Calibrating Real-World City Traffic Simulation Model Based on Vehicle Speed Data

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***Abstract*—Large-scale traffic simulations are necessary for the planning, design, and operation of city-scale transportation systems. These simulations enable novel and complex transportation technology and services such as optimization of traffic control systems, supporting on-demand transit, and redesigning regional transit systems for better energy efficiency and emissions. For a city-wide simulation model, big data from multiple sources such as Open Street Map (OSM), traffic surveys, geo-location traces, vehicular traffic data, and transit details are integrated to create a unique and accurate representation. However, in order to accurately identify the model structure and have reliable simulation results, these traffic simulation models must be thoroughly calibrated and validated against real-world data. This paper presents a novel calibration approach for a city-scale traffic simulation model based on limited real-world speed data. The simulation model runs a microscopic and mesoscopic realistic traffic simulation from Chattanooga, TN (US) for a 24-hour period and includes various transport modes such as transit buses, passenger cars, and trucks. The experiment results presented demonstrate the effectiveness of our approach for calibrating large-scale traffic networks using only real-world speed data. This paper presents our proposed calibration approach that utilizes 2160 real-world speed data points, performs sensitivity analysis of the simulation model to input parameters, and genetic algorithm for optimizing the model for calibration.**

***Index Terms*—Transit simulation, large-scale traffic simulation, calibration, microscopic simulation, mesoscopic simulation, transportation planning, SUMO**

I. INTRODUCTION

Traffic simulation is used to simulate the movement of vehicles, people, and other components of the transportation system in a virtual environment. Traffic simulations provide a cost-effective, secure, adaptable, and repeatable environment for evaluating traffic management and safety scenarios, offering a wide range of conditions for analysis and data collection while minimizing risks to drivers and passengers. Additionally, simulations allow for precise data collection and analysis, contributing to the improvement of traffic management and safety. The planning, design, and operation of these transportation systems require large-scale city-wide traffic simulations that mirror real-world operations. Such simulations can also help with designing and optimizing transit systems for better energy efficiency and emissions. However, this is computationally hard due to the immense size and high complexity of the decision space. Data-driven strategies are also not practical, as they require large data sets that cover all variations observed in the real world. In order to deal with these challenges, we previously developed some dynamic simulation platforms, called *Transit-Gym* [1], *BTE-Sim* [2] and *E-transit-bench* [3] that provided a novel intuitive method to specify, generate, execute, and analyze a variety of transit scenarios through integrated transit simulations. However, for direct application of these simulation-based analyses of alternative transit scenarios, the underlying traffic simulation models must closely mirror the real world.

Urban planners utilize large-scale traffic simulation to assess traffic flow and congestion after installing highways or public transit systems. Small-scale traffic model on the other hand can help urban planners and traffic researchers optimize traffic flow in specific places and evaluate traffic management measures including traffic signal timing and lane arrangement. The scale of the network is an important consideration in traffic simulation models and calibration. One key issue related to the scale of the network is the trade-off between model complexity and computational efficiency. As the size and complexity of the network increase, the computational demands of the simulation also increase, which can lead to longer simulation times and more difficulty in calibrating the model. This can be particularly challenging in urban areas, where the network may be very large and complex. The calibration of large-scale traffic simulation models is a crucial step adjusts a traffic simulation model's parameters and assumptions to approximate real-world traffic. Despite its importance, there is a lack of studies in this area, and existing calibration techniques often focus on small-scale networks. The current academic literature is deficient in the realm of calibration techniques for large-scale microscopic traffic models. To address this gap, the present paper introduces a pioneering methodology for calibrating such city-wide models.

For the calibration of traffic simulations, real-world speed data is advantageous. By adjusting the simulation to reflect actual driving patterns and conditions, it enhances traffic flow and behavior modeling. This can improve simulation forecasts and assist researchers in finding problems with traffic control and safety. In addition, speed data calibration enables the validation of simulation precision. By comparing simulated findings to actual data, researchers can assess the simulation's accuracy and identify errors. This can help the simulation's ability to predict traffic patterns and identify issues. Finally, calibrating the simulation using real-world speed data aids in taking into account changes in behavior and traffic flow over time. This aids in improving forecasts by allowing researchers to modify the simulation to account for seasonal or other variations in traffic patterns. Overall, a traffic simulation's accuracy, dependability, and effectiveness in predicting traffic patterns and identifying weaknesses are improved by calibrating it using actual speed data. Calibrating a traffic simulation model using real-world speed data can be a complex process, and it requires a good understanding of the underlying traffic dynamics and the characteristics of the road network being studied.

