Tennessee's unique traffic dynamics.

These findings have practical implications for TDOT's traffic management and planning efforts, providing tools that better reflect the local conditions, which can be used to assess and optimize infrastructure projects and traffic policies. The recommendations and user guides developed from this research will support more effective and regionally appropriate application of VISSIM, enhancing TDOT's capacity to manage traffic flow and improve road safety across the state. Additionally, our study highlights the importance of ongoing data collection and model updates to maintain the relevance and accuracy of simulation tools in a rapidly evolving urban environment.

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1 Introduction

1.1 Background

Microscopic simulation models have been widely used in both transportation operations and management analyses because simulation is safer, less expensive, and faster than field implementation and testing. In that regard, the calibration and validation of the simulation model are crucial for the appropriate decision-making process. Also, a not-so-well-calibrated model can often yield erroneous results on which significant engineering and investment decisions can be unfortunately based. The Tennessee Department of Transportation (TDOT) has started using the microsimulation tool, PTV VISSIM, more frequently for in-house traffic analysis. Microsimulation tools allow robustness and reliability in traffic analysis compared to the generalized approach in the Highway Capacity Manual (HCM). Current TDOT PTV VISSIM user manual uses calibration parameters based on best practices obtained from manuals developed by other state DOTs, and limited field data from VISSIM-based projects in Tennessee (TN). However, it is critical to determine various calibration parameters to develop calibrated models for local conditions which could provide reliable simulation results. In these contexts, data-driven and Tennessee-specific calibration parameter development would be beneficial in enhancing TDOT's model development and reliability of microsimulation-based traffic analysis. State specific calibration parameters could provide a more accurate representation of actual traffic flow, and reliable traffic analysis results will assist traffic operational decision-making process by balancing needs and resources.

1.2 Study objectives and VISSIM overview

The overarching goal of this research project is to determine TN-specific calibration parameters for PTV VISSIM microsimulation software using urban freeway data in TN. The specific objectives of this study are to: (i) identify and determine traffic characteristics (e.g., free-flow speed, capacity) of urban freeways in TN under different weather (e.g., day/night/snowy) and traffic conditions (e.g., peak/off-peak); (ii) identify and estimate TN-specific calibration parameters for PTV VISSIM microsimulation software using existing ITS data collection infrastructure and additional means (if needed); (iii) identify the variation in calibration parameters/metrics (e.g., driving behavior, lane changing behavior, speed distribution during different operating conditions) across urban areas in TN; (iv) develop recommendations, user guide, checklists for PTV VISSIM based microsimulation analysis for calibration and validation of VISSIM model; and (v) develop recommendations for future ITS infrastructure needs considering the existing data collection gaps. In addition, the research will recommend guidelines on how to adopt the findings of this project to be incorporated in SYNCHRO+SIMTRAFFIC based studies.

VISSIM is a microscopic, time-step and behavior-based model which analyzes multimodal traffic flows with the flexibility of modeling all types of geometries and traffic control schemes. Therefore, VISSIM simulation modeling is an extremely useful tool to help predict the outcomes of a proposed change to the roadway system and assist in evaluating the advantages and disadvantages of design alternatives within the urban environment. PTV VISSIM offers a comprehensive suite of performance measures that can be used for in-depth traffic operational analysis. These measures cover various aspects of traffic flow, including vehicle speed, travel time, queue lengths, intersection delays, and lane utilization. By analyzing these performance measures, transportation engineers and planners can gain insights into the efficiency and effectiveness of different road network configurations, signal timings, and traffic management strategies.

One notable feature of PTV VISSIM is its ability to generate trajectory files, which capture the movement of individual vehicles throughout the simulation period. These trajectory files can be integrated into the Federal Highway Administration's (FHWA) Surrogate Safety Assessment Model (SSAM). SSAM uses surrogate safety measures derived from vehicle trajectories to estimate the likelihood of accidents and their severity. By incorporating SSAM analysis into VISSIM simulations, transportation professionals can assess the safety implications of proposed roadway designs or operational changes before implementation, allowing for proactive safety planning and risk mitigation. Also, PTV VISSIM can generate AVI (Audio Video Interleave) files for 3D simulation runs. These files provide a visual representation of the traffic flow and operational performance of different improvement alternatives. Using 3D visualization, stakeholders, policymakers, and members of the public can better understand how proposed changes to roadways or intersections will impact traffic operations. This visual tool helps to bridge the gap between technical analysis and non-technical audiences, facilitating informed decision-making and garnering support for transportation projects.

1.3 Organization of the Report

The report is divided into seven chapters, each focusing on distinct aspects of the research, from initial conceptualization to final recommendations. Below is a detailed description of the contents of each chapter:

This initial chapter provides a foundational overview of the research. It begins by discussing the widespread use of microscopic simulation models in transportation operations and management analyses, highlighting the importance of accurate calibration.

The second chapter offers an extensive review of existing literature on freeway simulation calibration. It aims to establish a theoretical background for the study by analyzing previous research on calibration methodologies, effectiveness, and challenges.

Chapter 3 is the methodology used for data collection, which is crucial for accurate simulation. The process starts with the selection of appropriate urban freeway sites across Tennessee, using a well-defined algorithm to ensure a representative sample of traffic conditions.

Chapter 4 is central to understanding the technical processes involved in the research. It covers the development of VISSIM simulation models, detailing the step-by-step approach from setting up the initial scenarios to adjusting the calibration parameters based on field data.

Chapter 5 provides the detailed description of traffic flow variables and fundamental characteristics of car-following behavior that are required in VISSIM calibration. These definitions will be used to estimate the variables from the field data.

Chapter 6 includes the VISSIM calibration results for all the study sites including the sensitivity analysis, calibration and validation of VISSIM microsimulation model. The chapter also provides detailed discussion on the results of the calibration process.

The final chapter synthesizes the research outcomes, evaluating the effectiveness of the Tennessee-specific calibration parameters and offering recommendations for future research and application by TDOT.

2 Literature Review

Past studies on calibration and validation of microsimulation models applied step-by-step processes to calibrate and validate simulation models (e.g., Park and Schneeberger, 2003; Lu et al., 2016; Aghabayk et al., 2013). Table 1 summarizes selected past studies focused on calibrating simulation models in VISSIM in terms of the study context and significant findings. The table shows that simulation model calibration parameters and their values vary across areas and roadway types, indicating the need for identifying TN-specific simulation model calibration parameters.

Table 2-1 Summary of other localized studies on Microsimulation Model Calibration

Literature	Study Area	Major finding/ Remarks
Gomez et al. (2004)	15 miles segment of I-210 W in CA	Congested traffic conditions did not allow the selection of typical calibration parameters.
Lu et al. (2016)	Signalized intersections in Waterloo, Canada	Mean speed, desired acceleration, and the additional desired distance parameters strongly affected the measure of effectiveness (i.e., saturation headway).
Dong et al. (2015)	Freeways in Iowa	Standstill distance varied based on the freeway locations.
Asamer et al. (2012)	Snowy road conditions	The impact of desired deceleration parameter was reported negligible in snowy road conditions.
Chen et al. (2019)	Adverse weather conditions	Driving simulator-based VISSIM parameter calibration was effective in representing real-world traffic flow.
Mohamad et al. (2021)	Expressway segment in Malaysia	Standstill distance, gap time, following distance oscillations were identified as calibration parameters.
Srikanth et al. (2017)	Expressway segment in India	Standstill distance, minimum headway, and following variation were identified as calibration parameters.
Karakikes et al. (2016)	A motorway network in Germany	Minimum headway and following variation parameters were selected as calibration parameters.

Previous literature usually followed one of the two predominant strategies to calibrate microsimulation models. The initial step in both methods is selecting one or more measures of effectiveness to ensure that the microsimulation model accurately reflects the existing field conditions. Matching of the values of the selected measures of effectiveness between field conditions and the developed microsimulation models are achieved through adjustments of the model parameters. In one of the two strategies of calibration, the parameters are adjusted manually applying a trial-and-error process. In the second strategy, model parameters are changed automatically by applying heuristic algorithms. After calibration, the microsimulation model is validated by applying the calibrated model to a different traffic data to assess predictive capabilities of the calibrated model.

2.1 Calibration Procedures

Hourdakis et al. (2003) proposed a three-stages simulation calibration model. The first and second stages were volume and speed-based calibration. In the third stage, calibration was based on project-specific objectives to fine-tune the model. The authors applied the proposed methodology to a case study in Minnesota and reported effectiveness in representing field traffic conditions. Park and Schneeberger (2003) proposed seven-step calibration procedures-

(i) identifying the measures of effectiveness; (ii) collecting field data; (iii) identifying calibration model parameters; (iv) developing experimental designs; (iv) running simulation multiple times for each set of parameters; (v) developing function to connect the selected measure of effectiveness with the parameters; (vi) determining calibrated parameters; and (vii) validating simulation model with new dataset. The calibration procedure suggested by Dowling et al. (2004) closely matched with the above two studies. Dowling et al. (2004) recommended calibration based on capacity instead of demand as proposed in Hourdakis et al. (2003). Aghabayk et al. (2013) suggested following five-step calibration procedures- (i) developing simulation model with transportation network data, (ii) initially running simulation with default parameters, (iii) comparing simulated and observed measures of effectiveness, (iv) updating calibration parameters if the errors are not acceptable and repeating the above steps 2 and 3, (v) reporting parameters if the errors are acceptable. To calibrate car following parameters in VISSIM for urban roadway network, Lu et al. (2016) suggested following calibration steps- (i) collecting field data, (ii) selecting calibration parameters by performing sensitivity analysis, (iv) extracting certain microscopic calibration parameters from vehicle trajectories, (v) using optimization algorithm to identify other calibration parameters, and (vi) evaluating the calibration model. In this research, the authors directly extract some parameters from vehicle trajectories to strengthen the model credibility. Many previous research conducted sensitivity analysis, where each parameter was varied one at a time, while keeping other parameters fixed to default values. Sensitivity analysis helps to identify feasible regions of model parameters which best represents the measures of effectiveness. Also, this analysis approach can be used to identify key model parameters affecting the measures of effectiveness.

Manual calibration procedure is used frequently in private consulting for project level analysis. The advantages of manual calibration procedure are low computational demand, simple to implement, and compatible with qualitative measures of effectiveness (i.e., analyst can take his/her point of view into consideration). However, this procedure is not recommended for large number of calibration parameters (Dong et al., 2015). This process often leads to less-than-optimal calibrated parameters. Majority of this type of studies use automated calibration in some extent, as this procedure can provide near optimal solutions. Also, over the years the use of automated method has been increasing due to the ease access to higher computational power. Genetic algorithm is mostly used heuristic optimization method for calibrating simulation model parameters (Rrecaj and Bombol, 2015). To mention few, this strategy was applied by Kim (2006), Kim et al. (2005), Park and Schneeberger (2003), Park and Qi (2005), and Manjunatha et al. (2012). Other automated calibration strategies such as evolutionary algorithm (Menneni et al. 2008), nelder-mead optimization algorithm (Zenkov and Yurshevich, 2008), pareto archived dynamically dimensioned search algorithm (Duong, 2011), particle swarm optimization (PSO) (Aghabayk et al., 2013), and Monte Carlo method (Park et al., 2006) were also applied.

2.2 Calibration and Validation Parameters

Gomes et al. (2004) modeled 15 miles segment of I-210W located in California using a manual calibration approach. The authors did not select conventional measures of effectiveness such as traffic volume or travel time, rather focused on matching location of bottlenecks, start and end times of queue, and queue lengths with field data because of the congested traffic condition of the roadway segment. Lu et al. (2016) focused on calibrating car following model parameters- desired speed, desired acceleration/deceleration, and safe following distance for signalized intersections in Waterloo, Canada. Desired speed was assumed to follow uniform distribution, where distribution mean, and ranges were selected for calibration. Safe following distance in VISSIM is composed of two parameters- desired standstill distance between vehicles and additional desired distance for the moving vehicles. The authors selected the additional desired distance of moving vehicles as the calibration parameter, as it reflects drivers' aggressiveness. The desired standstill distance was assumed not varying significantly in an area. From sensitivity analysis, it was found that the mean speed, desired acceleration, and the additional desired distance parameters had a strong effect on the measure of effectiveness (i.e., saturation headway). Compared to Lu et al. (2016), Dong et al. (2015) found that standstill distance varied based on the locations of urban freeways in Iowa. Asamer et al. (2012) also tested the three car-following model parameters (i.e., desired speed, desired acceleration and deceleration, minimum following distance) of VISSIM to represent snowy road conditions, where saturation flow output and start-up delays were selected as the measures of effectiveness. The influence of desired deceleration parameter was reported negligible to represent snowy road conditions. Chen et al. (2019) determined VISSIM driving behavior parameters and desired speed distributions from driving simulators and used the calibrated values to determine traffic flow characteristics in various adverse weather conditions (e.g., fog, rainy, snow conditions). The authors found that driving simulator based VISSIM parameter calibration was helpful and representative of real-world traffic flow. Mohamad et al. (2021) emphasized the importance of the consideration of lane change parameters in traffic simulation and calibrated a segment of expressway in Malaysia using driving behavior parameters (i.e., standstill distance, gap time, following distance oscillations) and validated the calibrated model using a lane change parameter called following gap distance. The calibrated values of standstill distance, minimum headway, and following variation were reported. Srikanth et al. (2017) found same three driving behavior parameters while calibrating divided multilane highways in India. Two sets of calibrated value of standstill distance, minimum headway, and following variation were reported, which represented field capacity of multilane roadways. Karakikes et al. (2016) calibrated minimum headway and following variation parameters to simulate a motorway network in Germany. The authors performed model calibration and validation of the simulation model using travel time of vehicles in the network with a 15% tolerable limit between field and simulated travel time.

3 Field data collection

Several sites are selected for developing simulation scenarios representing a wide variety of traffic conditions along the urban freeways in TN. Hence, the research team presented a heuristic site selection approach with automatically selecting the best possible sites for traffic microsimulation. This selection strategy selects several urban freeway segments considering complexity (e.g., on-ramps, off-ramps, and weaving segments) in TN's four most populated cities (i.e., Nashville, Knoxville, Memphis, and Chattanooga). The selection of urban freeways from different cities will help understand regional variation in traffic characteristics (i.e., calibration parameters). Simulation scenarios will consider different time periods such as day/night, peak/off-peak traffic conditions, and different weather conditions (e.g., clear, cloudy, rainy, and snow conditions).

Site selection is crucial in calibrating microsimulation models, as it directly impacts the accuracy of the calibration process . Although simulating the entire study provides comprehensive and accurate results, it exponentially increases the complexity and computation time. Therefore, researchers mostly select a few test sites for developing their models. In the site selection process, the main goal is to keep the models accurate and comprehensive. The selected sites should be able to provide a variety of traffic environmental conditions while they should prevent the involvement of unnecessary complexity in the model. The remainder of this chapter will first present the site selection considerations, including the criteria used for selecting sites, followed by an overview of the proposed test sites for each region.

3.1 Site Selection Considerations

The test sites were selected based on specific criteria. First, the research team prioritized sites having calibrated and documented microscopic models available, in addition to readily available traditional data sources (e.g., travel times, throughput counts, traffic density). The following conditions are considered to select a test site:

1. Sites should have a variety of features (e.g., geometric layouts, congestion level, etc.) so that the models can be evaluated for distinct types of freeway sections.
2. Sites must experience some degree of recurrent congestion during either the morning or evening peak traffic period.
3. Availability of operational data and proximity to the traffic control stations.
4. The freeway corridor should have a low frequency of incidents that contribute to non-recurrent delays.
5. The main bottleneck must NOT be caused by un-controlled freeway-to-freeway exchange.
6. The AADT of the segment should be greater than the average AADT of the area’s freeways.
7. The peak hour percentage should be higher than 10%, to make sure that the selected segment experiences some degree of congestion in peak hour.
8. The difference between the traffic flows of different directions of a segment should not be more than 5%.
9. The percentage of passenger cars and trucks (heavy and light) should be considered.

10. The segment should be longer than 0.5 mile.
11. The neighborhood condition should cover different land use conditions.
12. To reduce the complexity of modeling, it is preferred to select a segment with a lower number of ramps (to avoid too many mixed traffic conditions)

Also, for modeling freeways, a minimum study period of two hours is recommended. This is from 7 AM to 9 AM for the AM peak and 4 PM to 6 PM for the PM peak. The length of time needed to seed the network should also be considered when determining the total simulation period. For large models with heavy congestion during the peak periods, a seeding period of one to two hours may be needed to reach the full level of congestion for the study period. Field observations and/or analysis of queue and count data should be used to help determine the appropriate time that should be modeled.

3.2 Site Selection Algorithm

Considering the criteria mentioned in the previous section, the research team developed an algorithm that calculates how suitable a segment is as a microsimulation calibration test site. The output of this algorithm is a calculated weight where the link with the higher weight has the higher priority (rank) to be selected as a test site. **Figure 3.1** presents the diagram of the provided site selection algorithm.

Step 1: The algorithm starts with eliminating segments that do not have traffic control stations, as data collection for those segments would be problematic. The weight of the segments with no traffic control station will be zero.

Step 2: Segments are categorized as highly congested, moderately congested, listed, and uncongested. This classification is based on the comparison of AADT to segment average AADT ($\frac{AADT-avg(AADT)}{avg(AADT)}$), peak hour percentage, and congestion observation (a binary variable provided by the traffic station). After categorizing segments, following are the congestion weights (W_C), given to links based on the level of congestion. Highly congested ($W_C = 4$), moderate congested ($W_C = 3$), low congested ($W_C = 2$), and uncongested ($W_C = 1$). The reason behind this scaling strategy is that a congested link is preferable to be selected as a test site because it can provide more information and adds diversity to the developed scenarios.

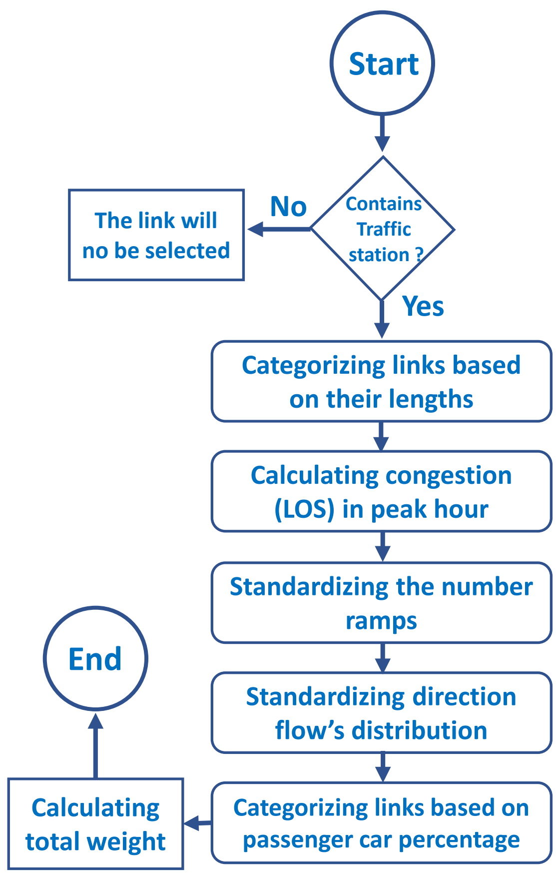


Figure 3-1. The diagram of the site selection algorithm

Step 3: Normalize the number of ramps close (within 0.3 miles) to the segment. The weight of the number of ramps are presented by W_R.
Step 4: normalizing the distribution of flow between directions will be used as the weight for the flow distribution and is indicated by W_D
Step 5: Assign weight (label) to each link based on its length. The purpose of this step is to reduce the chance of segments are too small (less than 0.5 mile) or too long (more than 3 miles). The given weights for segments length (l) are as follows: $if\ length(mile) \leq 0.5\ then\ W_L = -1$, $if\ 0.5 < length\ (mile) \leq 1.0\ then\ W_L = 1,\ \ if\ 1.0 < length\ (mile) \leq 2.0 then\ W_L = 2,\ \ if\ 2.0 < length\ (mile) \leq 3.0\ then\ W_L = 1$, and finally $if\ 3.0 < length\ (mile)\ then\ W_L = -1$.
Step 6: assigning weights to the links based on the variety of vehicle types (passenger and trucks). In this regard, the average of passenger car percentage needs to be calculated and then, if the link's passenger care percentage is higher than the average then the Vehicle Type Variety, $W_{VTV} = -1$, if it is equal to average, $W_{VTV} = 0$, and if it is less than the average $W_{VTV} = 1$.
Step 7: Calculating the total weigh of each segment following the equation below:

$$W_{tot} = W_C + (PHP - 10) + W_L - W_D - W_R + N_{TS} + W_{VTV}$$

Note: in the case of selecting multiple test sites in a region (e.g., Memphis area), it is highly recommended that the segments select from different parts of the area with the different traffic behaviors and land use conditions.

3.3 Selected Sites

In this section, the process of selecting test sites for each region will be discussed. Following the selection algorithm discussed in the previous section, a few sites are suggested for model development.