Traffic flow models are categorized based on their level of complexity and granularity as macroscopic, mesoscopic, and microscopic. Macroscopic models use queuing theory to analyze traffic at a high level without modeling individual vehicles. Microscopic models provide precise simulation of individual vehicles and paths, but are computationally expensive. Mesoscopic models use statistical methods and are a compromise between macroscopic and microscopic models in terms of model accuracy and simulation performance. For this study, we use both mesoscopic and microscopic simulations in order to accurately model travel demand by all agents and on all routes. For a realistic calibrated model, it must accurately reflect the local driver behavior and traffic conditions.

Overall, the contribution of this article has the following points:

1) We present a city-scale traffic simulation model of Chattanooga, Tennessee, provide several use cases for its analysis. The study focuses on implementing microscopic and mesoscopic large-scale (with the total lane length of 13455 km and 28311 junctions) SUMO [4] simulations using activity-based OD data.
2) While similar works have used flow and density for calibration [5],[6],[7], our paper uses real-world speed data (RSD). Calibration of traffic simulations with real-world speed data can improve accuracy, validation, and reliability. This can help predict traffic patterns and account for changes over time.
3) Using genetic algorithm (GA) to calibrate a traffic simulation by optimizing its parameters to minimize the difference between simulated and observed traffic data.

II. Related Work

In this section, we briefly review the existing literature on the development towards the calibration of traffic simulation models. The calibration variables for a simulation model are categorized by the constituent model component whose inputs and parameters are being considered. In general, there are two types of simulation model components: *demand models* for estimating and forecasting the OD trip volumes and simulating travel behavior parameters[5],[6],[7],[8] and *supply models* for capturing traffic dynamics and traffic flow parameters estimation [9],[10],[11],[12]. Moreover, traffic assignments are used in a loop to iteratively calibrate or relax trip generation, trip distribution, and mode choice models. These models allow the transportation planner to predict user behavior and traffic flows in response to changes in transportation infrastructure or services, containing a complete array of traditional demand and supply models [13]. However, the accuracy of these models heavily depends on their calibration, which involves adjusting the model parameters to match real-world data. Calibration ensures that the simulation results are reliable and can be used to make informed decisions.

There have been significant developments in recent years toward the calibration of traffic simulation models. One approach is to use machine learning techniques to automate the calibration process. This involves training a machine learning algorithm to predict the optimal parameter values based on historical data[14]. This method has been shown to be effective in reducing the time and effort required for calibration and improving the accuracy of the simulation results[15]. [16] used a deep reinforcement learning approach to calibrate traffic simulation models. Another approach is to use real-time data from connected vehicles to calibrate the simulation models. This involves collecting data from sensors in vehicles, such as GPS and accelerometers, and using this data to adjust the simulation parameters [17], [18]. This approach has the potential to provide more accurate calibration by incorporating real-time data, but it requires significant infrastructure to collect and process the data. In this paper, the RSD has used for the calibration.

Due to the complexity of highway traffic networks, determining the effects of a large-scale simulation, like the one in this case study, is frequently challenging. The related existing studies vary from small-scale traffic simulation models to medium and large-scale models [19–21]. Each available study on the calibration of a large-scale traffic simulation network concentrates on a set of parameters and algorithms[22].

The studies referenced above, calibration was performed on a small section of a city using available traffic flow data. However, in the real-world case study, only speed data other than traffic flow data can be accessed for the calibration of large-scale models. Therefore, it is necessary to be able to calibrate the traffic model with the speed data. This paper reports the calibration of a large-scale traffic network in Chattanooga, Tennessee, based on the RSD.

III. Methodology

Our proposed methodology is composed of microscopic and mesoscopic simulations, which is calibrated based on the RSD. The calibration procedure employs a measure that minimizes the difference between the RSD and the one obtained from microscopic and mesoscopic simulations. Calibration ensures that the simulation results are reliable and can be used to make informed decisions. Given the multitude of factors that influence traffic characteristics and flow, a consensus was reached to prioritize the parameters with the greatest impact. The utilization of sensitivity analysis and Analysis of Variance (ANOVA) test is employed to identify the most significant parameters of SUMO for the purpose of calibrating the microscopic and mesoscopic models. Subsequently, a genetic algorithm (GA) is devised to derive the optimal values of each of these parameters.

In the following sections, we describe the complete calibration methodology (simulation environment, the SUMO model, and the calibration procedure) for both the microscopic and mesoscopic simulations. Next, we develop a case study to implement and evaluate the calibration methodology.

A. Traffic Simulation Software

SUMO is a widely-used and open-source traffic simulation software that can be easily used on different platforms. It allows for the modeling and evaluation of traffic dynamics in a network and has both microscopic and mesoscopic simulation modes. The software also has an API called Traffic Control Interface (TraCI) which allows for interaction with the simulation.

B. Demand Data

For this study, the origin destination (OD) matrices are provided by the Chattanooga-Hamilton County regional planning agency. The OD matrices describe the demand as well as the mode choice such as the number of passenger cars, and trucks per hour from an origin traffic analysis zone (TAZ) to a destination TAZ.

C. Microscopic simulation

In SUMO microscopic simulation, three dynamical processes are considered:

1- Car-following model: It determines the speed of a vehicle in relation to the vehicle ahead of it.

2- Intersection model: It determines the behavior of vehicles at different types of intersections with regard to right-of-way rules, gap acceptance, and avoidance of blocking junctions.

3- Lane-changing model: It determines lane choices on multi-lane roads and speed adjustments needed for changing lanes.

1) Calibration Parameters: The calibration process is conducted to determine the best parameters for car-following and lane-changing so that our simulation model represents realistic field measurements. In a microscopic simulation model in SUMO, several parameters could be adjusted for model calibration. However, not all of these parameters have a significant effect on the output of the model. Therefore, we used an ANOVA test to determine the parameters that result in statistically significant differences in model outputs.

For the ANOVA test, after selecting a limited part of our network, we generated a set of 75 samples for each parameter within its maximal, normal, and real-world range. Next, we varied the parameters within the ranges to determine how significantly those variations impact the outputs of the simulation model. Because our data consists of a single factor with several levels and multiple observations at each level, we designed and conducted a novel ANOVA test with a one-way layout with a significance value α of 0.05. To evaluate the impact of the controlled parameter on the speed values obtained from SUMO, we kept all other parameters to their default values. The parameters that had p-values less than 0.05 were considered statistically significant. Figure 1 lists these parameters with their associated ranges and their corresponding p-values obtained from the ANOVA test. We found that the Krauß car-following model parameters had significant impact on the network speed. Therefore, for model calibration, we chose the parameters related to the Krauß model – which include the minimum gap allowed between two cars (minGap), the maximum acceleration, maximum deceleration, road speed limit, the driver imperfection (sigma), and the driver's reaction time (tau).

Fig. 1. SUMO parameters with ANOVA test results

parameter	Value		Model	ANOVA P-value
	Minimum	Maximum		
Sigma	0.5	1	krauss, SKOrig, PW2009	1.11E-09
Tau	0	-	all models	1.04E-08
minGap Value	0	-	all models	1.05E-05
accel	0	-	Krauss, SKOrig, PW2009, Kerner, IDM, EIDM, ACC, CACC	1.14E-05
decel	0	-	Krauss, SKOrig, PW2009, Kerner, IDM, EIDM, ACC, CACC	1.1E-08
emergencyDecel	0	-	Krauss, SKOrig, PW2009, Kerner, IDM, EIDM, ACC, CACC	0.504
speedDev	0	-	all models	1.09E-12
stepping	0	-	IDM, EIDM	0.638
adaptFactor	0	-	EIDM	1.18E-08
tpreview	1	-	EIDM	0.765
tPersEstimate	1	-	EIDM	0.9981
treaction	0	-	EIDM	0.441
ccoolness	0	1	EIDM	7.71E-05
sigmaleader	0	1	EIDM	0.69
sigmagap	0	1	EIDM	0.53
sigmaerror	0	1	EIDM	0.671
jerkmax	1	-	EIDM	0.66
epsilonacc	1	-	EIDM	0.815
taccmax	1	-	EIDM	0.953
Mflatness	1	0.5	EIDM	0.47
Mbegin	0	1.5	EIDM	0.73
maxvehpreview	0	-	EIDM	1.45E-07
vehdynamics	0 or 1	-	EIDM	0.77