3.3.1 Memphis Area

The Memphis area freeway network consists of 60 segments, presented in **Figure 3.2**. Based on our preliminary traffic data, the maximum, minimum, and average AADT were 206,483, 9,887, and 85,347, correspondingly. These segments were categorized into four categories based on their congestion condition. 32 segments were labeled as uncongested, 11 segment dropped in low congested class, 14 segments were in moderate congestion class, and 9 segments are labeled as highly congested. **Figure 3.3** showed all the segments in the Memphis area with their congestion classes. Also, among all segments, 8 segments were eliminated from the analysis due to the absence of the traffic section. The locations of the traffic stations are indicated in **Figure 3.3**. Following the proposed steps for site selection, the total weight of all links is calculated, and the result is presented in **Figure 3.4**. Considering the total weight of links, two test sites (M1, M2) were selected for model development. These two sites (M1, M2) consist of 3 segments and are presented in **Figure 3.5.**

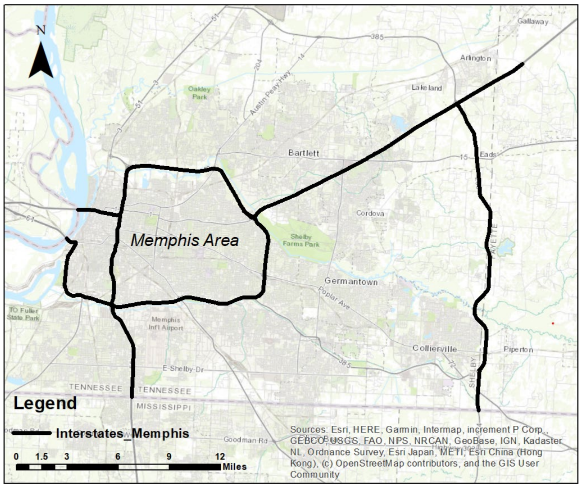


Figure 3-2. Freeway segments in the Memphis area

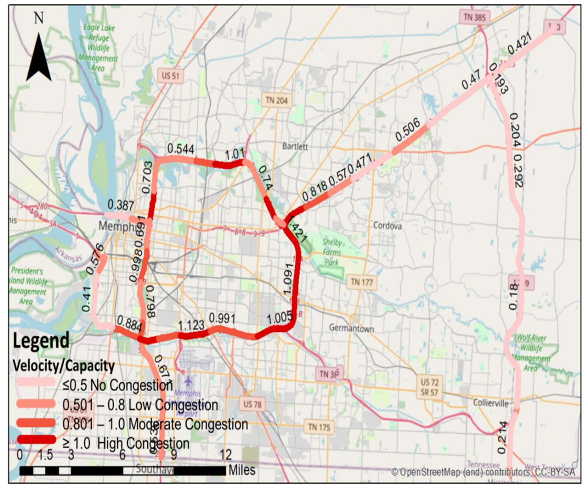


Figure 3-3. Memphis area's segments labeled with congestion classes

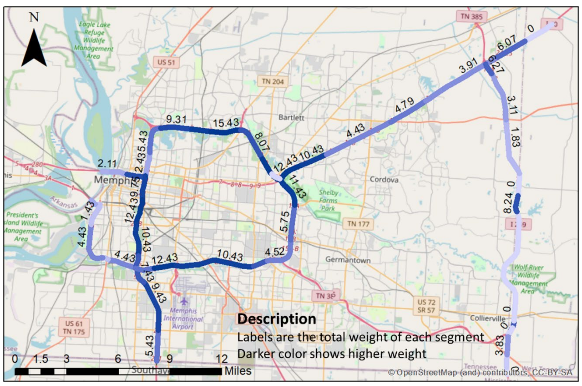


Figure 3-4. Presentation of links' total weight for Memphis area.

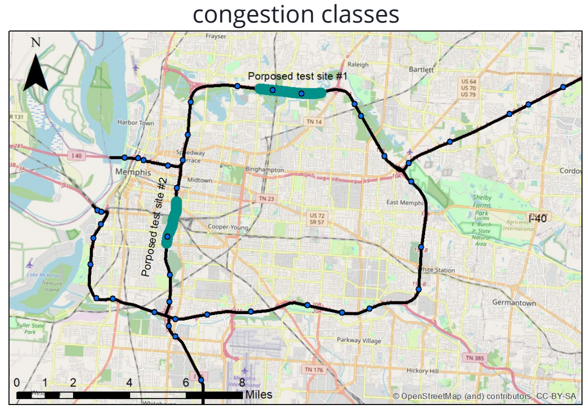


Figure 3-5. Proposed test sites for the Memphis area.

Table 3-1. Properties of proposed test site for Memphis area.

Proposed test site	**M1**	**M2**
Name	Dr. Martin Luther King Junior Expressway (I-40)	Dr. Martin Luther King Junior Expressway (I-40)
Number of segments	3	2
BLM	7.58	1.32
ELM	9.76	2.88
Length	2.18 mi	1.56 mi
Lanes	6	8
Land use	Rural	Mixed land use (Commercial and residential)
Direction flow distribution	55	55
Peak Hour Percentage	13%	10%

ADDT	100,331	105,381
Passenger car percentage	92%	92%
Truck percentage	3% SU and 5% MU	3% SU and 5% MU

3.3.2 Nashville Area

The Nashville area had 33 freeway segments which stretched for 36.25 miles, the data analyses showed that the maximum, minimum, and average AADT were 182,508, 73,149, and 124,137 vehicle per day, corresponding. **Figures 3.6** to **3.9** present the congestion level, total weights, and the proposed test sites, respectively. Two study areas (N1, N2) are proposed for the Nashville area, which the details are provided in **Tabel 3.2.**

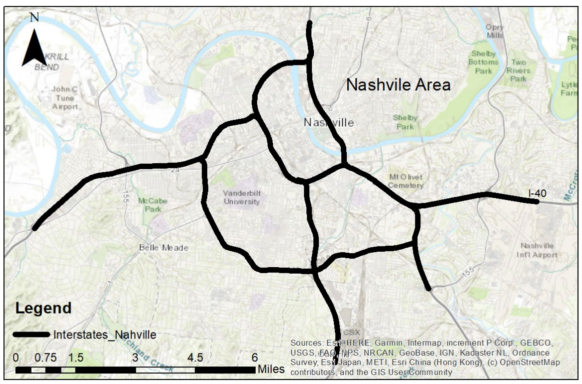


Figure 3-6. Freeway segments in the Nashville area.

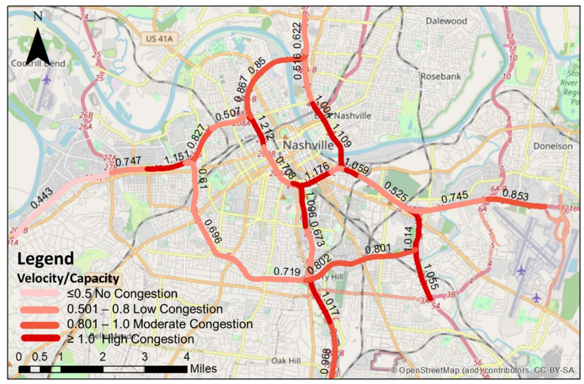


Figure 3-7. Nashville area's segments labeled with congestion classes.

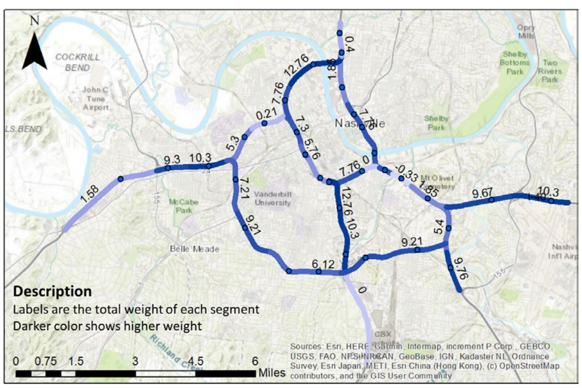


Figure 3-8. Presentation of links' total weight for Nashville area.

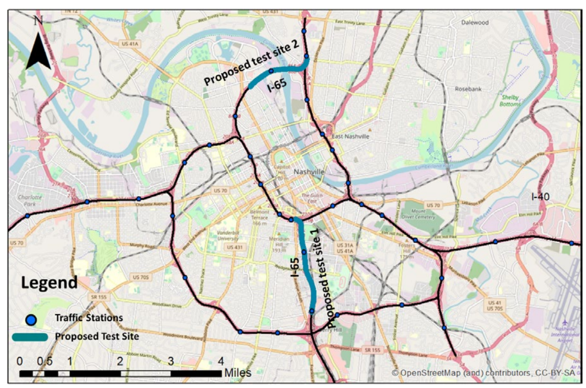


Figure 3-9. Proposed test sites for the Nashville area.

Table 3-2. Properties of proposed test sites for Nashville area

Propose test site	N1	N2
Name	I-65 South	I-65 North
Number of segments	3	2
BLM	6.41	9.56
ELM	8.34	10.85
Length	1.93 mi	1.29 mi

Lanes	8	6
Land use	Mixed land use (Commercial and residential)	Commercial
Direction flow distribution	65	60
Peak Hour Percentage	11%	11%
ADDT	107,707	101,986
Passenger car percentage	93%	93%
Truck percentage	3% SU and 4% MU	3% SU and 4% MU

3.3.3 Chattanooga Area

The Chattanooga area has 19 segments labeled as freeways. The maximum, minimum, and average AADT are 137,904, 64,258, and 94,905, respectively. These segments are presented in **Figure 3.10**. In addition to this figure, **Figure 3.11** presents the congestion level of each link and Figure **3.12** shows the calculated total weight of the whole links. Finally, a test site area is proposed for model development. The proposed test is presented in Figure 3.13 and Table 3 presents the proposed site properties.

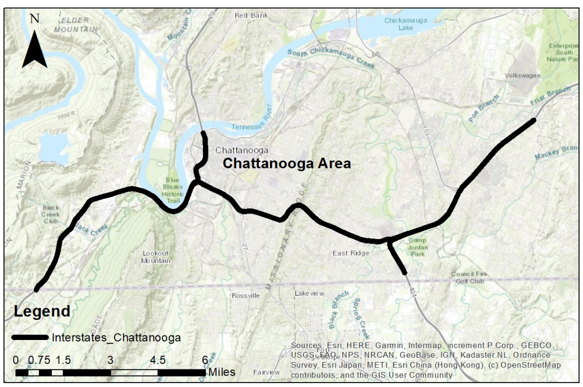


Figure 3-10. Freeway segments in the Chattanooga area.

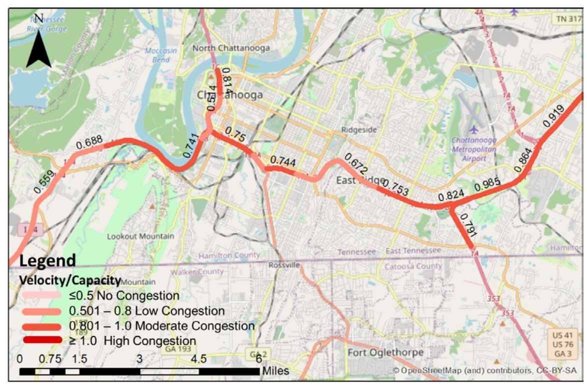


Figure 3-11. Chattanooga area's segments are labeled with congestion classes.

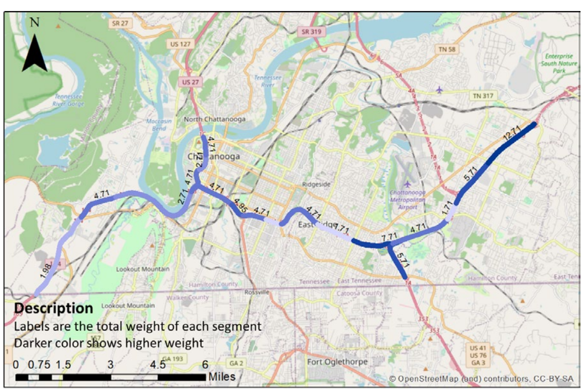


Figure 3-12. Presentation of links' total weight for the Chattanooga area.

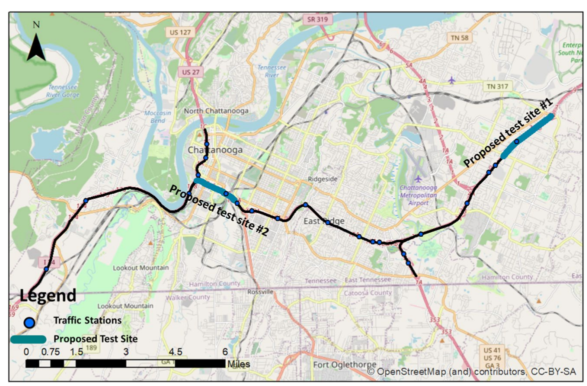


Figure 3-13. Proposed test sites for the Chattanooga area.

Table 3-3. Properties of the proposed test site for the Chattanooga area.

Proposed test site	C1	C2
Name	I-75	I-24
Number of segments	1(E-trims link 4304)	1 (E-trims link 4291)
BLM	5.62	7.52
ELM	7.51	8.82
Length	1.89 mi	1.3 mi
Lanes	6	6
Land use	Commercial	Residential
Direction flow distribution	60	60
Peak Hour Percentage	13	9
ADDT	99,576	105,057
Passenger car percentage	94%	93
Truck percentage	3% SU and 3% MU	3% SU and 4% MU

3.3.4 Knoxville Area

The Knoxville area has 24 segments of freeways. Where the total length is 39.53 miles; and the maximum, minimum, and average AADT were 182,502, 60,703, and 95,380 vehicles per day. **Figure 3.14** presents the entire study area. Like other areas, first, the congestion level of links is presented in **Figure 3.15** and then the calculated total weight of links is provided in **Figure 3.16**. A test site is proposed for the Knoxville area, presented in Figure 3.17 and Table 3.4, provides detail.

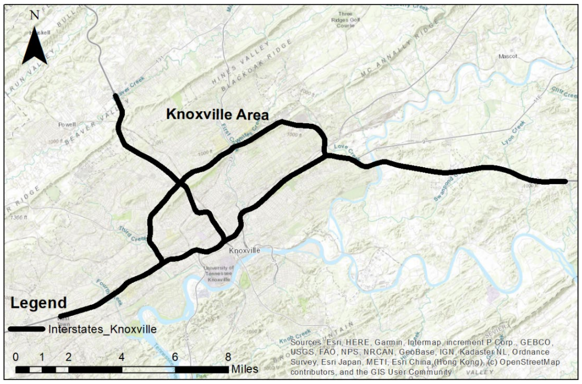


Figure 3-14. Freeway segments in the Knoxville area.

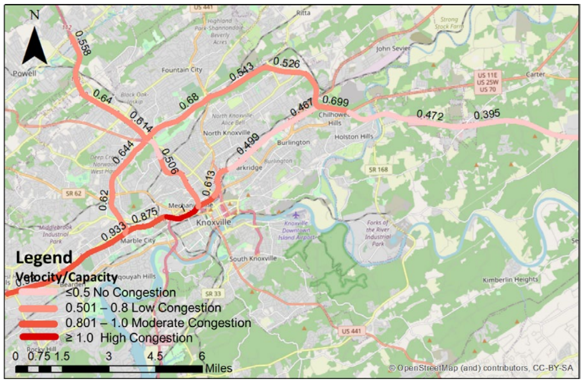


Figure 3-15. Knoxville area's segments are labeled with congestion classes.

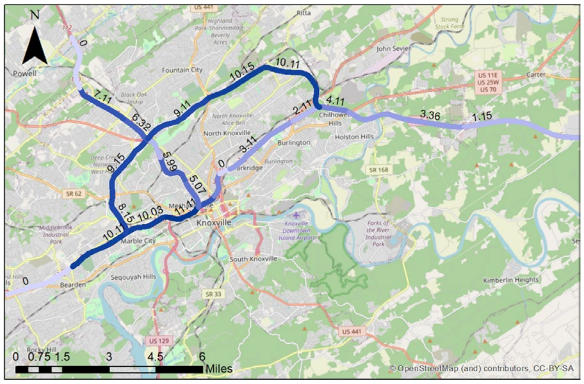


Figure 3-16. Presentation of links' total weight for the Knoxville area.

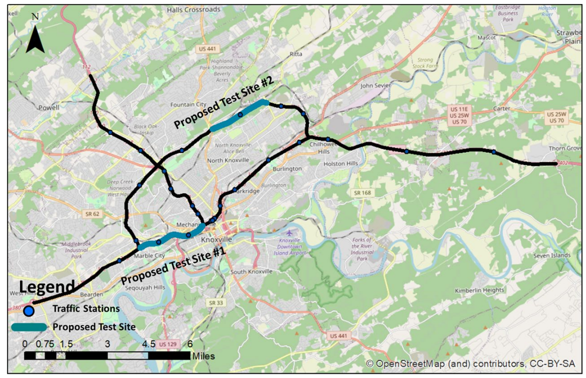


Figure 3-17. Proposed test sites for the Knoxville area.

Table 3-4. Properties of the proposed test site for the Knoxville area

Proposed test site	K1	K2
Name	I-40	I-640
Number of segments	2 (E-trims links 5899 5900)	1 (E-trims link 5926)
BLM	7.58	2.43
ELM	9.76	4.66
Length	2.18 mi	2.23
Lanes	6	6
Land use	Rural	Commercial
Direction flow distribution	55	55
Peak Hour Percentage	13	10
ADDT	100,331	71,684
Passenger car percentage	92%	94%
Truck percentage	3% SU and 5% MU	3% SU and 3% MU

3.3.5 Peak hour Selection

We have utilized existing TDOT Intelligent Transportation Systems (ITS) sources, including sensors, cameras, and loop detectors, along with the selected freeway segments, for comprehensive data collection. The ITS resources enabled us to gather essential geometric and traffic data. This data encompassed various parameters such as lane configurations, traffic volume, traffic speed, travel time, vehicle classification, lane assignments, headway, and the distances between stationary vehicles. Before doing the video data collection, we analyzed historical RDS data to look at the traffic pattern at the selected sites in TN. Hourly traffic flow from the RDS data at the selected locations are shown in Figure 3-18.

This step was crucial for understanding traffic patterns and ensuring that our data collection efforts are focused on the most critical periods. Subsequently, we collected video data from two specific sites of each of the four major cities of TN during the identified morning and evening peak periods. From this video data, we extracted key traffic metrics, including traffic volume, traffic composition, and speeds.

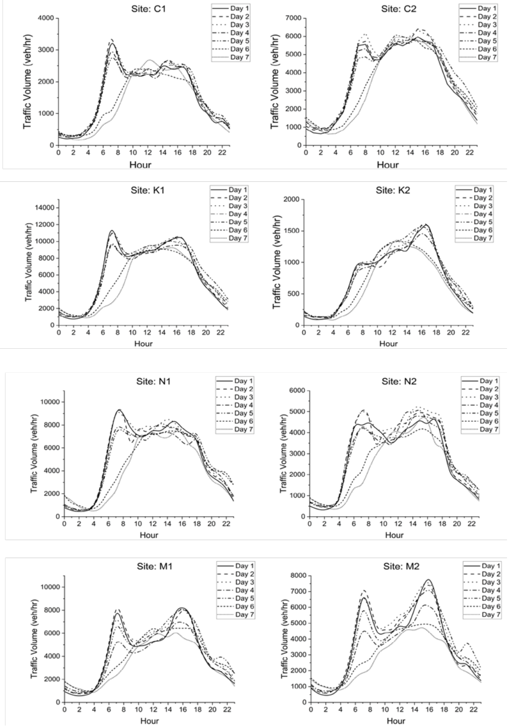


Figure 3-18 Hourly traffic volume distribution at the selected sites of Chattanooga, Knoxville, Nashville, and Memphis.

4 Methodology

The research study's overall approach can be broken down into the following categories.

1. Development of VISSIM Simulation Models
2. Selection of Calibration Parameters
3. Calibration and Validation of Simulation Models

Armed with a deep understanding of the collected data, the team embarked on developing detailed microsimulation models using PTV VISSIM software. Each model was constructed to mirror the real-world conditions observed at the selected sites, with configurations that included multiple traffic scenarios. The models were refined iteratively, with adjustments made to simulation parameters based on preliminary output comparisons to actual traffic data, ensuring that the models reliably replicated observed traffic behaviors.

The calibration process involved adjusting the simulation input parameters until the model outputs closely aligned with the real-world traffic data. This critical phase utilized a combination of manual tuning and automated optimization techniques to fine-tune the simulation models. Once calibrated, the models underwent a rigorous validation process using a separate set of traffic data not previously utilized to ensure that the models could reliably predict traffic behaviors under different conditions.

4.1 Development of VISSIM Simulation Models

In this task, VISSIM simulation models are developed for different sites selected. The simulation model scenarios are designed and created using geometric characteristics, traffic volume, and vehicle composition to determine calibration parameters. This chapter of the report first presents the process of developing a VISSIM scenario, followed by the outcomes of applying this process to the proposed project sites (discussed in Chapter 3).

4.2 Scenario development process

This section of the report emphasizes essential elements of the VISSIM network development procedure. The goal of this guide is not to serve as a comprehensive manual for coding all network objects. Instead, its purpose is to provide recommendations on the coding of crucial network objects and typical modeling situations.