When simulating traffic on a large-scale network with multi-lane roads, parameters related to lane-changing have a significant effect on the road traffic dynamics. Modeling and calibrating situation adaptive lane changing and merging behavior were discussed in [23] and [24]. According to these studies, there is a hierarchy of change incentives, with strategic lane changing being the most essential. Therefore, related to strategic lane changing behavior, cooperative speed adaptions by surrounding traffic (lcCooperative) in the range of [0,1] has been considered for the calibration, where 0 implies no cooperative lane changing and 1 implies fully automatic speed adjustments.

2) Calibration procedure: In order to find the optimal set of parameters, we used a GA method, and RMSE comparison. GA is a random search technique inspired by evolutionary biology (i.e., inheritance, mutation, natural selection, and recombination) and is used in computer science to find approximate solutions for optimization and search problems. When the search space is broad and complicated, adopting the GA technique can significantly reduce the number of search steps, and the time it takes to finish the search [25]. GAs are described by agents and genes. A *gene* is denoted by a binary digit with value 0 or 1. A single *agent* is defined as a set of genes that indicate the value of each parameter. Furthermore, a *generation* is defined as the number of agents supplied. The number of agents incorporated in one generation is referred to as the *population*, which is 16 in this paper. In a GA, crossover, mutation, and selection are three leading operators required in building the next generation of agents. Selection is a probability based, and the agents with costlier fitness values will most likely be picked. When two agents crossover, a portion of their genes are swapped, resulting in the creation of two new agents. One agent is mutated to create a new agent by adjusting one of its genes from 0 to 1. We use Root Mean Square Error (RMSE) analysis as the fitness function to test and determine the best set of parameters for model calibration.

D. Mesoscopic Simulation

It is time-consuming and difficult to calibrate a substantial urban region in microscopic simulation. Therefore, we have considered other modeling layers in traffic simulations, i.e., mesoscopic traffic simulations. Mesoscopic falls between the section-by-section basis of the macroscopic model approach and the unique interplay of the microscopic ones. The mesoscopic model of SUMO based on queuing theory has been developed by Eissfeldt [26].

1) Calibration parameters: The mesoscopic simulation is influenced by the following parameters: traffic light system penalty (*tls-penalty*), the minimum headway between vehicles, speed deviation factor, and the jam threshold associated with the main mesoscopic modeling hypothesis. Among these parameters, tls-penalty, and speed deviation have the highest impact and is adopted for the calibration procedure. The tls-penalty represents the quality of signal coordination its value ranges from 0 (for near perfect coordination) to 1 (for uncoordinated traffic lights) [27].

2) Calibration procedure: For the mesoscopic model calibration, similar to microscopic calibration, GA method and RMSE analysis were used to find which set of parameters will result in the optimal value of average speed data.

IV. Real-World Case Study and Evaluation

The Chattanooga SUMO Traffic Simulation (CSTS) scenario uses a large geographical area that includes Hamilton County in Tennessee, Catoosa County in Georgia, and two partial counties (Dade and Walker) in Georgia. The model contains 909 TAZs, where a TAZ is a geographic area that is used to divide the planning region into small and relatively homogeneous areas in terms of land use and activity.

A. Data collection

The data sources used in this simulation include the following.

1) Time of the Day: Although different trip purposes have different peaking characteristics, the peak hour periods were determined based on peaking characteristics of internal (travel during the selected counties) auto trips since they were the majority of the trips using the highway facility.