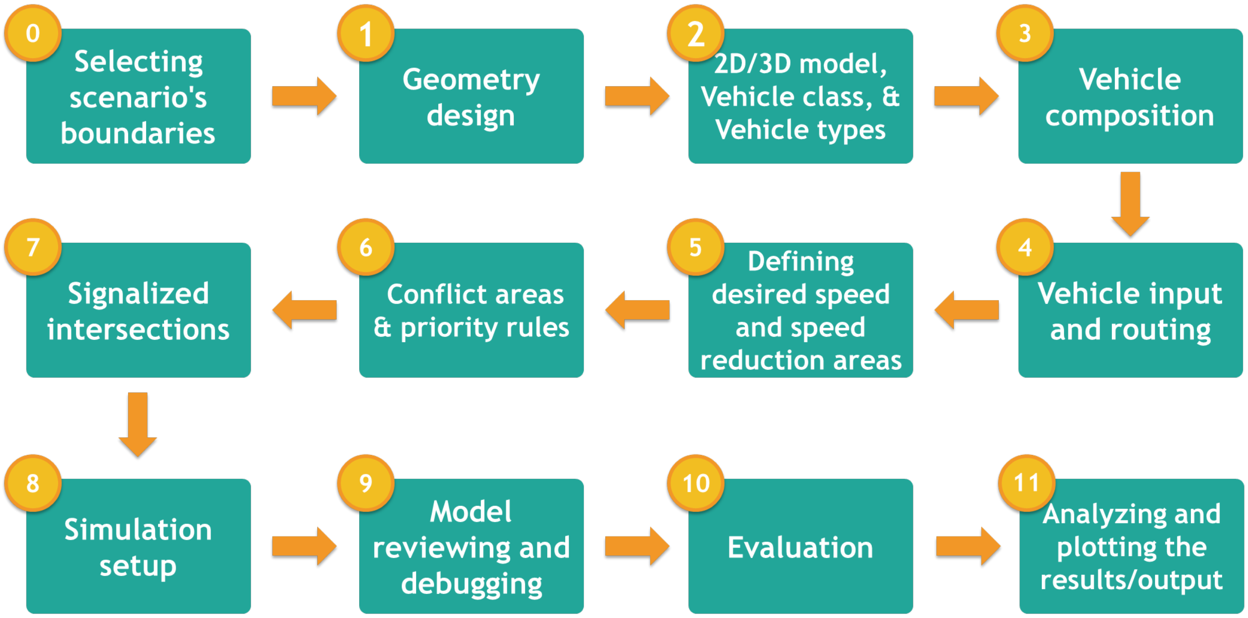


Figure 4-1 Scenario Development Process

This section provides guidance on best practices and standard procedure for coding of network objects required for most VISSIM networks.

4.2.1 Links and connectors

VISSIM follows a link-connector framework (instead of link-node modeling framework). Links and Connectors form the foundation of any VISSIM network. Links function as stand-alone objects while Connectors must be attached to a link at either end to be added to the network. A link cannot have multiple sections with a different number of lanes. Thus, multiple links need to be created for each section and connected through connectors. As a general note, in the process of developing a VISSIM network, it is always the best practice to minimize the length of connectors whenever it is possible during network coding.

In developing a network, it is needed to add curvature to the links or connector. To do that, spline points can be added to replicate curvature in the field/design plans; however, vehicle behavior is not affected by sharp versus gradual curves. In other words, a vehicle will maintain the same speed through a 1,000-foot radius curve as they would on a 100-foot radius curve unless Reduced Speed Areas are coded to account for reductions in speed due to curvature.

Link Behavior type determines how vehicles interact within a given link and controls the driving behavior. Several link types are defined in VISSIM by default, Urban, Freeway, Footpath, and Cycle-Path. Modifications are typically needed to create custom driving behaviors during the model calibration process. For each new Link Behavior Type created, a corresponding Link Display Type should also be developed and used with that Link Behavior Type on any link where it is implemented. Display Types are used to track where Link Behavior Types have been changed in the network.

4.2.2 2D/3D models and vehicles type

2D/3D Models, vehicle types, and vehicle class attributes allow the user to control the vehicle mix that is simulated in VISSIM networks. Although VISSIM provides default setting for these attributes, based on the collected and available data, adjustments are needed to replicate the vehicle mix present in the network.

An important point in creating a new network is a new VISSIM file. A new VISSIM file will reference a European vehicle fleet by default, which does not reflect the vehicle fleet typically found in Virginia. A default vehicle fleet for North America is provided by PTV in the Training Directory. This directory is accessible within VISSIM by navigating to “Help/ Examples/ Open Training Directory/ Vehicle Fleet & Settings Default/ USA”. The vehicle fleet contained in this VISSIM file should be used as a starting point for model development.

The next stage in determining the vehicle mix that will be simulated in a certain VISSIM network is to specify the vehicle types. The "Desired Acceleration Function," "Desired Deceleration Function," "Maximum Acceleration Function," and "Maximum Deceleration Function" are four additional significant attributes that will influence the behavior of simulated vehicle types. These attributes will be assigned to each vehicle type along with a 2D/3D model distribution. These four characteristics will influence how various vehicle types perform in simulation, together with driving behavior settings. For instance, the desired maximum acceleration of a passenger car will normally be higher than that of a Heavy Goods Vehicle (HGV). When information about observed field conditions is available, it is crucial that these qualities reflect them. To simulate vehicle types during a VISSIM run, they need to be assigned to a specific vehicle composition.

4.2.3 Vehicle composition, inputs, and routings

Vehicle Compositions, Inputs, and Routings control the number of simulated vehicles, the types of vehicles that are simulated, and the routes that the simulated cars take within the network. When creating a VISSIM network, these three network properties should be considered jointly because of their close relationship.

Each individual vehicle input has a certain vehicle composition, which controls the relative flow of various vehicle types into the simulation. The desired speed distribution and relative flow will be assigned to each vehicle type, and each vehicle composition will have one or more vehicle types assigned to it. The range of intended speeds that various simulated cars will have when they enter the network is determined by the desired speed distribution. Unless field data indicate otherwise, the desired speed distribution should generally be the same for each type of vehicle within a particular vehicle composition. The Relative Flow sets how much of each vehicle type's input volume should be represented in each vehicle composition. For instance, if a vehicle composition contains three different vehicle types with a total relative flow of one and a relative flow for vehicle type A of 0.25, then vehicle type A will be simulated for 25% of the vehicle input volume related to that vehicle composition.

Vehicle Compositions / Relative flows

Number: 3	No	Name
1	1	Default NA
2	2	Freeways
3	3	Urban

Number: 3	VehType	DesSpeedDistr	RelFlow
1	100: Car	60: 60 mph	0.950
2	610: SU-Truck	60: 60 mph	0.030
3	620: MU-TR	60: 60 mph	0.020

Figure 4-2 Vehicle composition.

Vehicle inputs determine the actual volume of vehicles entering the VISSIM network in vehicles per hour. Different flow rates can be adjusted for specified time intervals related to the simulation period and vehicle inputs can be given to specific links within the VISSIM network. In general, "entry links" (i.e., Links without upstream connectors) should be used to code vehicle inputs because they serve as the boundaries of the VISSIM network. It is recommended that inputs be created for each simulation interval of 15 minutes. If there are enough field data, it should be done to assign different vehicle compositions to each time interval for a given vehicle input. Otherwise, each time interval or specific Vehicle Input can be allocated a particular vehicle composition.

Vehicle Inputs / Vehicle volumes by time interval

Number: 8	No	Name	Link	Volume(0-900)	Volume(900-1800)	Volume(1800-2800)	Volume(2800-MAX)	VehComp(0-900)	VehComp(900-1800)	VehComp(1800-2800)	VehComp(2800-MAX)
1	1		45: I-40 WE	7500.0	7500.0	7500.0	7500.0	2: Freeways	2: Freeways	2: Freeways	2: Freeways
2	2		52: N Hollywood St SN	1900.0	1900.0	1900.0	1900.0	2: Freeways	2: Freeways	2: Freeways	2: Freeways
3	3		51: N Hollywood St SN	950.0	950.0	950.0	950.0	2: Freeways	2: Freeways	2: Freeways	2: Freeways
4	4		20: Warford St NS	1500.0	1500.0	1500.0	1500.0	3: Urban	3: Urban	3: Urban	3: Urban
5	5		19: Warford St SN	1500.0	1500.0	1500.0	1500.0	3: Urban	3: Urban	3: Urban	3: Urban
6	6		10: Jackson Ave NS	5000.0	5000.0	5000.0	5000.0	2: Freeways	2: Freeways	2: Freeways	2: Freeways
7	7		6: Jackson Ave SN	900.0	900.0	900.0	900.0	2: Freeways	2: Freeways	2: Freeways	2: Freeways
8	8		2: I-40 EW	10500.0	10500.0	10500.0	10500.0	1: Default NA	1: Default NA	1: Default NA	1: Default NA

Figure 4-3 Vehicle input.

VISSIM also provides an option for the vehicle inputs to be treated as either “stochastic” or “exact”, where “exact” vehicle Inputs simulate the exact number of vehicles indicated by the flow rate while “Stochastic” vehicle inputs vary according to stochastic functions based on the seed number for a given run.

VISSIM provides three types of vehicle routing: static, dynamic, and origin-destination. Static routing is the most commonly used method. When coding static routes, users can either code routes as “relay routes”, where a new routing decision is provided at each decision point (e.g., every off-ramp on a freeway or every intersection on an arterial facility), or as “end-to-end routes”, where a single continuous route is provided from the link where vehicles enter the network to the link where vehicles exit the network. “Relay routes” are often easier to code and do not require the user to account for travel patterns within the VISSIM network beyond the total demand volume on each link. “End-to-end routes” will account for travel patterns within a VISSIM network and are often based on trip tables obtained from external tools such as travel demand models or other origin-destination data sources.

Dynamic routes are used to reroute vehicles when a given situation happens, such as a parking lot destination becoming full or a gated crossing becoming obstructed. Using the VISSIM user interface, static routes must be coded for dynamic routing (not to be confused with dynamic traffic assignment), however, the percentage of those routes can change depending on simulation-related events. Although most VISSIM projects should not use dynamic routing, an at-grade gate crossing with a parallel grade-separated crossing might be an appropriate application. When the gate is up, traffic is directed through it; when it is down, traffic is diverted to the grade-separated crossing.

The static routing option is less effective when the number of lanes increases along the roadway. Using the Combine Routes feature with static routes for too many consecutive intersections can lead to unexpected results. This is true for both multi-lane arterial networks with many closely spaced intersections and freeway networks with closely spaced interchanges. In both situations, intersection-to-intersection (or ramp-to-ramp) routing is not detailed enough to provide adequate vehicle driving behavior. Vehicles do not have enough warning to make proper lane changes, which can lead to inaccurate weaving behavior and lane utilization in the simulation model.

A vehicle should be assigned one complete route upon entering the network that continues until the vehicle leaves the network. However, if the network includes both arterial and freeway links, it is acceptable to have separate O-D matrices for each roadway type. For example, one matrix routes arterial traffic to and from each freeway ramp, while the freeway matrix routes vehicles from entrance ramp to exit ramp.

If the freeway network is small enough, it may be possible to create manual static routes that extend from each entrance ramp to all downstream exit ramps. However, in most cases a more automated process to develop O-D routing is recommended. There are two options for automated O-D routing in VISSIM. Option 1 uses VISUM to macroscopically assign the O-D matrix to the network and then uses the ANM data transfer from VISUM to VISSIM to export all generated O- D paths as fixed routes to VISSIM. With this option, even very large numbers of static routes (over 10,000) can be managed and coded efficiently. Option 2 uses VISSIM's Dynamic Traffic Assignment (DTA) to generate the O-D routes.

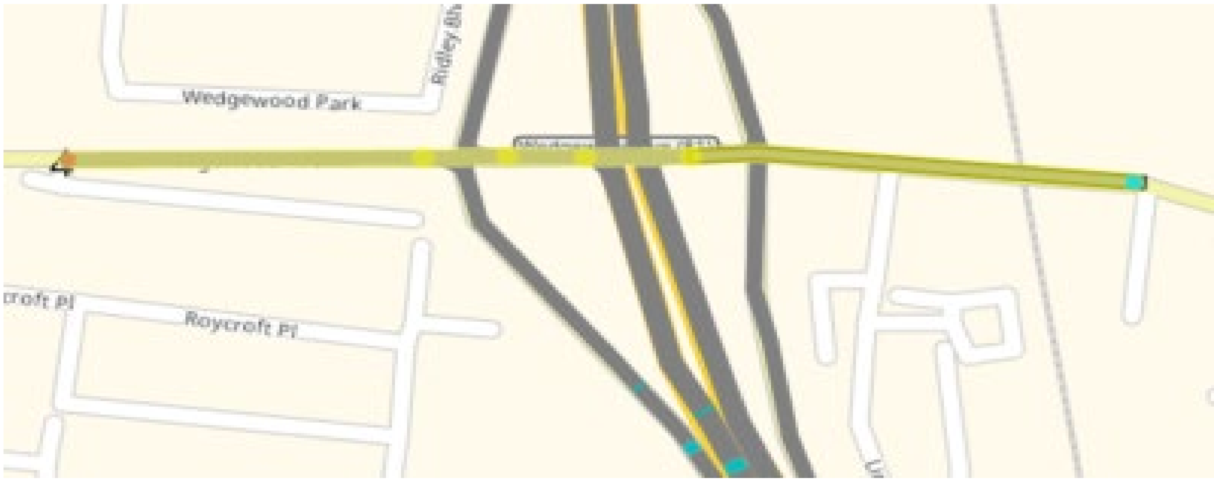


Figure 4-4 Vehicle Dynamic Route

4.2.4 Desire speed decisions and reduced speed areas

In setting up "Desire Speed Decisions and Reduced Speed Areas" for VISSIM simulation models, our focus is on configuring realistic driving behaviors. This involves accounting for factors such as road geometry, traffic density, weather conditions, and traffic regulations that influence drivers' desired speeds. Desire Speed Decisions allow the simulation to dynamically adjust vehicle speeds based on real-time conditions. These speeds are influenced by road features mapped using detailed GIS data, observed speed patterns during different traffic conditions, and the implementation of safety regulations in response to adverse weather conditions or special zones like school areas. Additionally, the methodology incorporates Reduced Speed Areas within the simulation to account for sections of the road where speeds need to be lowered for safety reasons. These areas might include sections near schools and hospitals, areas with frequent accidents, or segments with challenging road geometry like sharp curves or steep gradients. Historical accident data and traffic engineering assessments help in determining the exact locations and necessary speed reductions in these zones.

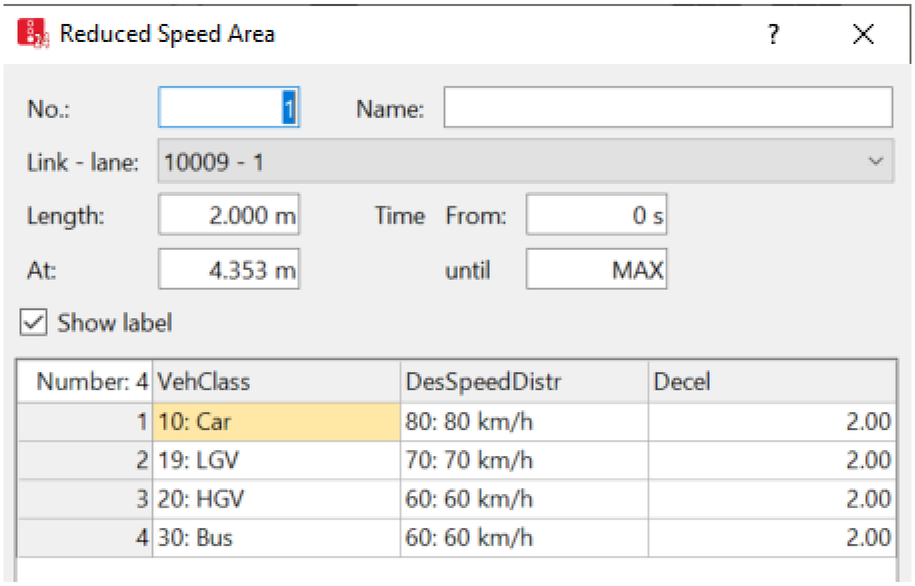


Figure 4-5 Reduced Speed Areas

Implementing these settings in VISSIM involves defining detailed speed parameters for each vehicle type under various conditions, using spatial analysis tools to map out and program the locations of reduced speed areas, and calibrating these settings by comparing the simulation outputs with real-world traffic speed data. A feedback loop is also established to refine the speed settings continuously based on new data and insights, ensuring that the simulation remains accurate and effective in predicting the impacts of speed management strategies and infrastructure modifications on urban freeway traffic flow and safety.

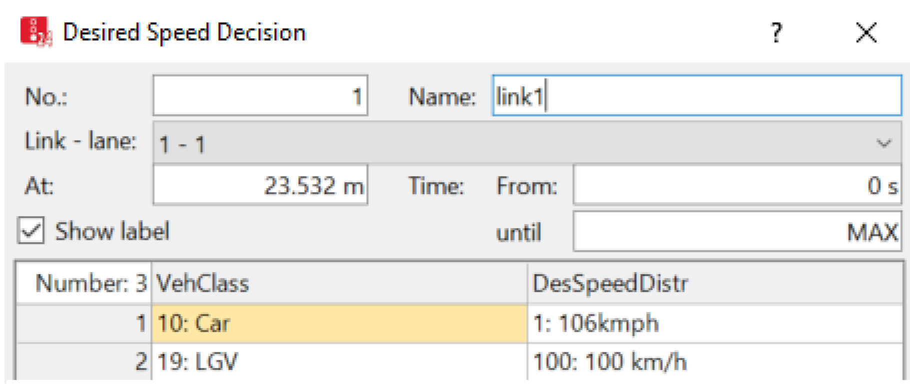


Figure 4-6 Desired Speed Decision

4.2.5 Simulation setup: period, resolution, random seed, and number of runs

The utilization of the random seed and random seed increment parameters enables the introduction of stochastic variations in vehicle arrivals within the VISSIM network, thereby accounting for fluctuations in real-world traffic conditions. The Random Seed value serves as the initial value for a random number generator. When two simulation runs employ the same network file and starting seed, they will yield identical results. However, if different random seed values are used in two runs of the same network file, the stochastic functions will generate distinct sequences, resulting in altered traffic flow within the network. The random seed Increment represents the difference between the

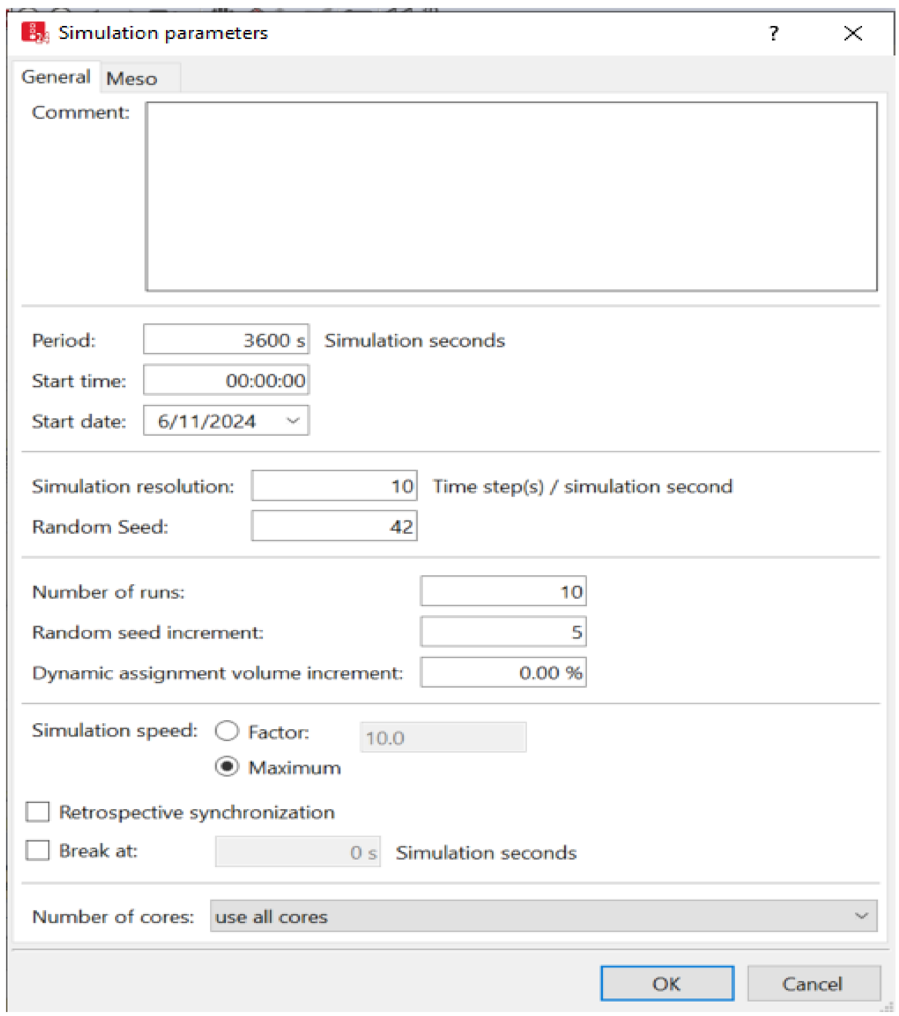


Figure 4-7 Simulation Parameters

random seed values when multiple simulation runs are conducted. For instance, in a scenario where a network has a random seed Increment of 10 and a starting seed of 100 for three runs, the Random Seeds for each run would be 100, 110, and 120, respectively. It is considered good practice to maintain a consistent combination of random seeds and random seed Increment for both existing and future year models.

The Number of Runs parameter will determine how many Random Seeds the model will be run for, provided that the random seed Increment is set to a value greater than 0. The minimum number of runs should be estimated using the sample size determination tool. In this project, a minimum of 10 runs with different random seeds for each run was considered to adequately account for variations in network operational performance.

4.2.6 Conflict areas and priority rules

The "Conflict Areas and Priority Rules" section is instrumental for accurately modeling interactions and establishing priority dynamics among various road users in congested and complex environments. This part of the methodology addresses how the simulation manages areas where vehicle paths intersect or merge, which are typically prone to conflicts and potential collisions. These include intersections, roundabouts, and highway merging lanes, where accurate simulation of vehicle interactions is crucial for both safety and traffic flow efficiency.

Conflict areas are mapped meticulously within VISSIM, utilizing precise geometric data and traffic flow parameters to reflect real-world conditions. The geometry of these areas—such as the angles of intersections or the curvature of merging lanes—is crucial as it influences how vehicles navigate these points. Priority rules, on the other hand, dictate the right of way at these conflict points. They are defined based on existing traffic regulations and the signage at intersections, such as stop signs or yield signs, as well as by traffic signal operations.

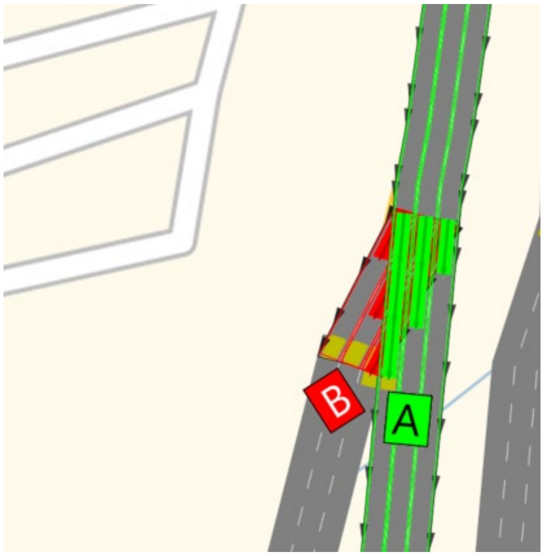


Figure 4-8 Conflict Areas

Incorporating these elements into VISSIM requires detailed mapping of all potential conflict points within the network. Priority rules are then assigned based on regulatory guidelines and empirical data observed from field studies. These rules are meticulously programmed to control how vehicles yield to each other at intersections, merge points, and pedestrian crossings, ensuring adherence to real-world traffic behaviors.

The integration process involves several critical steps. Firstly, all conflict areas are identified and defined with their specific traffic characteristics and geometric details. Priority rules are then established for each conflict area, incorporating yield points, stop conditions, and signal timings. Subsequent steps include the calibration of driving behaviors, such as adjusting deceleration rates, stopping distances, and acceleration as vehicles approach and depart these areas.

To validate the effectiveness of these settings, extensive testing is conducted to compare simulated outcomes with actual traffic patterns. Any discrepancies prompt adjustments to enhance the model's accuracy. This ensures that the VISSIM simulations reliably replicate complex traffic dynamics, aiding in the design and evaluation of traffic systems that are both safe and efficient.

4.2.7 Model review and debugging.

Review of Model Input Data is typically the first step in the Model Review and Model Debugging process. This step should include among other things: Verifying that link/connector geometry matches existing conditions or the proposed design plans; ensuring the simulated vehicle mix reflects the vehicle mix observed in the field; checking that compositions, inputs, and routings are coded such that link demand within the VISSIM network is consistent with volumes observed in the field; and confirming that desired speeds are correctly coded based on observed field data. For network objects such as Desired Speed Decisions, Reduced Speed Areas, signal heads, Vehicle Inputs, and others, reviewing the network object list can significantly improve the efficiency of the debugging process and can also allow for bulk editing of specific attributes.

VISSIM provides an error log file (.err) at the end of a simulation run that describes the time and location of an error. Modelers should review the error log file to ensure that messages that indicate potential model coding errors are addressed. Important error messages include:

- An entry link did not generate all vehicles (too big a demand or downstream congestion coding error causes spillback).

- A vehicle did not react to its designated route because of the short distance between the first connector and the start of the routing decision.

- Many vehicles were removed from the network because they have reached the maximum diffusion time before being able to make a lane change.

4.2.8 Common coding error

- Ensure adequate Conflict Areas are coded: at any grade crossing within the network, check that vehicles are not "running over each other" in locations where links overlap. If this behavior is observed, an additional Conflict Area is likely required so that vehicles on one link yield to vehicles on the other.

- Check that Lane Change Distances are coded correctly: A common issue, particularly in freeway coding, is the use of an insufficient Lane Change Distance for connectors. This error will typically manifest itself in VISSIM networks in the form of long, unrealistic queues at decision points in the network (e.g., an off-ramp on a freeway).

- Check that Desired Speed Decisions have been coded correctly: Desired Speed Decisions dictate the speed vehicles will travel at within the network. If a Desired Speed Decision is omitted for example on an on-ramp leading to a freeway facility, vehicles from that on-ramp will continue to travel at the desired speed from the arterial facility they came from, which is typically lower than the Desired Speed on the Freeway. Users should check for simulated vehicles moving at significantly different speeds on the same facility.

- Check that Reduced Speed Areas are coded at all intersections for right-turn and left-turn connectors: Reduced Speed Areas are required on all intersections right and left turns to account for reduced vehicle speeds as they make those movements.

- Check that correct vehicle types are coded on correct facilities: During Animation Review, users should check to make sure the mix of vehicles is realistic for that facility. An obvious example would be pedestrians being simulated on a freeway, which while technically possible within VISSIM, is never a realistic condition. A less obvious example would be a very large percentage of trucks (>20%) unless the user is modeling a unique facility where large percentages of trucks are common. In this case, it is important that the user be familiar with typical conditions on the facility being analyzed.

- Ensure entry links are sufficiently long for downstream routing decisions: Entry links, particularly those with two or more links, should be coded sufficiently long so that vehicles have space to make any necessary lane changes upon entering the network. If a user notes significant congestion at the beginning of their network, entry links may need to be extended further upstream.

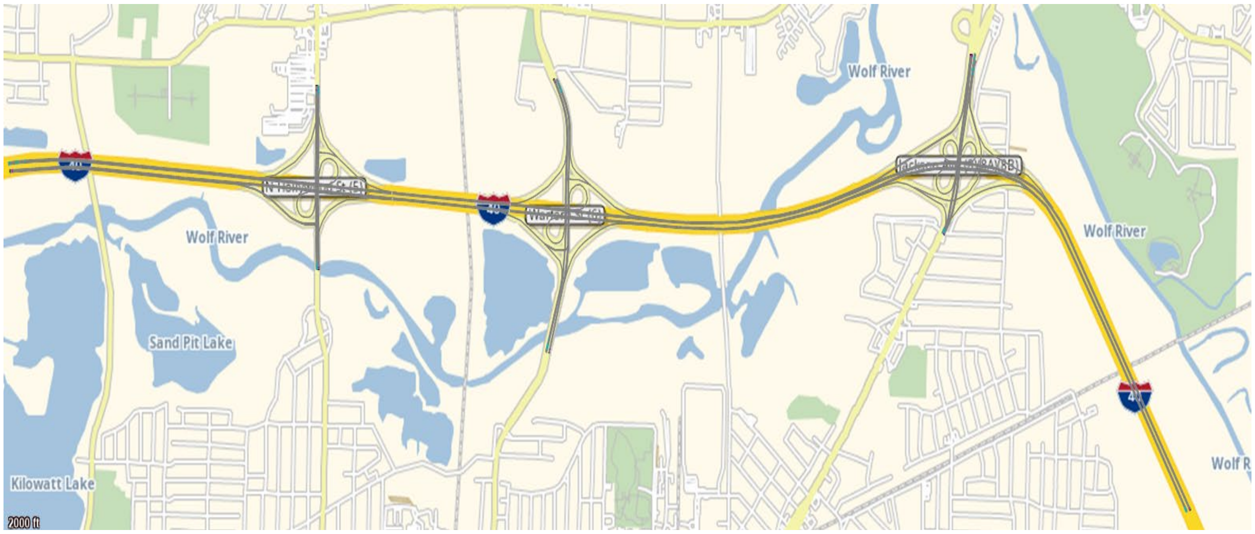


Figure 4-9 Memphis Site 1 (M1) Map

4.3 Selection of Calibration Parameters

The selection and calibration of parameters in traffic simulation models is a crucial process designed to ensure that these models accurately replicate real-world traffic conditions. This calibration process enhances the predictive reliability of the models and ensures that the simulations can be effectively used for traffic management and infrastructure planning decisions. Here's a more detailed breakdown of the entire process:

4.3.1 Identification of Calibration Parameters

The process begins by identifying which parameters are crucial for the accuracy of the simulation. This selection is based on the parameters' potential impact on the model's output, such as vehicle speed, following distance, and time gaps, which are integral to modeling the interactions between vehicles in traffic flow. The selection criteria often involve a preliminary review of literature and existing models to determine which parameters are typically sensitive and influential in traffic simulations.

Table 4-1 List of Weidman's parameters

Parameter	Default Value	Unit
CC0: Standstill distance	4.92	ft
CC1: Gap time distribution	0.90	s
CC2: Following distance oscillation	13.12	ft
CC3: Threshold for entering 'Following'	-8.00	Sec
CC4: Negative speed difference	-0.35	-
CC5: Positive speed difference	0.35	-
CC6: Distance dependency of oscillation	11.44	-
CC7: Oscillation acceleration	0.82	ft/s^2
CC8: Acceleration from standstill	11.48	ft/s^2
CC9: Acceleration at 50 mph	4.92	ft/s^2

4.3.2 Variation of Parameters

Once the key parameters are identified, each is systematically varied across a range of predefined values. This range might include the minimum, 25%, 50%, 75%, and maximum possible settings for each parameter. This step is essential to understand how sensitive the simulation outcomes are to changes in each parameter. By methodically adjusting these parameters and observing the resulting changes in traffic dynamics, the impact of each parameter on the overall simulation can be assessed. This sensitivity testing helps pinpoint which parameters are critical and need precise calibration.

4.3.3 Simulation Runs and Data Collection

For each variation of the parameters, the simulation is run, and data are collected on critical traffic metrics such as flow, speed, density, and congestion levels. These simulations need to be executed under controlled conditions to ensure that the data collected is reliable and reflects the changes due to parameter adjustments only. The simulation setup must be consistent across all runs to ensure that the observed differences in output are attributable solely to the changes in the parameters and not to any external variations.

The One-At-A-Time (OAT) analysis approach is a systematic method used to evaluate the sensitivity of a system's output to changes in individual input parameters while keeping other

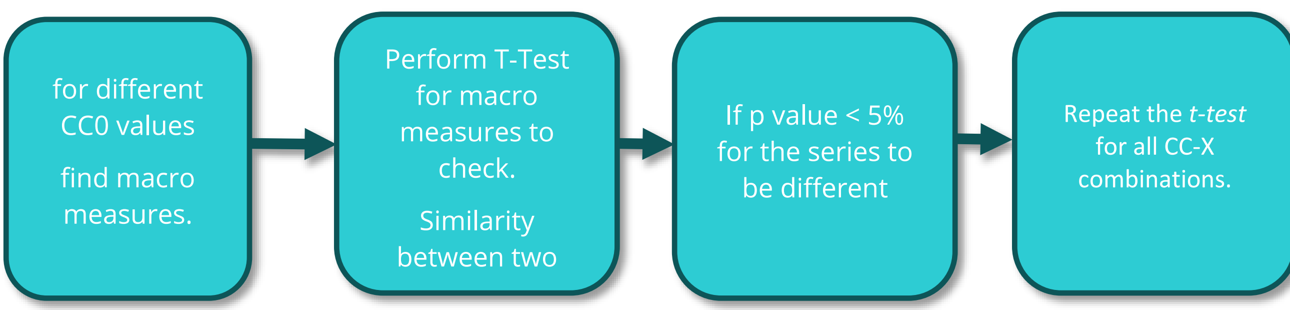


Figure 4-10 Flow chart of selecting a Wiedmann parameter.

inputs constant. This method is particularly useful for understanding the influence of each parameter in isolation, which simplifies the complexity associated with multi-parameter interactions. By adjusting one parameter at a time, we can directly observe the effect on system capacity, enabling precise identification of parameters that are most critical to system performance.

Iterative simulation runs are employed to further investigate the system under study. Initially, multiple simulation runs are conducted under a consistent scenario where variables such as the site location, peak hour, and day of the week are fixed. This consistency across runs ensures that any observed changes in system capacity can be attributed solely to the variations in the parameter being tested. Such a controlled setup allows for a clear assessment of the parameter's impact under specific, unchanging conditions.

Following the consistent scenario analysis, simulations are expanded to include varied scenarios. This involves changing one or more of the fixed variables (e.g., site, peak hour, day of the week) across different runs. By doing so, it is possible to evaluate the robustness of the system's response to the parameter changes across diverse conditions. This phase of testing is crucial for understanding how different scenarios might influence the sensitivity of the system to individual parameters, thereby providing a more comprehensive view of the system's behavior across a range of operational conditions.

Utilizing the OAT analysis combined with iterative simulation runs offers a structured approach to sensitivity analysis. It not only helps in pinpointing critical parameters but also aids in understanding how different conditions can affect the system's capacity and performance. This methodical analysis is vital for optimizing system design and enhancing operational efficiency.

4.3.4 Statistical Analysis

The collected data are then subjected to rigorous statistical analysis, typically involving T-tests to determine whether the differences in traffic metrics under different parameter settings are statistically significant. This step is crucial for identifying which parameters have a statistically significant impact on the model's outcomes. A p-value of less than 5% is generally considered to indicate a significant difference, suggesting that the parameter's influence on the simulation results is substantial.

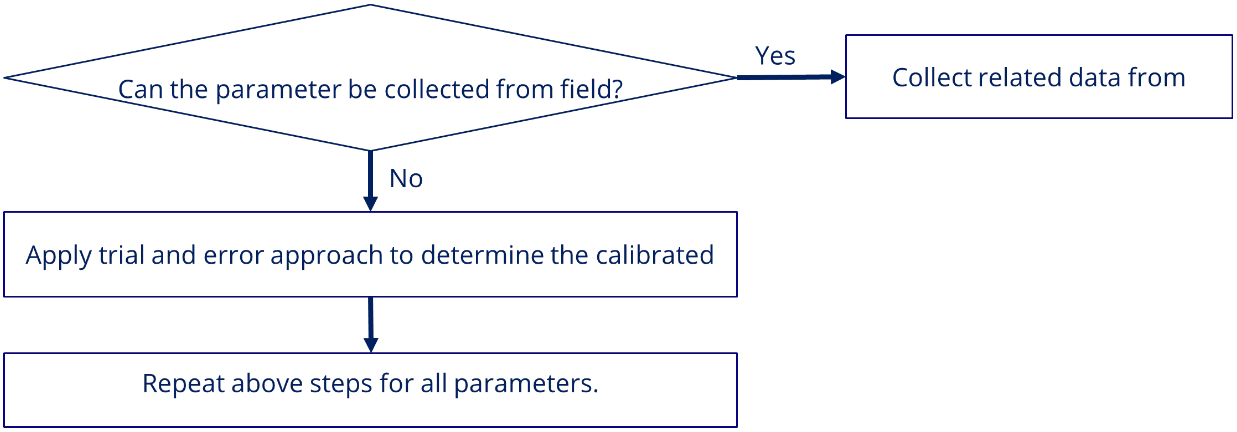


Figure 4-11 Flow chart of Statistical analysis.

4.3.5 Sensitivity Analysis

Following the initial statistical tests, a more detailed sensitivity analysis is conducted for each parameter. This analysis involves a deeper examination of how variations in a parameter affect the simulation results, helping to identify the most sensitive parameters that have the most substantial impact on the simulation. This step is critical for prioritizing which parameters to calibrate most carefully.

4.3.6 Iterative Refinement

Based on the insights gained from statistical and sensitivity analyses, the parameters are then iteratively adjusted and refined. This refinement process involves fine-tuning the parameters, running simulations, and reanalyzing the outcomes until the simulated data closely aligns with actual traffic data. This iterative process is crucial for achieving a high degree of accuracy in the simulation model.

4.4 Link Segment Data

The table provided represents a structured approach to analyzing traffic data over various time intervals along a specific traffic link, designated as Link 67 (I40 West-East). This analysis helps in understanding traffic flow characteristics—specifically speed, volume, and density—across different periods of the day. Here's an elaboration on how these measurements are calculated and interpreted:

Traffic data such as speed, volume, and density are collected using sensors placed along the traffic link. These sensors record data continuously, which are then aggregated into 5-minute intervals. This time interval provides a balance between capturing detailed fluctuations in traffic flow and maintaining manageable data volumes for analysis.

Speed: The average speed is calculated by determining the rate at which vehicles pass over a sensor in the road. It is typically measured in kilometers per hour (km/h) or miles per hour (mph). For each 5-minute interval, the speeds of all vehicles are averaged to obtain the period's average speed.

Volume: This refers to the total number of vehicles that pass a point on the highway within a given time interval. In this table, the volume is aggregated every 5 minutes, providing insight into traffic flow and its fluctuations throughout the day.

Density: This is calculated as the number of vehicles per mile or per kilometer at any given time. It is derived by dividing the volume by the flow speed and represents the closeness of vehicles on the road, which impacts speed and flow rates.

The data spans from early morning (300 seconds, or 5 minutes, into the day) to late evening (3600 seconds, or 60 minutes). Each interval captures a snapshot of traffic characteristics. By comparing volumes and speeds across intervals, one can identify peak hours where traffic congestion is highest and speeds are lowest. Variations in speed and density can indicate how traffic conditions change due to factors like road capacity, incidents, or traffic control measures. Data across different times can help assess the effectiveness of traffic management strategies aimed at reducing congestion and improving flow.

The tabulated data provides a comprehensive view of traffic dynamics on Link 67 (I40 W-E), crucial for traffic management and planning. By analyzing variations in speed, volume, and density across different times, stakeholders can develop targeted strategies to enhance road safety and efficiency, ultimately facilitating smoother transportation systems.

This structured and detailed analysis not only aids in immediate traffic management but also contributes to long-term planning and infrastructure development.

4.5 Calibration and Validation

Once the parameters are optimized, the final set of calibrated parameters is validated against additional real-world traffic data to ensure that the model can reliably replicate actual traffic conditions. This validation step is essential to confirm the robustness and accuracy of the calibrated simulation model. The calibrated model is applied to various traffic scenarios to test its effectiveness and reliability in predicting traffic behaviors under different conditions. This application helps verify that the model is robust and can be reliably used for traffic management and infrastructure planning.

This detailed methodology ensures that traffic simulation models are not only theoretically sound but also practically viable and ready for application in real-world traffic management and planning scenarios. Each step is crucial for building confidence in the model's ability to accurately predict and manage traffic flows, thereby aiding in the effective design of traffic systems and infrastructure developments.

The initial decision point in the **Figure 4-12** asks whether the parameter can be collected from the field. This step is crucial as it dictates the method of data acquisition for the calibration process. If field data are available and reliable, they can be directly used to calibrate the model. Field data are often preferred as they reflect real-world conditions and provide the most accurate basis for calibration.

If the answer to the first decision point is "Yes," the next step involves collecting related data from the field. This involves systematic data gathering, which might include measurements, surveys, or observations, depending on the nature of the parameter. This step is aimed at acquiring precise and contextually relevant data that directly influence the parameter under consideration.

If the parameter cannot be directly collected from the field, as determined in the first decision point, the flowchart directs you to apply a trial and error approach. This method involves estimating the parameter values through iterative testing and modification. The goal here is to adjust the parameter values manually until the model outputs align closely with known or expected outcomes. This method, while less direct than using field data, allows for the calibration of parameters that are difficult to measure directly or are influenced by complex interactions that are not easily quantifiable. Whether the parameter values come from direct field data or from trial and error, the next step involves the calibration itself. This process adjusts the model or system settings to match the collected or derived parameter values, ensuring that the model behaves in a manner that is consistent with real-world observations or desired outcomes.

Finally, the flowchart emphasizes the iterative nature of this process. Each parameter identified as critical to the model or system must undergo this process to ensure comprehensive calibration. The repetition of these steps for all parameters ensures that the model or system is fully calibrated, enhancing its accuracy and reliability.

This structured approach to parameter calibration is vital for developing models and systems that are both accurate and reliable. By methodically assessing the availability of direct measurements and applying a trial-and-error method where direct measurement is not possible, researchers and engineers can fine-tune their models to better reflect the complexities of real-world conditions. This not only enhances the predictive capabilities of models but also ensures that they are robust and applicable across various scenarios.

4.5.1 Calibration and Validation Methodology for Traffic Simulation Models

The primary aim of calibration is to tailor the parameters of the Wiedemann 99 model, particularly the CC0-CC9 parameters, to accurately reflect the observed traffic behaviors specific to each city. This process is essential because real-time traffic data can substantially differ from one location to another.

For effective calibration, traffic data including vehicle speed, density, and volume are collected at five-minute intervals for specific links within each city. This data collection allows for forming a detailed and continuous data series necessary for the subsequent calibration of the simulation model.

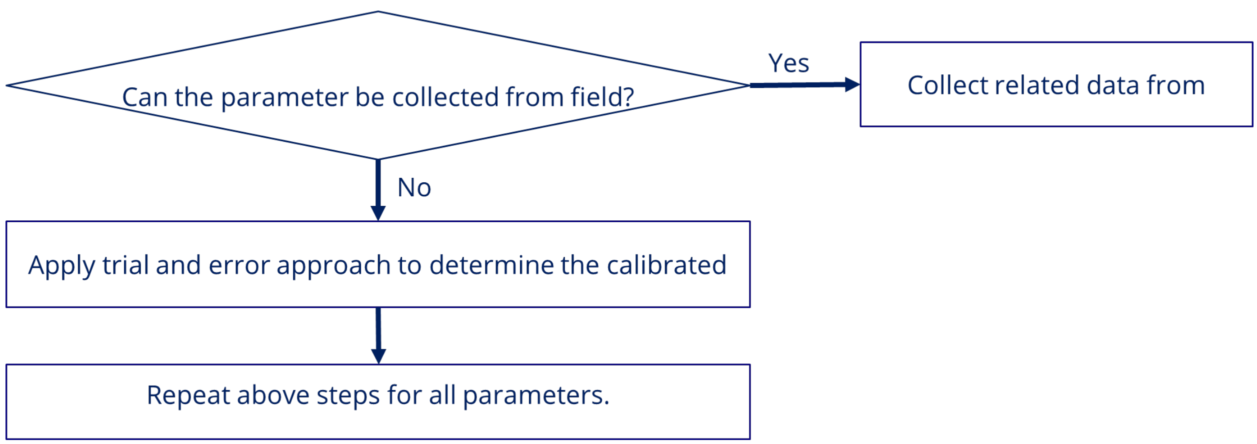


Figure 4-12 Calibration Procedure

4.5.2 Parameter Calibration Process

The calibration process encompasses the following critical steps:

Data Segmentation: Traffic data for each city is segmented by specific road links. Maximum traffic volumes are recorded within 5-minute intervals for each link to identify peak conditions.