Mode choice models were developed for the following seven trip purposes: Home-Based Work (HBW), Home-Based School (HBSC), Home-Based Shopping (HBSP), Home-Based Social-Recreational (HBSR), Home-Based Pick-up Drop-off (HBPD), Home-Based Other (HBO), and Non-Home-Based (NHB). The distribution of the trips by hour for each trip purpose shows in Figure 2. The criteria used for selecting the peak periods in the Chattanooga model include:

1) Approximately 20%-35% of the total daily trips should occur in each peak period.
2) Peak periods should capture the significant peak hours for HBW, HBSC, and HBPD trips.
3) Selected peak periods should allow for capturing peak spreading in the future because the same time-of-day factors will be applied to the base year and future years.

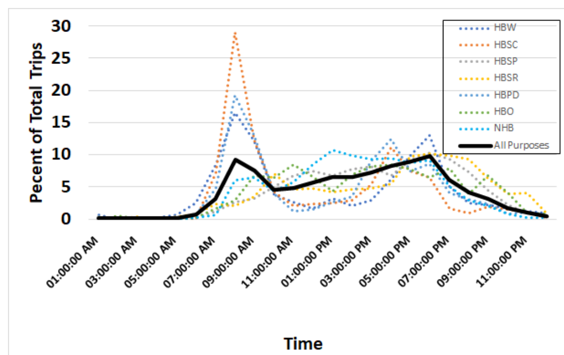

Fig. 2. Hourly Trip Distribution for Each Trip Purpose

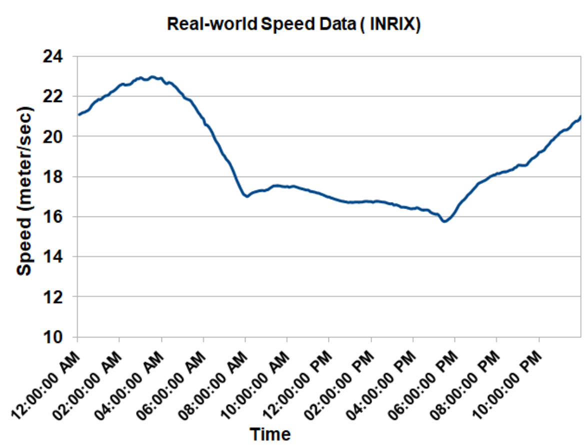

Fig. 3. Annual Average Speed from INRIX Speed Database

Based on the criteria above in the ODs, 6 to 9 AM was selected for *AM peak* period, and 3 to 6 PM was selected for *PM peak* period. The *midday off-peak* period lasts from 9 AM to 3 PM. The *night off-peak* period lasts from 6 PM to 6 AM.

2) Empirical data: For the purpose of calibration, we used the speed-based method. The objective is to match the simulated and actual average speed. We selected 2160 points in the study area. These points are spread over the network and include points on the main street and highways. Owing to the COVID-19 pandemic since 2020, the traffic patterns have changed unexpectedly; however, it is assumed that traffic is getting back to the pre-pandemic level. Therefore, we used data from 2019 to 2020. We developed the model for 24 hours with a time interval of 5 minutes. Hence, 288 5-minute-interval speed data for each point are aggregated from INRIX speed database [28].

The annual average speed for a 24-hour five-minute interval is presented in Figure 3. This figure shows the network speed fluctuates throughout the day. The INRIX date-set speed diagram is very well aligned with the volume of travel during the day (Figure 2). It is clearly demonstrated that the average speed during morning and evening peak hours from 6-9 AM and from 3-6 PM is $16.98m/sec$ and $16.10m/s$, respectively (shown as two minimum points in the curve). These two time periods are morning peak hours and evening peak hours. However, the morning peak has a more pronounced, shorter spike, while the evening peak is spread over a longer time period.

B. Simulation Generation and Execution

The following 1 through 9 steps explains the major processes to generate the SUMO model.

1- Network modification: *OSMWebWizard* is a tool in SUMO that was used to convert the network directly imported from OSM. OSM is a community-generated map, and sometimes important information such as speed limits and traffic signals needs to be inferred from the road category. To ensure accuracy, the study manually checked major road intersections.

2- Vehicle trip generation: *od2trips* is another tool in SUMO that converts each OD pair to a trip throughout a large-scale network.