Statistical Analysis: The RMSE is utilized to quantify the discrepancy between the simulated data (using initial or default parameters) and the actual field data. This statistical analysis is performed iteratively for various parameter adjustments.

Parameter Adjustment: The focus is on adjusting the model parameters to minimize the RMSE. Lower RMSE values indicate a closer match between the simulation outputs and the actual traffic data, reflecting more accurate model calibration.

After calibration, the RMSE is again used to validate the accuracy of the simulation model. This measure assesses the average magnitude of the errors between the predicted traffic volumes by the model and the observed data, providing a clear metric to gauge the effectiveness of the calibration.

Calibration is an iterative process. Modifications in parameters intended to optimize one aspect of the traffic model might necessitate further adjustments elsewhere. This iterative refinement is crucial to align the simulation outputs closely with real-world data.

Traffic patterns vary significantly across different cities; therefore, the calibration approach must be tailored for each city independently. A model calibrated for one city might not yield accurate results when applied to another, underscoring the need for a customized calibration process for each urban environment.

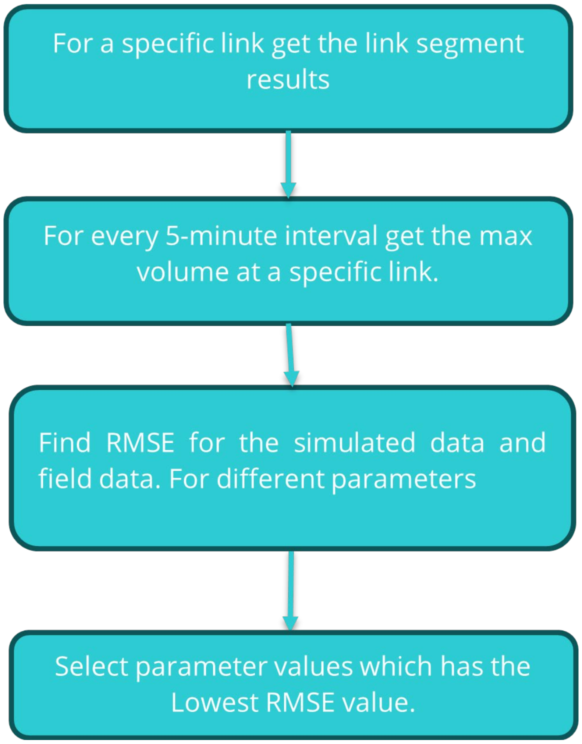


Figure 4-13 Calibration Strategy

By focusing on minimizing RMSE during both calibration and validation stages, this methodology ensures that traffic simulation models are finely adjusted to specific urban conditions and validated rigorously against actual traffic data, thus improving their reliability and applicability in traffic management and urban planning scenarios.

5 Empirical Analysis of Traffic Flow Characteristics

The video data was collected by screen recording the live video feed from the traffic cameras. YOLOv8, the latest version of YOLO algorithm, was used for analyzing the traffic videos. The state-of-the-art YOLO v8 (You-only-look-once) model has recently been developed (it came out in 2023) by Ultralytics, the creators of the widely used YOLOv5 model. YOLOv8 has been designed to perform several complex computer vision tasks, including object detection, image classification, and instance segmentation. The latest model offers several notable changes and improvements over YOLOv5 in terms of architectural and developer experience.

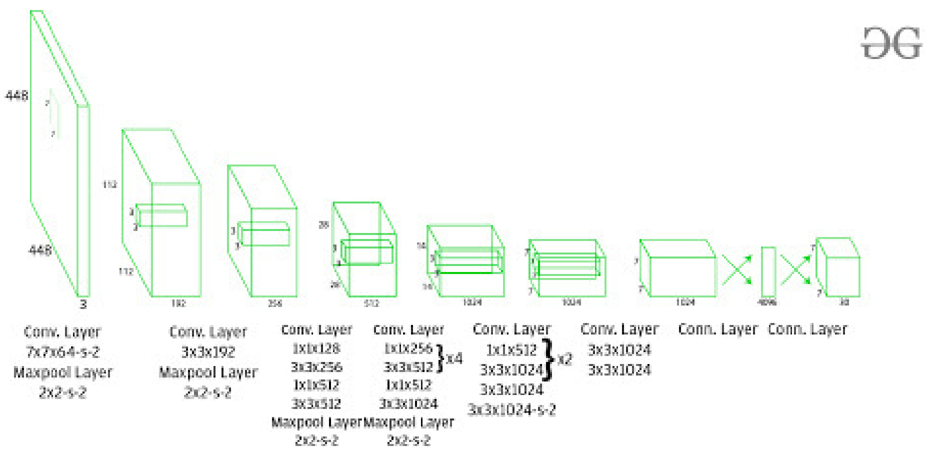


Figure 5-1 YOLO architecture.

Peak hour traffic volume (7-8 am, collected on Tuesday May 2, 2023) at the selected site, which is the along the roadway segment at I-65 (denoted by N-1 in figure 1) is shown in Figure 5-2.

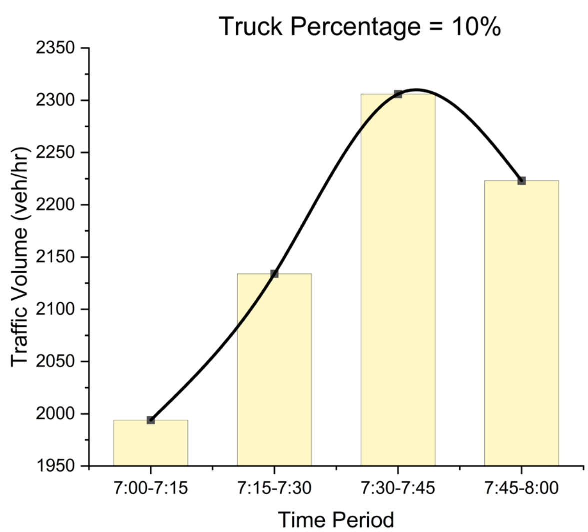


Figure 5-2 Traffic volume count from YOLOv8 for I-65 at Nashville, N1.

5.1 *Identification of Traffic Characteristics*

Collected data was analyzed to identify traffic characteristics, calibration, and validation parameters for the VISSIM microsimulation-based analysis. In this task we extracted the following data-

Headway- filtering operation was performed to determine headways for different lead vehicles and following vehicle combinations (e.g., car-car, car-truck, truck-car).

Average Standstill distances were obtained from the stationary images by using photoshop cc. We have analyzed the three main parameters of traffic flow such as headway (CC1), time gap, and average standstill distance (CC0) based on the field data for the Nashville Site1 (N1) for the morning peak period.

5.1.1 Sample Size Calculation for headway and time gap.

To be 95% confident that the true mean is within ±0.2 seconds of the estimated mean, at least 78 observations are necessary, according to the sample size formula in equation (1) based on the normal distribution and using a standard deviation of 1.75 (when considered headway <= 3 sec which is the cutoff value from our analysis).

$$n = \left(\frac{Z_{\frac{\alpha}{2}} * \sigma}{E}\right)^2 \qquad (1)$$

Where,

N= number of observations needed

$Z_{\frac{\alpha}{2}} = \text{the critical z} - \text{score for a significance level of } \frac{\alpha}{2}$

σ = sample standard deviation.

E = acceptable error

5.1.2 Headway and Time Gap Calculation

Headway and time gaps are two different variables that need to be calculated from the video data. Headway is the time between successive vehicles measured from the same point on each vehicle. Time gap is the time from the back bumper of the leading vehicle to the front bumper of the following vehicle.

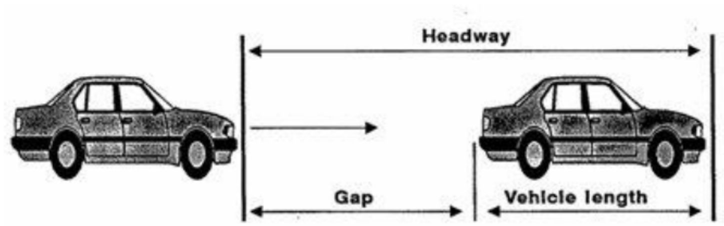


Figure 5-3 Difference between headway and time gap.

To calculate the headway for each vehicle, the differences between successive vehicle arrival times in the same lanes were found.

$$Headway_{ij} = t_{ij} - t_{(i-1)j} \tag{2}$$

Where,

$Headway_{ij}$ = the headway of the ith vehicle in the jth lane (in seconds)

t_{ij}= time of arrival of the *i*th vehicle in the jth lane

$t_{(i-1)j}$= time of arrival of the *(i-1)* th vehicle in the *j*th lane

Because the headways are measured from the front bumper of the leader to the front bumper of the follower, and the time gap is measured from the back bumper of the leader to the front bumper of the follower, the only difference between headway and time gap is that the time gap is shorter by the length of time it takes for the leading vehicle to clear the detector.

$$TimeGap_{ij} = Headway_{ij} - \frac{length_{(i-1)j}}{speed_{(i-1)j}} \tag{3}$$

Where,

$TimeGap_{ij}$ = the time gap of the ith vehicle in the jth lane (in seconds)

$length_{(i-1)j}$=the length of the (i-1) th vehicle in the jth lane (in feet)

$speed_{(i-1)j}$= the speed of the (i-1) th vehicle in the jth lane (in feet per second)

5.1.3 Vehicle Following Threshold and Filtering

Another step in the analysis was determining the maximum headway at which the second vehicle could still be considered following the first vehicle. There have been a few efforts to establish this threshold in past studies, but these studies were mostly focused on rural two-lane roads. For example, the *HCM 2010* sets the threshold for rural two-lane roads to 3 seconds, but it does not offer any explanation for how this value was determined (TRB 2010). However, a study from Sweden outlined a process for determining which vehicles can be considered "free" by finding the correlation between leading and following vehicle speeds at different headway values (Vogel 2002). This methodology was applied with the opposite mentality in mind: which vehicles can be considered following? Thus, for the data from each of the detectors, the headways were rounded to the nearest second, and the Pearson correlation coefficient was calculated between the leading vehicle's speed and the following vehicle's speed (as long as both vehicles were assigned speeds) for each group of rounded headway data, and the results were plotted.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

Where r_{xy} = Pearson correlation coefficient, x_i = the ith value of variable x, y_i = the ith value of variable y, $\bar{x}$ = the mean value of variable x, $\bar{y}$= the mean value of variable y, and n = number of observations.

Figure 5-4 shows vehicle following threshold and filtering from the collected headway data. The y-axis represents the Pearson correlation coefficient was calculated between the leading vehicle's speed and the following vehicle's speed. From the figure, it can be said that the two drivers follow each other closely at smaller headways and as the headway increases the dependency between their relative speed and headway becomes less and beyond 3 seconds of headway, car-following behavior cease to exist. This indicates that beyond average flow rates values of 1200 vehicles/hour/lane, free-flow conditions (i.e., LOS B) exist on the Nashville site. This further corroborates with the HCM (2016) specifications for freeways.

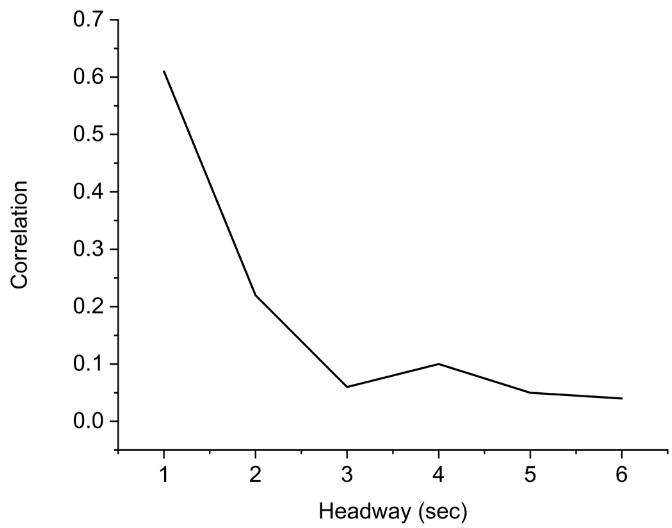


Figure 5-4 Correlation of leading and following vehicle speeds versus headway at the selected segment of I-65 near Nashville Site1, N1.

Time gap was calculated using equation 3. Figure 5-5 indicates that the headway distribution is not the same across different lanes of traffic. Lanes 1 and 4 has wider variability in headways compared to that of Lanes 2 and 3. This indicates that Lanes 2 and 3 has higher interaction as compared to the Lanes 1 and 4.

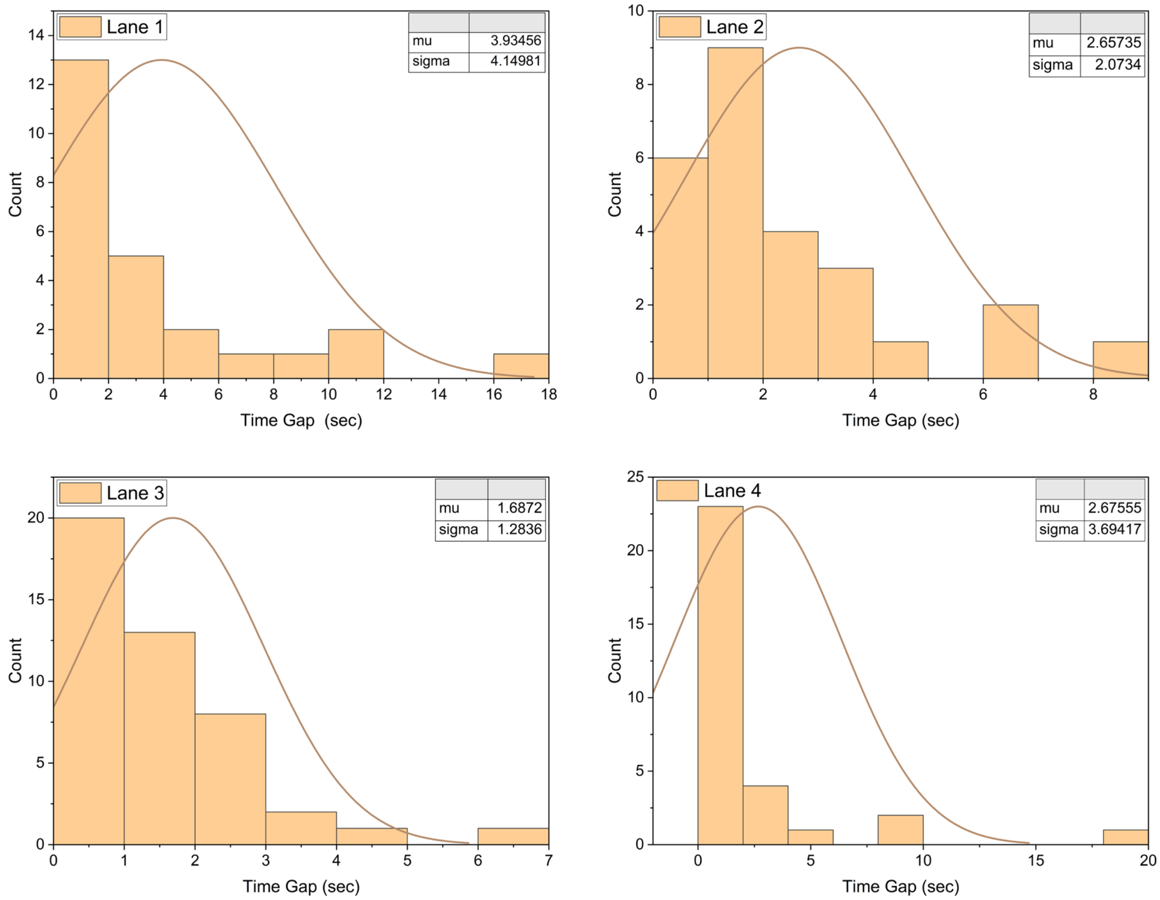


Figure 5-5 Time gap distribution at the selected segment of I-65 near Nashville Site1, N1.

5.1.4 Average Standstill Distance Calculation

Average standstill distance was calculated from Photoshop CC 2023. Examples of standstill distance calculation are shown in Figure 5-6.

Figure 5-6 Average standstill distance Calculation

Figure 5-7 shows that the distribution of standstill distance has a longer tail towards right indicating that there are fewer instances of larger standstill distances. The average standstill distance is 11.2 feet that indicates that drivers tend to maintain sufficiently larger gaps during standstill situations.

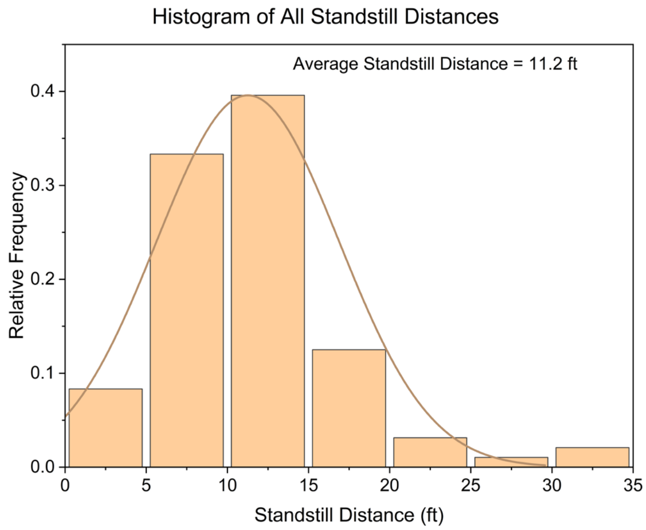


Figure 5-7 Histogram of unfiltered standstill distances for Nashville Site1 (N1)

Table 5-1 compares standstill distances during the Fall and Summer seasons at various sites in Tennessee, including Chattanooga, Knoxville, Memphis, and Nashville. Only two sites showed significant differences in standstill distances between Fall and Summer seasons namely Knoxville Site1 (p-value = 0.017), and Chattanooga Site2 (p-value = 0.110, although this is marginally significant). Knoxville Site1 (K1) had the lowest standstill distance of 9.78 ft and Chattanooga Site2 (C2) had the highest standstill distance of 12.59 ft. Chattanooga Site1, Memphis Site1, and Memphis Site2 did not experience stop-and-go situations, indicating that traffic flow was smoother at these sites.

Table 5-1 Seasonal Variation on Standstill Distance (CC0)

Standstill Distance, CC0 (ft)			
Sites	**Fall**	**Summer**	**p-value**
Chattanooga Site1 (C1)	N/A	N/A	
Chattanooga Site2 (C2)	12.59	11.62	0.110
Knoxville Site1 (K1)	9.78	10.79	0.017
Knoxville Site2 (K2)	10.49	N/A	N/A
Memphis Site1 (M1)	N/A	N/A	N/A
Memphis Site2 (M2)	N/A	9.54	N/A
Nashville Site1 (N1)	10.03	11.42	0.051
Nashville Site2 (N2)	9.92	10.80	0.047

The results suggest that standstill distances vary across sites and seasons. The significant differences observed at Knoxville Site1 and Chattanooga Site2 may be attributed to factors such as changes in traffic volume or composition, road geometry or infrastructure, weather conditions, and time of day or day of the week. The lack of significant differences at other sites may indicate that traffic conditions are relatively consistent across seasons. The absence of stop-and-go situations at some sites suggests that traffic flow is more stable, potentially due to factors like traffic management strategies or road design.

Transportation agencies might need to consider these seasonal variations when planning traffic control measures or road maintenance schedules. For example, if certain roads consistently show significant seasonal variation in standstill distances, it might indicate a need for seasonal adjustments to traffic signals or signage to optimize traffic flow and safety.

6 Analysis of Simulation Results

This chapter presented an in-depth investigation into how VISSIM model parameters influence key traffic metrics such as volume, density, and speed. We explored the sensitivity of the VISSIM model to calibration parameters, evaluating the model's accuracy through the RMSE for each site. The findings are crucial for understanding the operational characteristics of Tennessee's freeway network and for developing localized traffic management strategies. Through comparative analysis of field and simulated data, this chapter highlighted the effectiveness of site-specific calibration in improving the fidelity of traffic simulations, ultimately contributing to more efficient and safer road networks in the state.

6.1 Effect of Standstill Distance (CC0) on Traffic Flow Variables

We analyzed the effect of standstill distance (CC0), which is one of the important parameters of microsimulation model, on the 5-min average speed, volume, and density variables. Figure 6-1 illustrates the relationship between traffic volume and density on the I40 West-East link across various standstill distances. The figures clearly show how different levels of traffic congestion impact volume and density metrics.