3- Conversion of TAZ shapefiles to polygon and polygon to edges: *polyconvert* is another tool in SUMO that imports geometrical shapes and converts them to a representation that can be visualized using SUMO-GUI. With a python script, *edgesInDistricts*, we can parse the network and TAZ files with shapes. This script creates a TAZ file that includes all of the edges within the appropriate TAZ.

4- Trip assignment: Trip assignment involves assigning traffic to a transportation network using a static user equilibrium process. Link travel times are modeled based on their volume-to-capacity ratio, and trips are assigned to the shortest travel time path in each iteration. The process is repeated until an equilibrium is reached, where no user benefits from changing their path. In SUMO, this process is performed using a python script called duaIterate, which computes a dynamic user assignment. In SUMO, this process is done by *duaIterate*, a python script to perform the computation of a dynamic user assignment (DUA).

5- Define induction loop detectors: In the simulation model, we defined 2160 induction loop detectors at various locations that correspond to the exact places in the RSD. Detectors in the simulation models perform a different role depending on the direction of traffic flow. The detectors extract the flow characteristics at the time the vehicle is on the detector. Similar to RSD, we have set the aggregation period values as 300 seconds. The output of detectors includes times the vehicle enters and leaves the detector, and average speed during the interval time, occupancy, flow.

6- Set the parameters into a vehicle distribution file: The most significant parameters, identified by ANOVA analysis, were changed around corresponding default values. The optimal set of parameters was determined using a modified genetic algorithm (GA).

7- Configuration generation: The configuration file is a text file that contains all the required input information, network files, trips file, TAZ file, and additional files such as vehicle distribution file.

8- Simulation run: SUMO can be executed with the command line or with a generated configuration file. The execution time is related to the number of vehicles and the scale of the network.

9- Analyzing the results: The output of traffic simulation includes detectors' output data, and trajectories of vehicles should be processed to obtain traffic data for 2160 points at every five-minutes interval.

A flow chart showing the whole of the calibration procedure is shown in Figure 4.

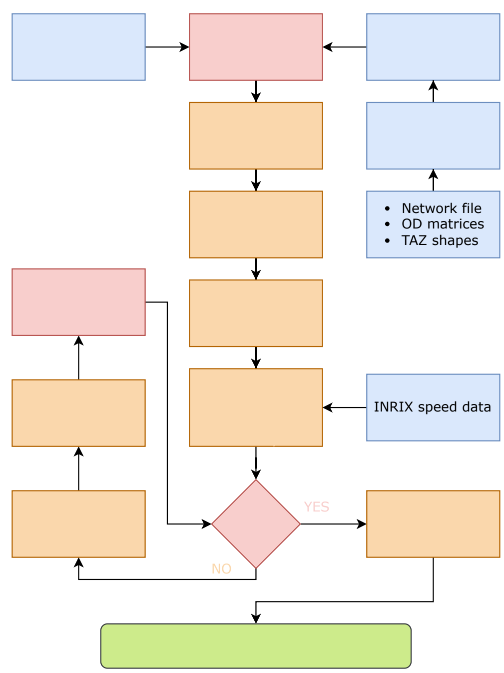

Fig. 4. Calibration Procedure

C. Calibration

In this section, first we introduce the microscopic calibration and then the mesoscopic calibration.

1) Microscopic model calibration : In order to find the optimal set of parameters, we used the ANOVA analysis method, which involved a GA method, and RMSE comparison. GA is a random search technique inspired by evolutionary biology (i.e., inheritance, mutation, natural selection, and recombination) and is used in computer science to find approximate solutions for optimization and search problems. GAs are described by agents and genes. A *gene* is denoted by a binary digit with value 0 or 1. A single *agent* is defined as a set of genes that indicate the value of each parameter. Furthermore, a *generation* is defined as the number of agents supplied. The number of agents incorporated in one generation is referred to as the *population*, which is 16 in this paper. In a GA, *crossover*, *mutation*, and *selection* are three leading operators required in building the next generation of agents. Selection is a probability based, and the agents with costlier fitness values will most likely be picked. When two agents crossover, a portion of their genes are swapped, resulting in the creation of two new agents. One agent is mutated to create a new agent by adjusting one of its genes from 0 to 1. We use Root Mean Square Error (RMSE) analysis as the fitness function to test and determine the best set of parameters for model calibration. The user's statement highlights the process of defining agent and the number of genes, followed by the automatic execution of the SUMO simulation with the specified parameters. The resulting output from SUMO consisted of speed data for vehicles, which was captured at 2160 detectors at regular intervals of five minutes. When the search space is broad and complicated, adopting the GA technique can significantly reduce the number of search steps, and the time it takes to finish the search. Here, the smaller the RMSE, the higher is fitness of the chosen parameter.

For the microscopic simulation, a total of 38 genes are needed to interpret these seven parameters I. Then, using the procedure shown in Figure 4 the minimum RMSE calculated is $1.52m/sec$ which is about 8.09% of the RSD average speed of $18.79m/sec$. Table III illustrates the results from the microscopic calibration, in which the criterion is met after the SUMO runs for 45 generations. The parent list that meets the constraint of RMSE$\leq$ 10% is considered the calibrated parameters of the model, which are listed in Table III. Figure 5 shows the annual average speed of RSD; the results from the simulation running in SUMO before and after calibration. It shows that the calibration improves the model, particularly during the peak hours.

2) Mesoscopic model calibration: Similar to the microscopic simulation calibration, we repeated the entire procedure with the parameters impacting mesoscopic simulation mentioned in Table II. The parameters include speed deviation and tls-penalty. Figure 7 illustrates the RMSE calculated with the contribution of speed deviation and tls-penalty. The minimum RMSE calculated is $1.53m/sec$, which is about 8.14% of the RSD average speed of $18.79m/sec$. The lowest network RMSE value corresponds to SpeedFactor and tls-penalty of 0.17 and 0.7, respectively.

The results presented in Figure 8 show the annual average speed of RSD and the results from the mesoscopic simulation

TABLE I
SET OF PARAMETERS FOR MICROSCOPIC SIMULATION

SUMO Parameter	Min	Max
MinGap	1.5	2.5
Tau	1.0	2.0
Sigma	0.0	1.0
Speed Deviation	0.1	0.2
acceleration	2.5	3.5
deceleration	5.0	5.5

TABLE II
SET OF PARAMETERS FOR MESOSCOPIC SIMULATION

Speed Deviation	0.1	0.11	0.12	...	0.18	0.19
tls-penalty	0.1	0.2	0.3	...	0.9	1.0

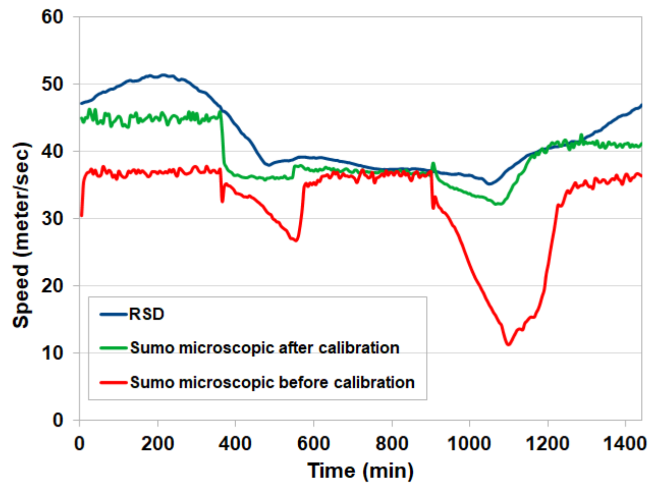

Fig. 5. Comparison of speeds obtained from microscopic simulation before and after calibration against real speed data (RSD)