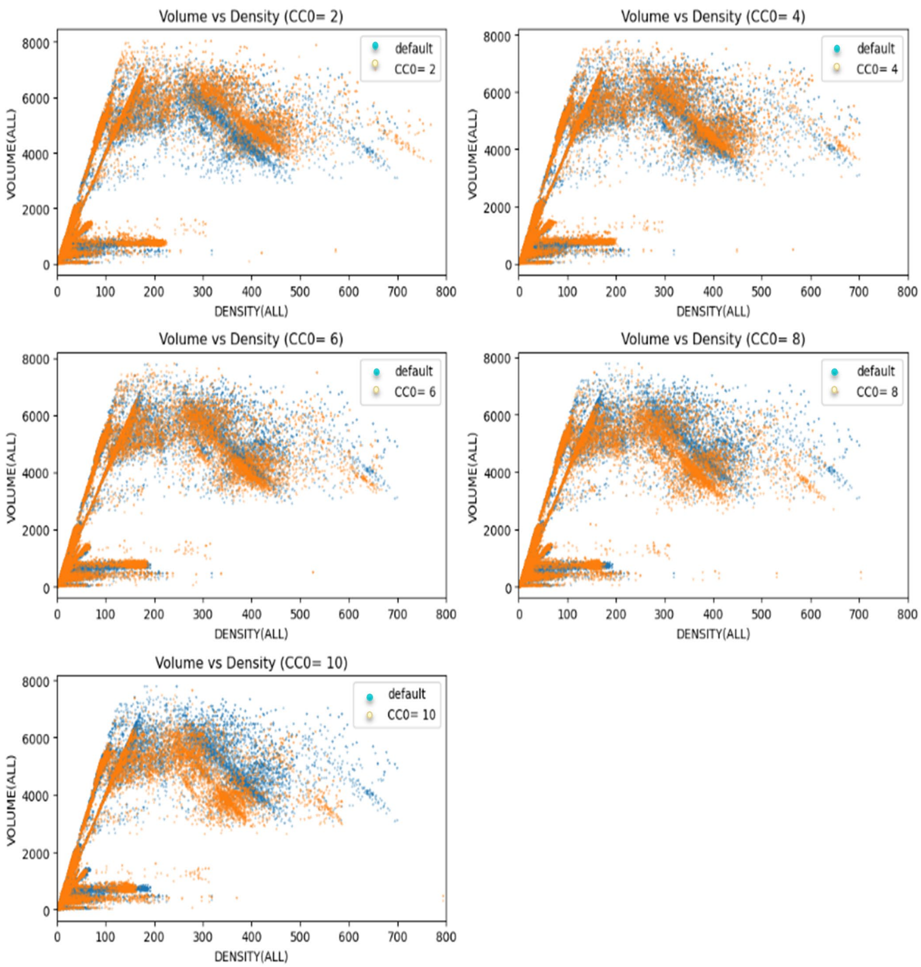


Figure 6-1 Volume and Density Variation for Memphis Site1 (M1)

Each plot in the series represents a different standstill distance setting, ranging from CCO=2 to CCO=10. These standstill distances correspond to different levels of traffic control measures or congestion scenarios. The points are color-coded to distinguish between default conditions (blue) and specific CCO settings (orange), allowing for a comparative analysis of how congestion influences traffic dynamics.

All plots show a generally increasing trend where traffic volume rises with density until a certain point, after which it either stabilizes or slightly decreases. This indicates a typical traffic flow pattern whereas more vehicles accumulate on the road (increased density), the volume initially increases until the road capacity is maximized, leading to congestion. As the CCO value increases, the plots exhibit variations in the spread and slope of the data points. Higher CCO values appear to correlate with lower peak volumes, suggesting that increased congestion leads to a reduced capacity for traffic flow, as vehicles move more slowly and closely together.

The scatter and spread of the points in each plot illustrate the variability in traffic conditions within the same congestion setting, reflecting factors like time of day, day of the week, and external influences (e.g., weather conditions, accidents). Max Volume indicates the highest traffic volume observed under each CCO setting. Notably, CCO=10 shows a significantly higher max volume, which might indicate an outlier or exceptional scenario where density was high but still allowed for considerable traffic flow.

Mean Volume shows the average traffic volume, which decreases as CCO increases from 2 to 8 but then increases at CCO=10, possibly suggesting different traffic management strategies or the non-linear effects of congestion. Max Standard Deviation reflects the variability in volume measurements at each CCO setting, with higher values indicating more fluctuation in traffic volume, likely due to inconsistent traffic conditions.

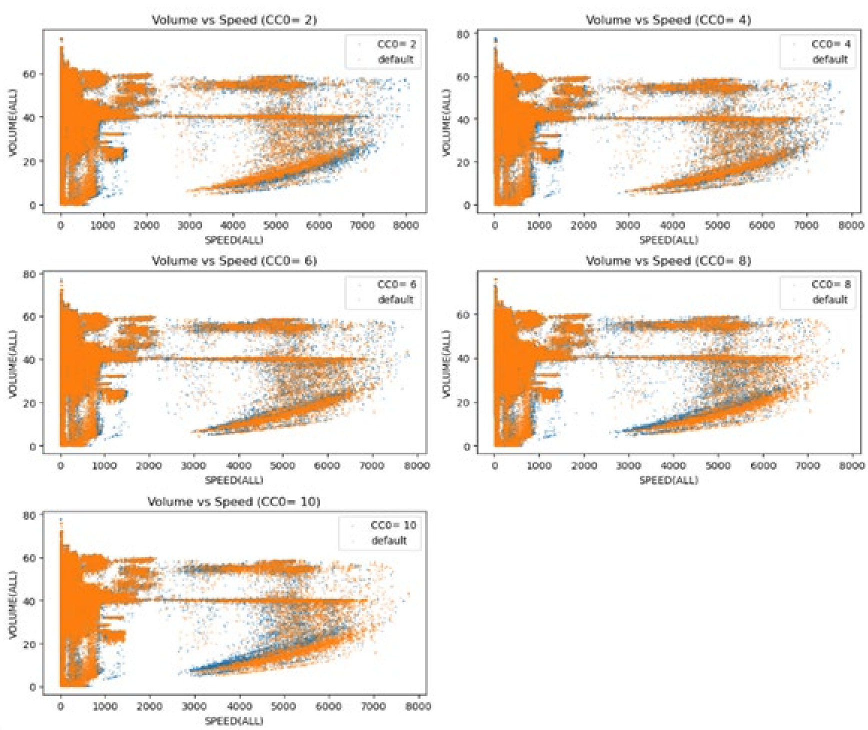


Figure 6-2 Speed Volume Variation for Memphis Site1 (M1)

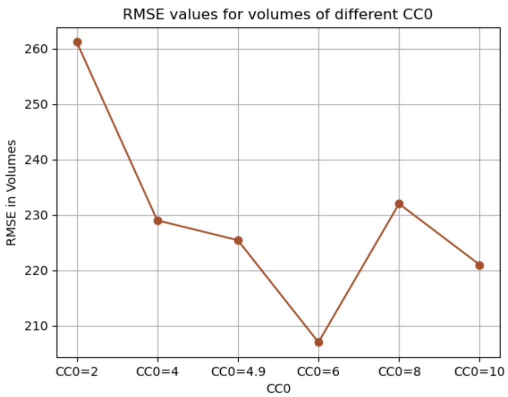
Figure 6-2 display traffic volume on the vertical axis and speed on the horizontal axis for different congestion settings. By comparing the default (blue points) and specific CCO conditions (orange points), these plots effectively visualize the impact of varying traffic congestion on speed and volume dynamics.

A common trend across all plots is the inverse relationship between speed and volume. Generally, as speed increases, volume decreases, and vice versa. This relationship is fundamental in traffic flow theory, where higher speeds typically correspond to lower vehicle densities, allowing for a smoother flow of traffic. With increasing CCO values, the plots show a shift in the distribution of data points. Particularly, as the CCO increases, there is a noticeable compression in speed ranges, indicating that higher congestion levels directly impact and reduce vehicle speeds. This can be interpreted as the effect of tighter traffic control or more congested conditions reducing the overall speed of traffic. Spread and Density of Data Points: The density and spread of the points suggest variability in traffic conditions under each CCO setting. For example, denser clusters of points at lower speeds in higher CCO settings may indicate frequent traffic jams or slower moving traffic, a typical characteristic of higher congestion levels.

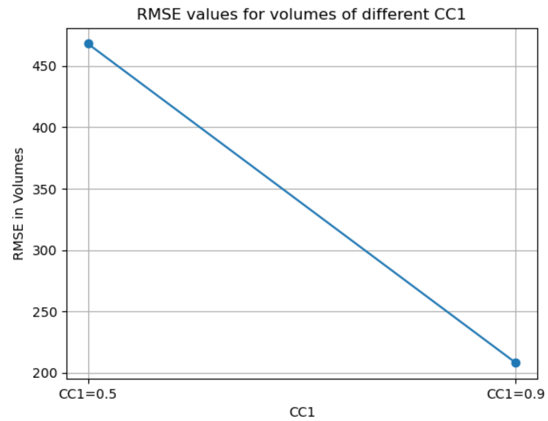
The CCO parameter modulates the relationship between volume and speed. Lower CCO values generally allow for higher speeds at similar volumes compared to higher CCO values, suggesting that traffic management strategies that result in lower CCO values could effectively mitigate congestion and maintain higher speeds. While speed varies considerably across different CCO settings, the volume appears relatively stable, especially in high congestion scenarios (CCO=6, 8, 10). This indicates that despite slower speeds, the road segment continues to handle a consistent flow of traffic, albeit at reduced efficiency. The analysis of volume versus speed under varying congestion coefficients provides valuable insights into the operational dynamics of Memphis Site 1's traffic network. It illustrates how congestion (as quantified by CCO) significantly affects speed but less so the volume, highlighting the critical role of speed management in congestion control strategies. The findings suggest that effective traffic management could benefit from focusing on strategies that maintain or increase speed without significantly impacting the volume capacity of the road. This balance is crucial for optimizing traffic flow and enhancing road usage efficiency.

6.2 Sensitivity Analysis of VISSIM Model Parameters

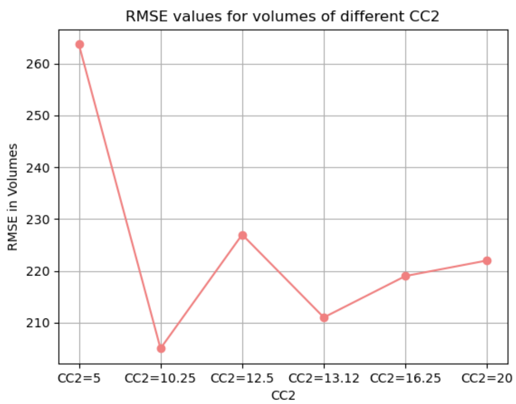
The set of graphs provided in Figure 6-3 represents the RMSE values for different car-following parameters (labeled CC0 to CC9) at Memphis Site 1 (M1). The RMSE values fluctuate considerably across different car-following parameters (CC0 to CC9). This indicates that the accuracy of the models (in terms of RMSE) varies depending on the parameter settings.



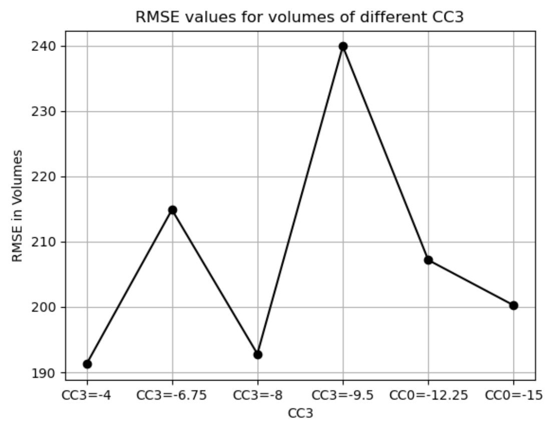
(a) CC0



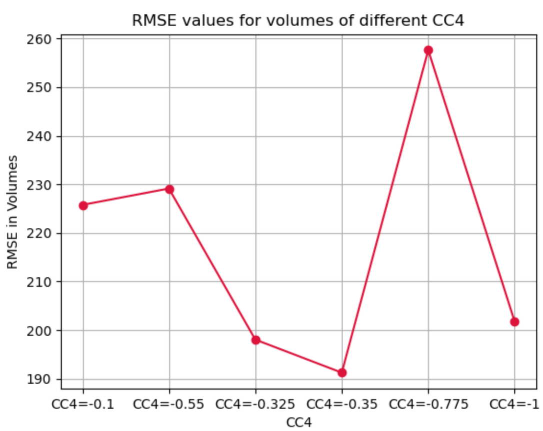
(b) CC1



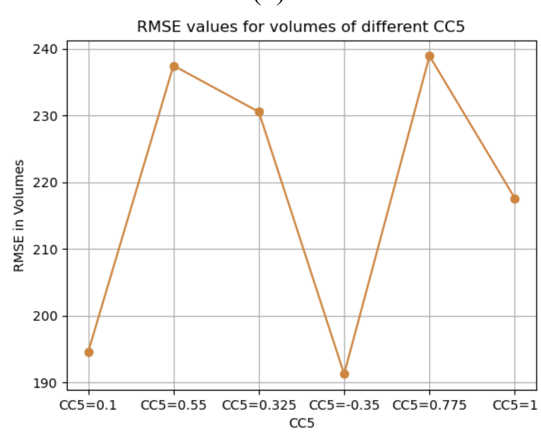
(c) CC2



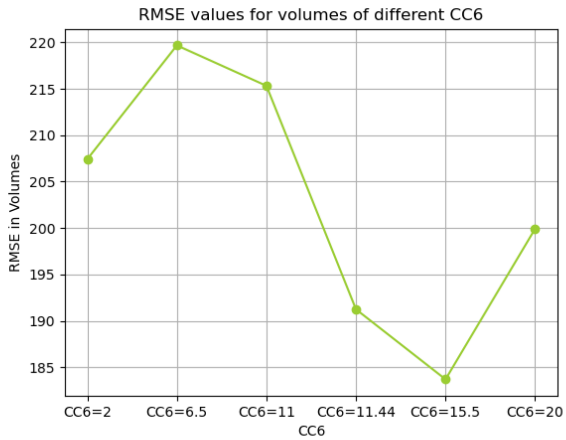
(d) CC3



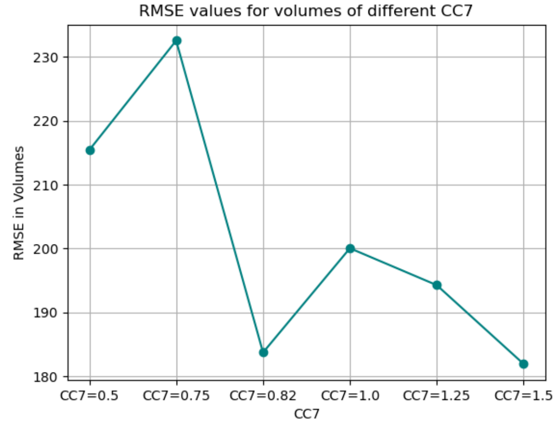
(e) CC4



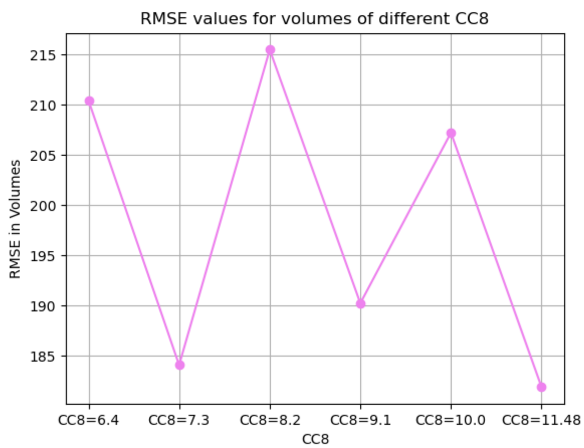
(f) CC5



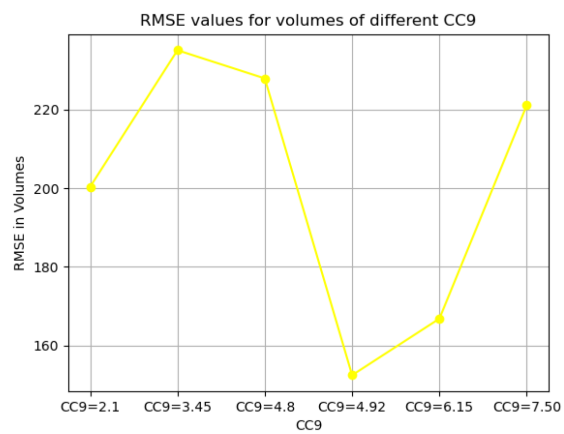
(g) CC6



(h) CC7



(i) CC8



(j) CC9

Figure 6-3 Sensitivity Analysis of Car-following Parameters (CC0-CC9) for Memphis Site1 (M1)

For **CC1** (Graph (b)), there is a linear decrease in RMSE, suggesting a clear trend or relationship between the parameter and the model's accuracy. Conversely, other parameters such as **CC0** (Graph (a)), **CC2** (Graph (c)), **CC3** (Graph (d)), **CC5** (Graph (f)), and others show more erratic trends with peaks and troughs, indicating that certain volumes lead to better or worse performance depending on the specific parameter settings. The RMSE values across the graphs suggest that different parameters contribute to better or worse modeling outcomes depending on the scenario. For instance, certain volumes under **CC3** and **CC7** (Graph (d) and (h)) seem to result in higher RMSE values, potentially indicating suboptimal parameter settings for those scenarios.

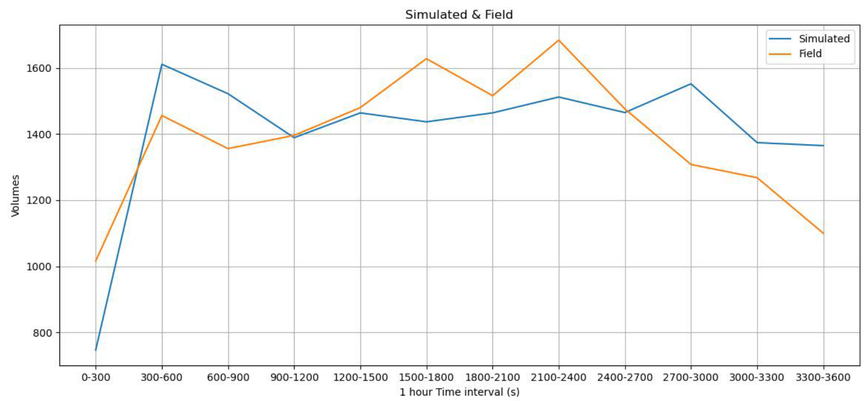


Figure 6-4 Comparing field and simulated volumes for Memphis Site1 (M1)

The graph presented in Figure 6-4 illustrates a comparison between the simulated and field-observed traffic volumes at Memphis Site 1 over various time intervals. The blue line indicates the simulated volumes, and the orange line represents the field-observed volumes.

The comparison reveals that the simulated volumes closely follow the general trend of the field data, with some discrepancies at certain intervals. In some periods, the simulated volumes exceed the field volumes, particularly in the early and middle intervals, while in the later intervals, the field volumes tend to be lower than the simulated ones.

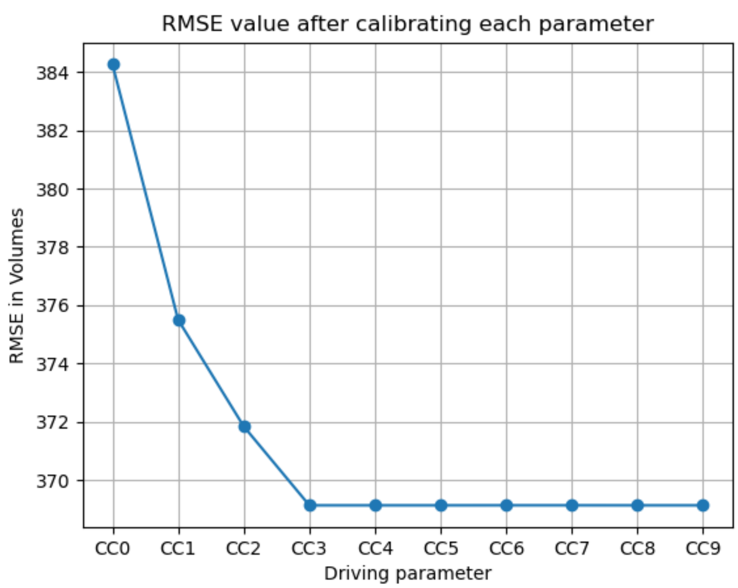


Figure 6-5 RMSE value after calibrating each parameter for Memphis Site2 (M2)

The graph in Figure 6-5 shows the RMSE values after calibrating each car-following parameter (CC0 to CC9) for Memphis Site 2. The results indicate a significant reduction in RMSE after calibrating the initial parameters, particularly from CC0 to CC3. Beyond CC3, the RMSE values stabilize, with minimal further improvements, suggesting that the calibration of parameters CC4 to CC9 has little to no additional impact on reducing the RMSE. This trend highlights the importance of early parameter calibration in achieving a more accurate model.