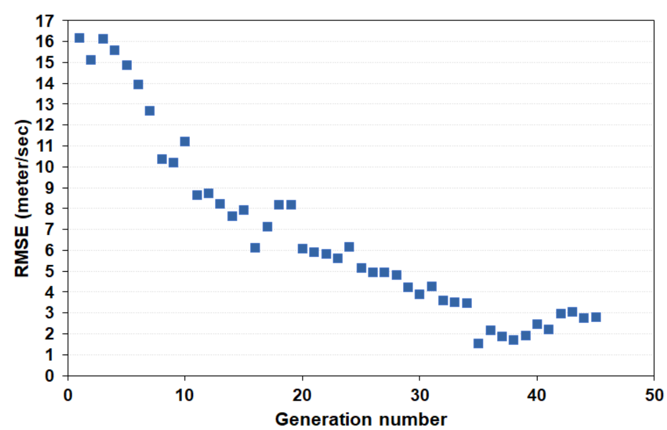

Fig. 6. RMSE in Microscopic Simulation

TABLE III
CALIBRATED VALUES FROM THE TRIAL-AND-ERROR AND GA METHOD

SUMO Parameter	Default Value	Value after Calibration
tau	1.00	1.2
sigma	0.5	0∼0.2
minGap	2.5	1.5
speed deviation	-	0.11
acceleration	2.6	2.5
deceleration	4.5	4.5
lcCooperative	-	0.1

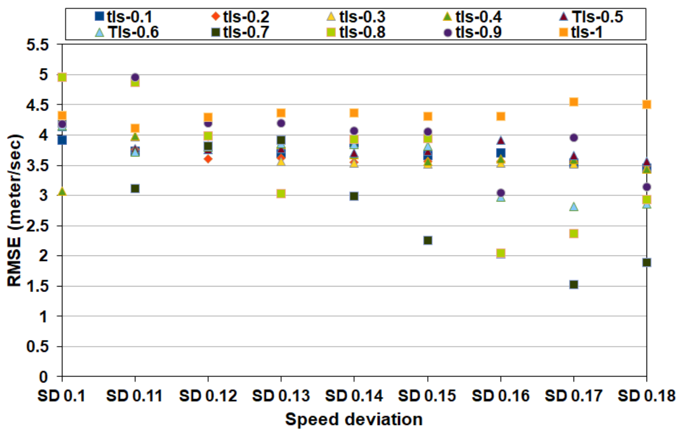

Fig. 7. RMSE in mesoscopic simulation

model of SUMO before and after calibration.

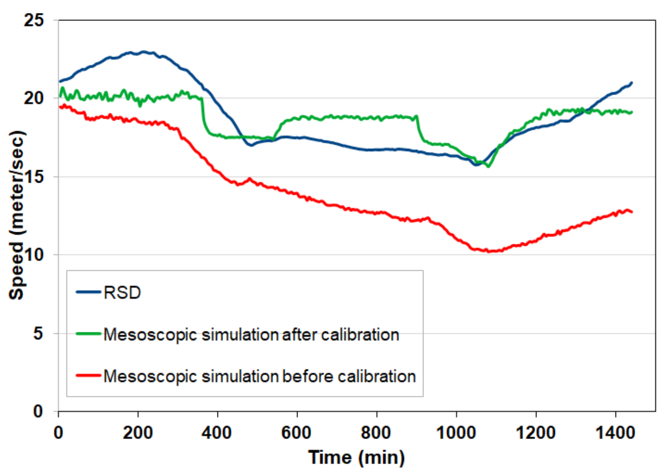

Fig. 8. Comparison of speeds obtained from mesoscopic simulation before and after calibration against real speed data (RSD)

V. CONCLUSION

This paper investigates the potential of speed-based calibration methods for microscopic and mesoscopic simulation models. Based on the OD matrices provided by the Chattanooga-Hamilton County Regional Planning Agency and the CSTS network using a dynamic user assignment method, the trips file was built. We generated microscopic and mesoscopic simulation models of the wider Chattanooga region in SUMO by leveraging its tools for developing and evaluating large-scale traffic scenarios. In our calibration approach, we applied the ANOVA test method for performing a sensitivity analysis on model parameters in affecting the simulation model outputs, designed a novel modified genetic algorithm for optimal value selection of chosen parameters, and simulated with the reference real-world speed data derived from the INRIX dataset. In addition, in order to validate our calibrated models, we compared the network's speed predicted by the model with the real-world traffic counts at each detector. Our experiment results clearly demonstrate the feasibility and effectiveness of travel demand calibration using only limited real-world speed data. All of our software and related calibration documentation is available freely as open source at url: https://github.com/smarttransit-ai/transit-gym/tree/master/calibration.

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