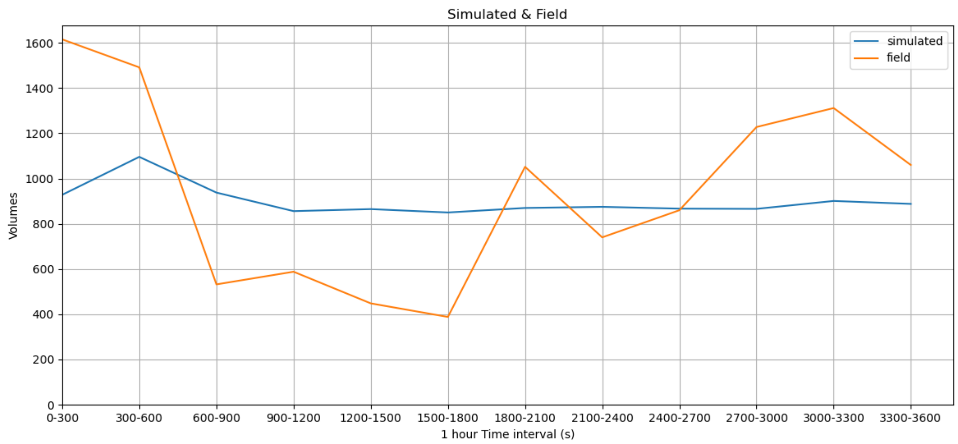


Figure 6-6 Comparing field and simulated volumes for Memphis Site2 (M2)

The graph in Figure 6-6 compares the field-observed and simulated traffic volumes for Memphis Site 2 over various 1-hour time intervals. The field data (orange line) shows more significant fluctuations in volume across the time intervals, with noticeable peaks and troughs. In contrast, the simulated data (blue line) remains relatively stable, with only minor variations. The discrepancy between the field and simulated data suggests that while the simulation model captures a general trend.

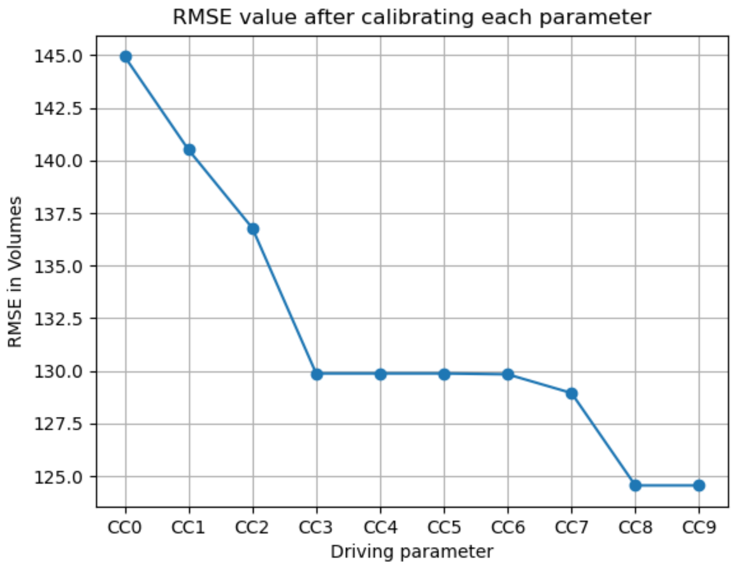


Figure 6-7 RMSE value after calibrating each parameter for Nashville Site1 (N1)

The graph in Figure 6-7 shows the RMSE values after calibrating each driving parameter (CC0 to CC9) for Nashville Site 1. The trend indicates a significant reduction in RMSE as parameters CC0 to CC3 are calibrated, followed by a plateau where further calibration of parameters CC4 to CC7 shows minimal improvement. However, a notable decrease in RMSE occurs again at CC8 and CC9, suggesting that these parameters have a considerable impact on reducing the error and improving the model's accuracy at Nashville Site 1.

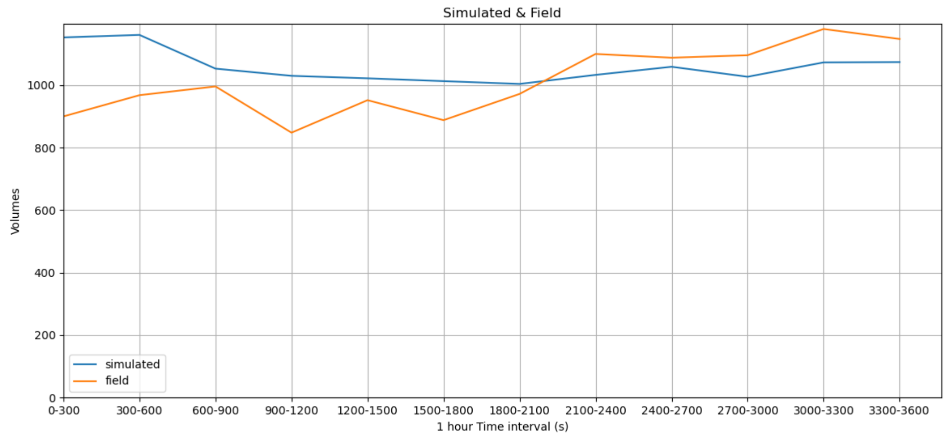


Figure 6-8 Comparing field and simulated volumes for Nashville Site1 (N1)

The graph in Figure 6-8 compares the field-observed and simulated traffic volumes for Nashville Site 1 across different 1-hour time intervals. The simulated volumes (blue line) remain relatively stable throughout the time intervals, showing minor fluctuations. In contrast, the field volumes (orange line) exhibit more variability, with significant peaks and troughs, particularly in the earlier intervals. This comparison suggests that while the simulation model maintains a consistent estimate.

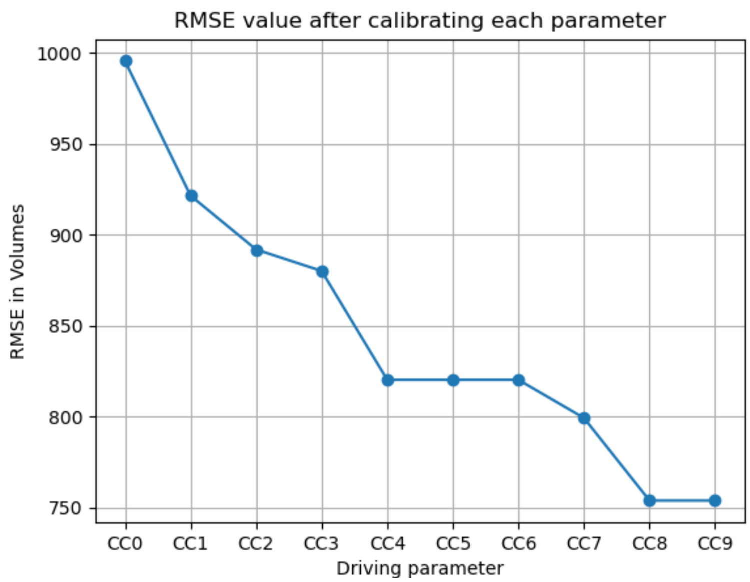


Figure 6-9 RMSE value after calibrating each parameter for Nashville Site2 (N2)

The graph illustrates the RMSE values after calibrating each driving parameter for Nashville Site 2. The x-axis represents various driving parameters labeled from CC0 to CC9, while the y-axis shows the RMSE values in volumes. The graph demonstrates a consistent decline in RMSE as each subsequent parameter is calibrated, indicating an overall improvement in model accuracy. The RMSE decreases significantly from CC0 to CC3, followed by a slower decline up to CC7. The most substantial reduction is observed between CC7 and CC9, where the RMSE reaches its lowest point. This suggests that the final parameters (CC8 and CC9) play a crucial role in optimizing the model, further reducing the error and enhancing the model's performance.

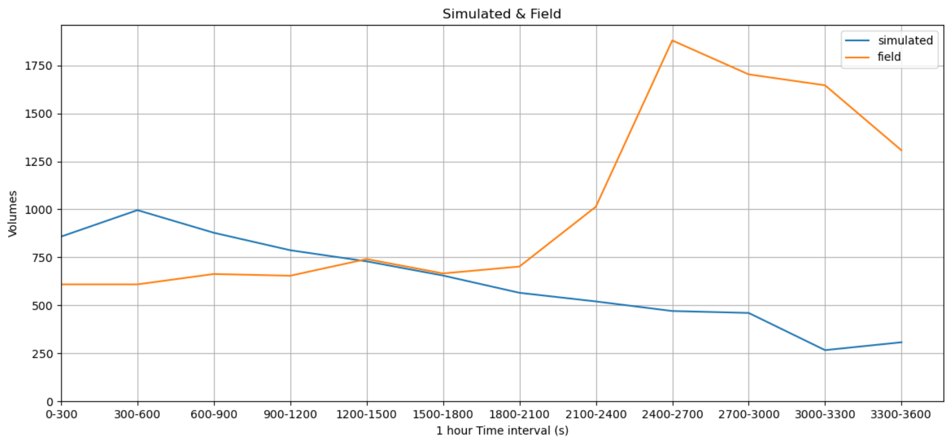


Figure 6-10 Comparing field and simulated volumes for Nashville Site2 (N2)

The graph compares the field and simulated volumes for Nashville Site 2 across various 1-hour time intervals, represented on the x-axis in seconds. The y-axis displays the volume. The blue line represents the simulated volumes, which show a gradual decrease over time, with slight fluctuations. In contrast, the orange line represents the field volumes, which start lower but display a significant increase after the 1500-1800 second interval, peaking between 2400-2700 seconds before declining again. The disparity between the simulated and field volumes becomes more pronounced in the latter half of the time intervals, particularly around the 2400-2700 second mark, where the field data significantly surpasses the simulated values. This indicates that the simulation may not fully account for certain dynamic factors observed in the field, leading to a divergence between predicted and actual volumes as time progresses.

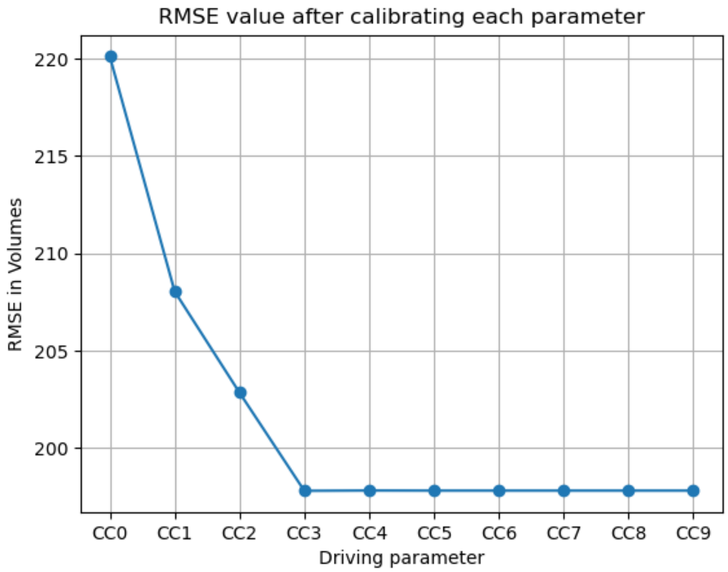


Figure 6-11 RMSE value after calibrating each parameter for Chattanooga Site1 (C1)

The graph in Figure 6-11 illustrates the RMSE values after calibrating each driving parameter (CC0 to CC9) for Chattanooga Site 1. The graph shows a sharp decrease in RMSE from CC0 to CC3, indicating that the calibration of these initial parameters significantly improves the model's accuracy. Beyond CC3, the RMSE values level off, showing little to no further improvement with additional parameter calibration. This pattern suggests that the most critical adjustments for reducing error and enhancing model performance at Chattanooga Site 1 are achieved through early parameter calibration.

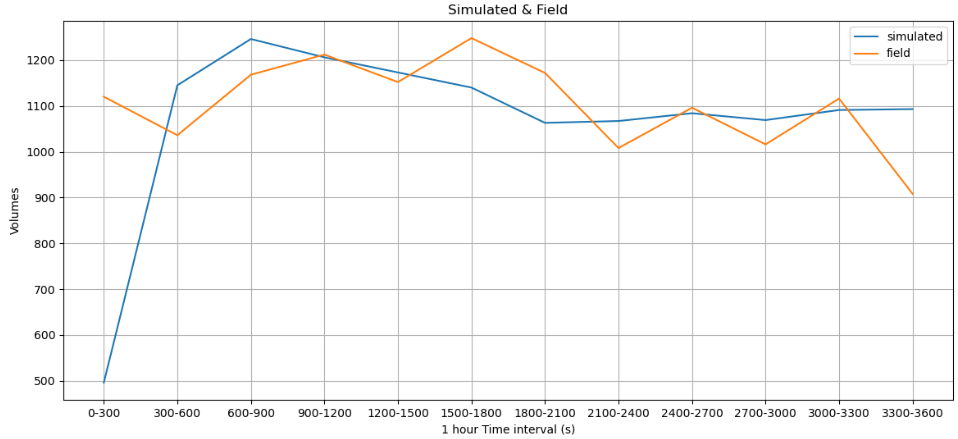


Figure 6-12 Comparing field and simulated volumes for Chattanooga Site 1 (C1)

The graph in Figure 6-12 compares the field-observed and simulated traffic volumes for Chattanooga Site 1 across different 1-hour time intervals. The simulated volumes (blue line) closely follow the trend of the field volumes (orange line), with the two lines almost overlapping in several intervals. This alignment suggests that the simulation model for Chattanooga Site 1 is well-calibrated and accurately replicates the real-world traffic conditions observed in the field. Although there are minor discrepancies in certain intervals, the overall agreement between the simulated and field volumes indicates a high level of model accuracy for this site.

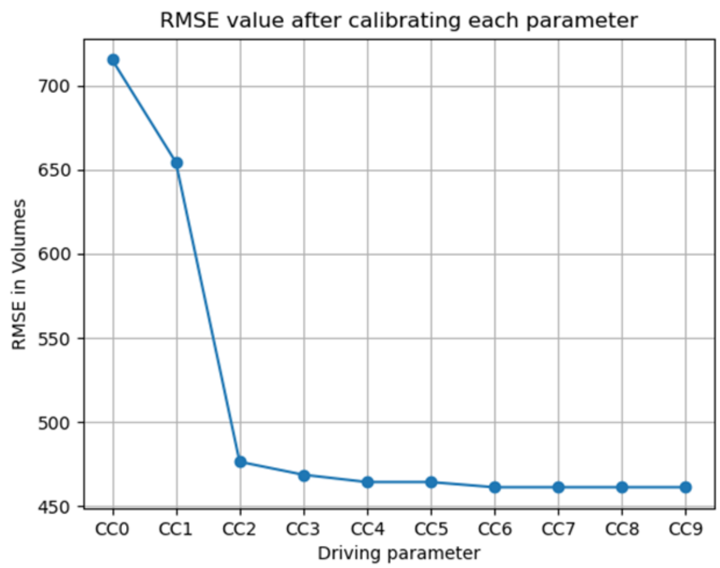


Figure 6-13 RMSE value after calibrating each parameter for Chattanooga Site2 (C2)

The graph in Figure 6-13 shows the RMSE values after calibrating each driving parameter (CC0 to CC9) for Chattanooga Site 2. The graph indicates a significant reduction in RMSE from CC0 to CC2, with the RMSE value dropping sharply. After CC2, the RMSE values plateau, showing minimal further reduction with the calibration of subsequent parameters. This suggests that the early parameters (CC0 to CC2) play a crucial role in improving the model's accuracy, while additional parameter calibration beyond CC2 has a limited impact on further reducing the RMSE at Chattanooga Site 2.

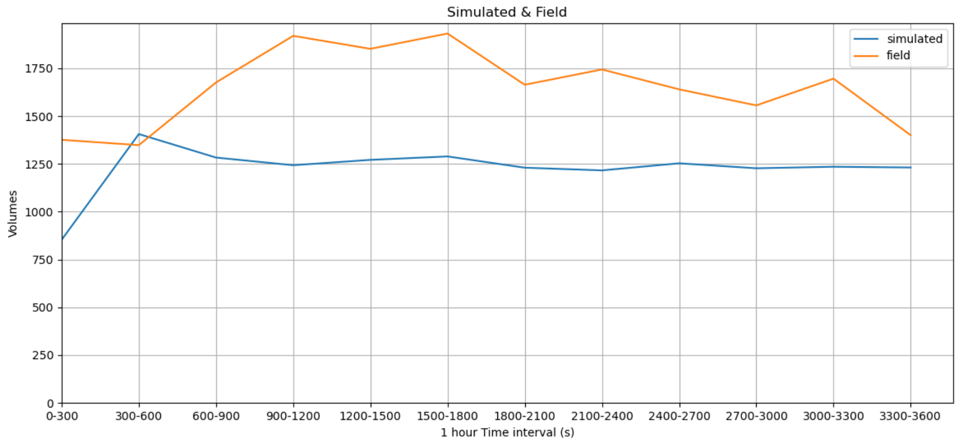


Figure 6-14 Comparing field and simulated volumes for Chattanooga Site2 (C2)

The graph in Figure 6-14 compares the field-observed and simulated traffic volumes for Chattanooga Site 2 across various 1-hour time intervals. The field volumes (orange line) exhibit a noticeable upward trend initially, peaking around the middle intervals, and then slightly decreasing towards the later intervals. In contrast, the simulated volumes (blue line) remain relatively stable throughout the entire time, showing little fluctuation.

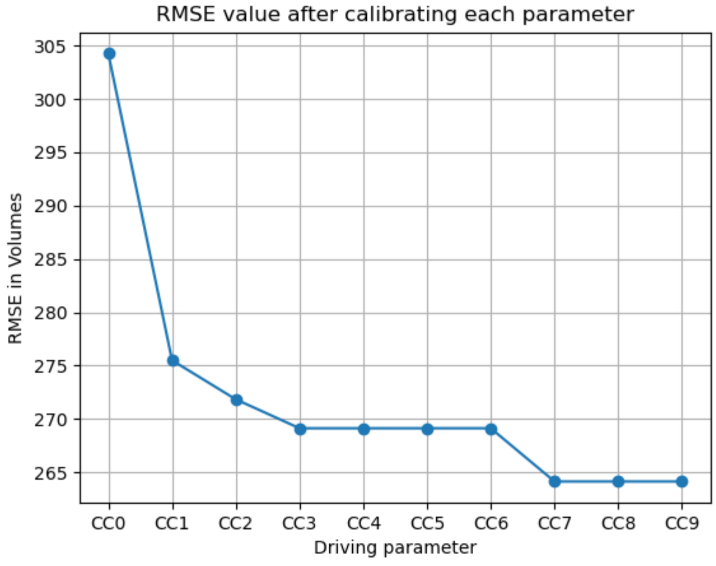


Figure 6-15 RMSE value after calibrating each parameter for Knoxville Site 1 (K1)

The graph presents the RMSE values after calibrating each driving parameter for Knoxville Site 1The trend of the graph indicates a significant decrease in RMSE from CC0 to CC1, followed by a gradual decline in RMSE as subsequent parameters are calibrated. The RMSE value stabilizes around CC7, indicating that beyond this point, further calibration of additional parameters has minimal impact on reducing the error. This suggests that parameters up to CC7 contribute most significantly to improving the model's accuracy.

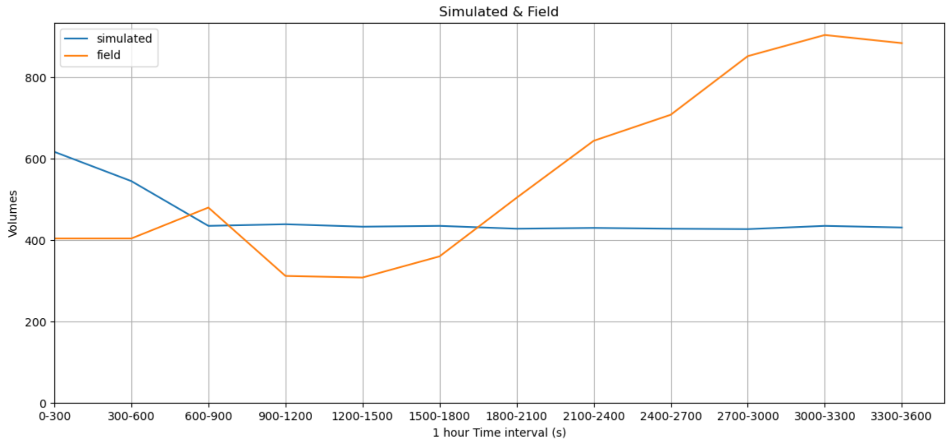


Figure 6-16 Comparing field and simulated volumes for Knoxville Site1 (K1)

The graph compares the simulated and field volumes for Knoxville Site 1 over different time intervals. The x-axis represents 1-hour time intervals in seconds, ranging from 0-3600 seconds, while the y-axis displays the volume. The blue line represents the simulated volumes, which remain relatively stable throughout the time intervals, with minor fluctuations. In contrast, the orange line represents the field volumes, which start near the simulated values but show a significant dip between 600-1200 seconds, followed by a gradual increase, peaking towards the end of the interval. The divergence between the field and simulated volumes indicates a disparity between the model's predictions and actual field observations, especially in the later time intervals.

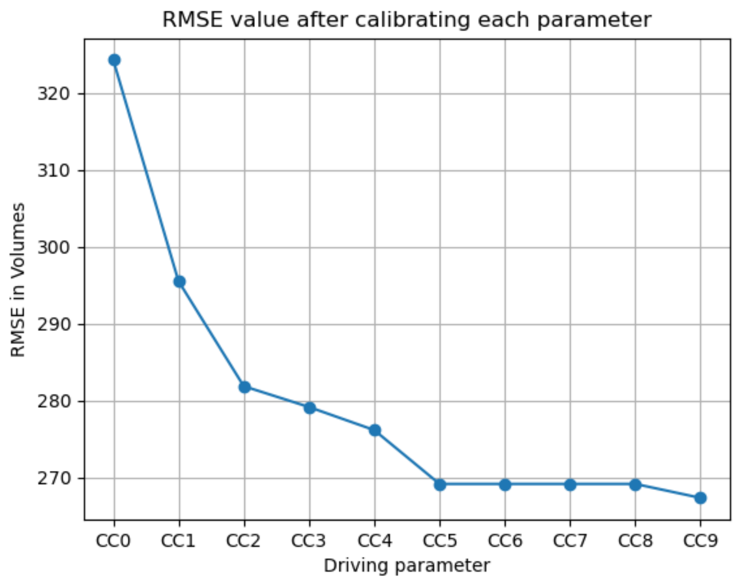


Figure 6-17 RMSE value after calibrating each parameter for Knoxville Site2 (K2)

The graph illustrates the RMSE values after calibrating each driving parameter for Knoxville Site 2. The graph demonstrates a sharp decrease in RMSE from CC0 to CC1, followed by a more gradual decline through CC4. From CC5 onwards, the RMSE values stabilize, with minimal changes observed between CC6 and CC9. This trend suggests that the initial parameters (CC0 to CC4) have a significant impact on reducing the RMSE, while further calibration beyond CC5 yields diminishing returns. The final RMSE value settles close to 270, indicating a well-calibrated model with reduced error by the time all parameters have been adjusted.

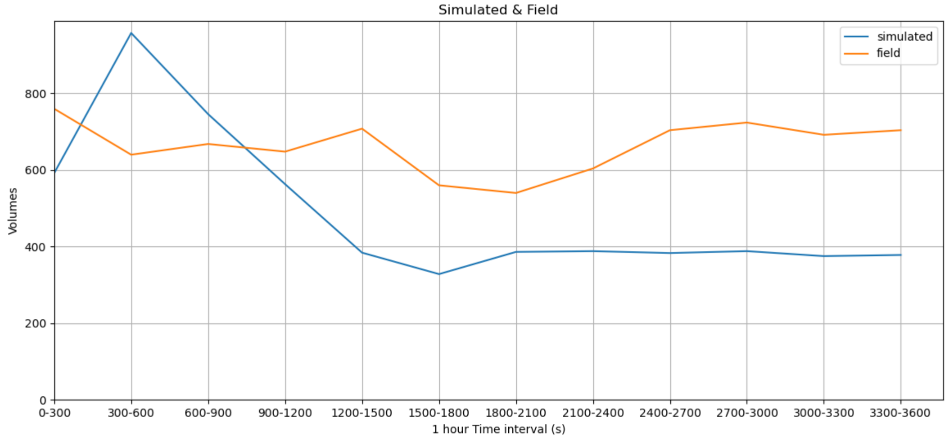


Figure 6-18 Comparing field and simulated volumes for Knoxville Site2 (K2)

The graph compares the field and simulated volumes for Knoxville Site 2 across various 1-hour time intervals, depicted on the x-axis in seconds. The y-axis represents the volume. The blue line corresponds to the simulated volumes, which show a noticeable decline between the 0-1500 second mark, reaching a low point between 1500-1800 seconds before stabilizing with slight fluctuations. The orange line represents the field volumes, which remain relatively stable with minor variations throughout the time intervals, consistently higher than the simulated volumes after the 1500-1800 second interval. The initial period shows the simulated volumes exceeding the field data, but the trend reverses as time progresses. This divergence highlights potential discrepancies between the model's predictions and actual field observations, particularly in the later time intervals, where the field data does not match the decreasing trend of the simulated volumes.

6.3 Comparative Assessment of VISSIM Model Parameters Across Various Freeway Segments

The VISSIM simulation model is widely used to replicate real-world traffic behavior, and its accuracy depends significantly on the calibration of various parameters. The comparison between default and calibrated values across different freeway segments in Memphis, Nashville, Knoxville, and Chattanooga highlights the differences in driving behaviors and road characteristics (Table 6-1).

The calibrated values of standstill distance (CC0) ranges from 2 ft to 10 ft across different sites. The calibrated values for CC0 show considerable variation, indicating that drivers at different sites maintain different following distances when stopped. For instance, Chattanooga and Knoxville have higher calibrated values, aligning with field data (see Table 5-1) that suggests drivers in these areas tend to maintain larger gaps, particularly during certain seasons.

The calibrated values of headway (i.e., time gap CC1) are uniformly adjusted to 0.5 sec across all sites. The reduction in CC1 from the default value suggests that the typical headway between vehicles was shorter than initially assumed in the model, which might indicate denser traffic conditions or more aggressive driving behavior across all sites.

Table 6-1 Final VISSIM Model Parameters for the Chosen Study Sites

Sites		M1	M2	N1	N2	K1	K2	C1	C2
Parameters	Default	Calibrated Values							
CC0: Standstill distance	4.9	6	2	2	6	10	4	2	2
CC1: Gap time distribution	0.90	0.9	0.5	0.5	0.5	0.5	0.5	0.5	0.5
CC2: Following distance oscillation	13.12	10.25	20	5	12.5	16.25	10.25	12.5	5
CC3: Threshold for entering 'Following'	-8.00	-4	-8	-4	-6.75	-9.5	-6.75	-6.75	-15
CC4: Negative speed difference	-0.35	-0.35	-0.35	-0.35	-0.55	-0.35	-0.55	-0.35	-0.78
CC5: Positive speed difference	0.35	0.35	0.35	0.35	0.35	0.35	0.78	0.35	0.33
CC6: Distance dependency of oscillation	11.44	15.50	11.44	15.5	11.44	11.44	11.44	11.44	11
CC7: Oscillation acceleration	0.82	1.50	0.82	0.75	1.25	1	0.82	0.82	0.82
CC8: Acceleration from standstill	11.48	11.48	6.4	8.2	10	11.48	11.48	11.48	11.48
CC9: Acceleration at 50 mph	4.92	4.92	4.92	4.92	4.92	4.92	6.15	4.92	4.92

The wide range in calibrated following distance oscillation (i.e., CC2) values (ranging from 5 ft to 20 ft) indicates varying levels of driver comfort with maintaining a steady following distance. For example, Knoxville Site2 (K2) shows a higher following distance oscillation (i.e., 16.25 ft), implying that drivers in this area may exhibit more fluctuation in following distance, possibly due to less consistent traffic flow or varying road conditions.

The calibrated values of threshold for entering 'Following' (i.e., CC3) range from -15 ft/s^2 to -4 ft/s^2, with Chattanooga Site2 (C2) and Memphis Site1 (M1) having the lowest and highest values, respectively. The negative values reflect how quickly drivers are willing to start following the vehicle in front closely. The higher calibrated threshold at Chattanooga Site2 (i.e., -15 ft/s^2) suggests more cautious driving, aligning with the longer standstill distances (i.e., CC0) observed in the field data.

The final values of distance dependency of Oscillation (i.e., CC6) range from 11 ft to 15.5 ft. The variations in this CC6 parameter suggest that in some areas, like Nashville Site1 and Site2 (i.e., N1 and N2), the oscillation in following distance is more sensitive to changes in headway, potentially indicating more unstable traffic conditions. The calibrated values of CC8 (i.e., acceleration from standstill) range from 6.4 ft/s^2 to 11.48 ft/s^2. The lower CC8 values at some sites suggest drivers accelerate more slowly from a stop, possibly due to more cautious driving behavior or road conditions requiring slower starts.

The differences between default and calibrated values highlight the limitations of using generic parameter settings in traffic simulations. Localized calibration is essential for creating realistic traffic models that reflect actual driver behavior and roadway conditions. Understanding the variability in parameters like CC0 and CC1 helps in designing better traffic flow management strategies. For example, if drivers at a particular site are observed to follow more closely, interventions such as adjusting speed limits or implementing more aggressive traffic calming measures might be necessary to reduce collision risks. Finally, out of all the ten Wiedmann 99 car-following parameters, six parameters namely CC0, CC1, CC2, CC3, CC6, and CC8 came out to be influencing the traffic flow variable such as average traffic flow rate across the various urban freeway segments situated in the four major cities of Tennessee.

7 Summary and Conclusions

The research project has successfully identified and calibrated critical simulation parameters for urban freeway traffic in various Tennessee cities, including Memphis, Nashville, Chattanooga, and Knoxville. The results highlight the significant impact of calibration parameters on the accuracy of traffic simulation models. The calibration process considering all the ten Wiedmann 99 car-following parameters led to a noticeable reduction in RMSE values across all sites, underscoring the effectiveness of considering the higher number of parameters in replicating real-world traffic conditions.

The comparative analysis of calibrated parameters across different urban sites revealed notable variations. Memphis and Nashville sites exhibited higher sensitivity to certain parameters such as standstill distance (CC0) and headway time gap (CC1), which required more extensive calibration efforts. In contrast, the Chattanooga and Knoxville sites displayed relatively stable traffic patterns, with calibration results indicating lower RMSE values after fewer iterations. These differences emphasize the need for location-specific calibration when modeling urban freeway traffic.

Parameters such as standstill distance (CC0), time gap (CC1), following distance oscillation (CC2), and acceleration from standstill (CC8) were critical to achieving accurate simulations. These parameters, when calibrated, significantly influenced traffic flow variables, such as average speed, volume, and density.

The analysis of standstill distance (i.e., CC0) across different sites highlighted its critical role in traffic dynamics. Variations in CC0, ranging from 2 ft to 10 ft, directly impacted volume and density metrics under different congestion scenarios. Higher CC0 values were associated with lower peak volumes, suggesting reduced traffic flow capacity under increased congestion.

The study's analysis of the Wiedemann 99 car-following parameters, particularly CC0, CC1, CC2, CC3, CC6, and CC8, provided insights into driver behavior across the different urban segments. The variability in these parameters emphasized the need for localized calibration to account for regional differences in driving patterns and road conditions.

The calibrated simulation models offer valuable insights for traffic management and infrastructure planning in Tennessee's urban areas. By accurately replicating traffic conditions, these models can be used to test various traffic management strategies, such as optimizing signal timings, modifying lane configurations, or implementing congestion mitigation measures. The ability to simulate the impact of different strategies before implementation can lead to more informed decision-making and improved traffic flow.

Despite the success of the calibration process, several challenges were encountered. The availability and quality of real-world traffic data were critical factors in ensuring accurate calibration. In some cases, data limitations required the use of alternative approaches or assumptions, which could impact the reliability of the simulation models. Additionally, the complexity of the calibration process, particularly in highly congested areas, highlighted the need for further refinement and automation of the calibration techniques.

Future research should focus on refining the calibration methodologies and expanding the scope of the models to include additional factors, such as weather conditions, incidents, and varying traffic compositions. Integrating real-time data into the simulation models could also enhance their accuracy and applicability. Moreover, exploring the use of advanced machine learning techniques for automated calibration could streamline the process and improve the models' predictive capabilities.

The calibrated models developed in this research provide a robust foundation for traffic simulation and management in Tennessee's urban areas. It is recommended that transportation agencies and planners use these models to evaluate potential infrastructure projects and traffic management strategies. Regular updates to the models, based on new data and evolving traffic patterns, will be essential to maintaining their relevance and accuracy over time. Additionally, collaboration with local authorities to integrate these models into broader transportation planning efforts will maximize their impact on improving traffic conditions across the state.

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Glossary Items and Definitions

VISSIM	A microsimulation software used for modeling traffic operations and evaluating transportation systems, including urban freeways.
Calibration	The process of adjusting model parameters to ensure the outputs of a simulation replicate observed real-world traffic conditions.
Validation	The process of comparing simulation results with independent real-world data to confirm the model's accuracy after calibration.
Microsimulation Model	A traffic simulation model that represents the movement of individual vehicles based on driver behavior and vehicle dynamics.
Urban Freeways	High-capacity roadways located in urban areas designed for high-speed vehicular traffic with controlled access points.
Free Flow Speed	The speed at which a vehicle travels under low traffic density and without impedance from other vehicles.
Headway	The time or distance between two consecutive vehicles traveling in the same lane.
Gap Acceptance	The minimum acceptable time or distance gap between vehicles that a driver considers safe for merging or crossing.
Driver Behavior Parameters	Parameters in microsimulation models that influence how drivers interact with traffic, such as car-following, lane-changing, and gap-acceptance behavior.
Car-Following Model	A model used in traffic simulation to describe how a driver adjusts their speed to maintain a safe distance from the vehicle ahead.
Lane-Changing Model	A component of traffic simulation models that determines how and when a vehicle changes lanes based on traffic conditions and driver behavior.
Capacity	The maximum hourly rate at which vehicles can traverse a point on a roadway under prevailing conditions.
Traffic Flow Characteristics	Metrics that describe the behavior of traffic on a roadway, including speed, density, and volume.
Root Mean Square Error (RMSE)	A statistical measure used to evaluate the difference between observed and simulated data during calibration and validation.
Mean Absolute Percentage Error (MAPE)	A measure of prediction accuracy in a calibration process, expressed as a percentage of observed data.
Traffic Volume	The number of vehicles passing a point on a roadway within a specified time period, usually expressed in vehicles per hour (vph).

Queue Length	The length of vehicles waiting at a bottleneck or traffic signal.
Bottleneck	A section of roadway where traffic flow is restricted, leading to congestion or queues.
Speed-Flow Relationship	A functional relationship describing how traffic speed varies with traffic volume or density.
Time Step	The smallest unit of time used in the simulation model to update the positions and movements of vehicles.
Sensitivity Analysis	A method used to determine how changes in input parameters affect the outputs of a simulation model.
Simulation Run	A single execution of the microsimulation model with specified input parameters to generate traffic performance outputs.
Iterative Process	A repetitive process of adjusting model parameters, running simulations, and comparing results with observed data until calibration criteria are met.
Congestion	A traffic condition characterized by slower speeds, longer trip times, and increased vehicle queue lengths due to high traffic demand.
Observed Data	Real-world traffic measurements, such as speed, volume, and density, collected through field studies or traffic sensors for model calibration and validation.
Default Parameters	The preset values in VISSIM may need adjustment during the calibration process to better reflect local traffic conditions.
Traffic Demand	The volume of traffic generated by users of the roadway system, often represented in origin-destination matrices for simulation inputs.
Origin-Destination (O-D) Matrix	A table representing the demand for travel between different zones in a simulation model.
Stochastic Variability	The random variability inherent in simulation outputs due to probabilistic inputs and modeling assumptions.
Scenario Analysis	The evaluation of different traffic conditions, such as peak hour or incident scenarios, using a calibrated microsimulation model.
GEH Statistic	A formula used to compare observed and simulated traffic volumes, particularly in traffic model validation.
Travel Time	The time taken by a vehicle to traverse a specific segment of the roadway, often used as a performance measure in calibration

Appendices

A. Checklist for Calibration and Validation of VISSIM Models

Task	Details	Completion Status
1. Data Preparation		
Traffic Volume Data	Ensure real-world traffic volumes are collected and properly formatted for use in VISSIM.	✓
Vehicle Composition	Verify that observed vehicle mix (cars, trucks, buses, etc.) aligns with VISSIM model inputs.	✓
Speed and Density Data	Use speed and density metrics from real-world observations for comparison during calibration.	✓
2. Model Setup		
Network Geometry	Match VISSIM links/connectors to actual site geometry or proposed designs in project plans.	✓
Lane Configuration	Confirm that lanes, turn bays, and merges match real-world or planned configurations.	✓
3. Calibration Parameters		
Wiedemann 99 Parameters	a) *Identify Key Calibration Parameters to Adjust:* Begin with incremental adjustments to the following parameters CC0 (Standstill Distance), CC1 (Headway Time), CC2 (Following Distance Oscillation), CC3 (Threshold for Entering Following), CC6 (Oscillation Dependency Distance), and CC8 (Acceleration from Standstill).	✓
	b) *Avoid Adjusting Non-Essential Parameters Without Robust Data*: Do not adjust the following parameters unless specific issues are observed. CC4 (Negative Speed Difference) is not	✓

	critical unless behavior-specific calibration is required. CC5 (Positive Speed Difference) is typically less impactful on MOEs, and CC9 (Acceleration at 50 mph) can be kept at default values unless high-speed behavior modeling is necessary.	
	c) *Perform Systematic Adjustments*: Adjust one calibration parameter at a time to identify its effect on model results. Document the impact of each adjustment on the Measures of Effectiveness (MOEs).	✓
	d) *Iterative Refinement*: Evaluate the changes in model performance after each parameter adjustment. Fine-tune parameters iteratively until MOE targets (e.g., travel time, queue lengths, vehicle delay) are met.	✓
Desired Speed Distribution	Set realistic speed ranges reflecting observed field data for each lane and vehicle type.	✓
4. Model Validation		
Volume Comparison	Compare simulated and observed volumes at key points; adjust as needed.	✓
Speed Comparison	Ensure simulated speeds reflect observed speeds, considering regional traffic flow characteristics.	✓
Density and Headway Checks	Validate density metrics and headway distributions against real-world measurements.	✓
5. Performance Metrics		
Root Mean Square Error (RMSE)	Calculate RMSE between simulated and observed data; target minimal deviation.	✓

Additional MOEs	Verify MOEs such as travel time, queue lengths, or vehicle delay align with field observations.	✓
6. Final Adjustments		
Iterative Calibration	Refine key parameters through iterative calibration to minimize error metrics.	✓
Sensitivity Analysis	Conduct sensitivity testing on critical parameters to understand model stability.	✓
7. Documentation		
Calibration Report	Document calibration/validation process, parameter adjustments, and rationale.	✓
Final Model Validation	Summarize final MOEs, calibration results, and any validation adjustments for record.	✓

B. Recommendations on ITS Infrastructure Needs

1. Future ITS Infrastructure Needs and Recommendations

Objective: Create a robust framework of guidelines and recommendations for enhancing ITS infrastructure in Tennessee, focusing on filling data collection gaps, improving model integration, and making infrastructure adaptable to changing urban traffic conditions.

Key Recommendations:

1. Enhanced Data Collection and Integration

- **Automated Data Sources**: Leverage automated systems, such as traffic counters, speed sensors, and cameras, especially in high-traffic urban areas, to maintain continuous data collection on traffic volumes, speed distributions, and congestion patterns. Automated systems ensure that data is consistently available, allowing more accurate tracking of traffic changes and patterns over time.
- **Data Gaps Identification**: Identify areas lacking sufficient traffic data, particularly at high-risk intersections, key freeway corridors, and zones that frequently experience congestion. Understanding these gaps enables targeted efforts to improve data coverage, helping create more representative traffic models and effective ITS solutions.
- **Dynamic Data Collection**: Use real-time data collection systems—such as connected vehicle data or adaptive signal controllers—that feed into VISSIM and other traffic simulation models. Real-time data allows for adaptive responses to current conditions, providing a basis for dynamic traffic flow adjustments and more accurate model calibration.

2. Real-Time Data and Adaptive Modeling

- **Connected Infrastructure**: Integrate real-time data from connected infrastructure components, such as traffic signal controllers, ramp meters, and connected vehicle systems. This integration allows for adaptive simulation and traffic management, adjusting traffic flows based on current conditions rather than relying on static pre-set configurations. Real-time connectivity is key for enabling adaptive responses to congestion, incidents, and peak demand.

- **Integration of ITS Technologies**: Deploy advanced ITS solutions, such as adaptive signal controls (adjusting traffic light timing based on real-time conditions) and variable speed limits that respond dynamically to congestion levels. These technologies help manage traffic flow and reduce congestion at critical sites, improving efficiency across the urban network.

3. Automated Calibration through Machine Learning (ML)

- **Automated Calibration**: Use ML techniques for the automated calibration of traffic simulation models. With real-time data input, ML algorithms can optimize parameters like headway (the distance or time between vehicles) and vehicle spacing, ensuring models adapt to actual driving behaviors and regional variations. This automated calibration reduces the manual effort required and enhances model accuracy.
- **Predictive Traffic Modeling**: Leverage ML and AI to predict traffic patterns based on historical data and current real-time inputs. By anticipating future congestion or traffic events, these predictive models enable proactive traffic management, allowing planners to deploy strategies before issues arise.

2. Guidelines for ITS Infrastructure Expansion

Objective: Establish a structured approach for deploying ITS technologies suited to the unique requirements of Tennessee's urban transportation network, ensuring systems are responsive, scalable, and efficient.

Guidelines:

1. Site Selection for ITS Deployment

- **Criteria for Selection**: Prioritize urban regions with high traffic volumes, diverse vehicle types (e.g., trucks, buses, passenger cars), and frequent congestion. Focusing on these areas ensures that ITS resources are directed to where they will have the most substantial impact on traffic flow, safety, and efficiency.
- **Proximity to Key Facilities**: Target deployment near key locations like the interstate I-40 (an area of high traffic activity) and major commuter routes. These areas will benefit from enhanced connectivity and adaptive ITS

solutions, improving travel times and reducing congestion impacts on surrounding regions.

2. Technical Specifications for ITS Components

- **Data Compatibility**: Ensure that ITS hardware and sensors (such as traffic detectors, cameras, and controllers) are compatible with existing traffic management software. This compatibility allows for seamless data transfer and integration, enhancing real-time responsiveness and simplifying data sharing across platforms.
- **Future-Proof Technology**: Select ITS infrastructure components that are modular and upgradeable. Technologies should accommodate evolving traffic patterns, new developments in vehicle automation, and emerging trends in connectivity. For instance, adaptive signal controllers should be capable of incorporating future data sources from autonomous vehicles.

3. Evaluation and Reporting Standards

- **MOE (Measures of Effectiveness) Standards**: Define specific MOEs and KPIs, such as congestion reduction, average delay, fuel consumption, or emissions levels, to evaluate ITS systems' effectiveness consistently. These metrics provide an objective basis for assessing how well ITS implementations meet traffic management goals.
- **Performance Audits**: Conduct quarterly audits to evaluate the ongoing impact of ITS solutions. These audits should compare observed traffic conditions against baseline metrics, using data-driven adjustments to optimize performance. Regular performance audits enable quick responses to any emerging inefficiencies, keeping the ITS system effective over time.