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CALIBRATION OF MICROSCOPIC TRAFFIC SIMULATION OF URBAN ROAD NETWORK INCLUDING MINI-ROUNDABOUTS AND UNSIGNALIZED INTERSECTION USING OPEN-SOURCE SIMULATION TOOL

Summary. Microscopic traffic simulation models offer an effective way to analyze and assess different transportation systems thanks to their efficiency and reliability. As traffic management issues become more prevalent, notably in urban areas, simulation tools enable a significant opportunity to replicate real-world conditions before implementation. Therefore, the calibration of traffic simulation models plays a substantial role in obtaining accurate and confidential results. Nowadays, urban regions are facing the challenge of restricted space for developing traffic solutions. As a consequence of environmental restrictions, the use of mini-roundabouts rather than larger roundabouts is increasing. Based on the given literature review, it is seen that not much attention was given to the complex modeling and calibration of microsimulation models of mini-roundabouts and unsignalized intersections. The objective of this study is to offer the calibration of microscopic traffic simulation of urban road network, including closely located mini-roundabouts and unsignalized intersection. To this end, an open-source tool called SUMO (Simulation of Urban Mobility) was utilized as a simulation

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environment in this study. The necessary data for developing a microsimulation model in SUMO was gathered using a videography technique. The traffic count data and speed were considered performance measures between field observations and simulation outputs. The routeSampler tool of SUMO, which has recently emerged in the literature, was used to match traffic count data and the corresponding time interval for traffic volume data calibration. The calibration of car-following model parameters using a trial-and-error approach was employed based on mean absolute percent error (MAPE) between simulated speeds and field-measured speeds. According to the findings of the study, the simulation model fulfilled the calibration aims of the FHWA guideline and is suitable for further research.

Keywords: microscopic traffic simulation, sumo, calibration, trial and error approach

1. INTRODUCTION AND LITERATURE REVIEW

Transportation engineering has significantly benefited from the development of simulation models over the past few years. Due to increasing concern regarding traffic management, especially in urban areas, simulation tools offer a great opportunity to replicate real-world conditions. Traffic simulation can be defined as the mathematical modeling of transportation systems with the aid of software applications in order to improve system planning, design, and operation. Traffic simulation models can be categorized according to their level of detail: macroscopic, mesoscopic, and microscopic. In contrast to macroscopic models, which describe the deterministic relationship of traffic flow characteristics such as density, flow, and speed through the network, microscopic models describe how individual vehicles interact with one another by utilizing car-following and lane-changing models. Mesoscopic models have a moderate level of detail compared to macroscopic and microscopic models [1,2].

There are several widely used microsimulation tools, including PTV Vissim, AIMSUN, Paramics, and SUMO (Simulation of Urban Mobility) in the literature. While some of the simulation tools are commercially available, some of them are open-source. All of these simulation tools have numerous parameters that are used to describe vehicle-class properties or driving behaviors. Therefore, it is necessary to calibrate and validate the parameters of microscopic simulation models according to local conditions and driver characteristics. The objective of the model calibration process is to diminish the discrepancy between the simulation outputs and analogous field measurements such as traffic volume, speed, and travel time [3]. Field conditions can be reliably reproduced by a calibrated microsimulation model. A poorly calibrated model frequently produces inaccurate findings, which can lead to faulty investment decisions. Given its importance, the calibration process is a time-consuming and challenging duty for modelers. As microsimulation models have sub-models such as car-following, lane-changing and gap-acceptance models, which have various modifiable parameters, there are a huge number of parameters that need to be taken into account to replicate real-world conditions [4]. Because of the great effort required, different approaches have been adopted in the literature. In a broad sense, these approaches are divided into two categories: manual and automated procedures. Until the determined objective function criteria is achieved, the manual model calibration process includes an iterative trial-and-error procedure employing possible range values for each parameter and/or combination of several parameters [5,6]. The downside of this approach is that each parameter has a different effect on the simulation output, and it requires significant effort to find the right combination of parameters. This approach is feasible with a few input parameters. In contrast to manual procedures, automated procedures using mathematical optimization-based algorithms such as the Genetic Algorithm (GA) [7–11], Simulated Annealing (SA) [4,12-14], Tabu Search (TS) [3,4], and Simultaneous Perturbation Stochastic Approximation (SPSA) [15–17] are widely used in recent studies.

In order to calibrate simulation models, researchers may compare different performance measures obtained from simulation models with those obtained from field data, depending on attainability by utilizing different approaches. For instance, in the study [15], link counts were used as a measure of effectiveness in two CORSIM models to propose a calibration methodology that enables considering all model parameters simultaneously by using the SPSA algorithm. In another study [18], a two-fold calibration process was suggested by considering two different goals so that the simulation model reproduces field conditions more accurately, both in terms of traffic safety and operation. Multi-objective particle swarm optimization (MOPSO) was used to calibrate VISSIM model. In the study [1], SUMO microscopic traffic simulation software was employed to calibrate car-following and lane-changing model parameters in Sri Lanka's heterogeneous traffic conditions with an automated calibration framework. It was found that the calibrated parameters provided a good fit to the observed traffic speed measurements. Another study [19], in the case of India's heterogeneous traffic conditions, proposed a calibration methodology for unsignalized intersections by calibrating the accepted gap time parameter. In this study, calibration parameters were determined by Morris sensitivity analysis, and their ideal values were established by GA. Similar to [19], sensitivity analysis and GA were employed for calibrating two signalized intersection simulations using the PTV Vissim tool [9]. In the study [8], the GA tool in MATLAB and AIMSUN microsimulation tool were used for calibrating the case study, including two roundabouts. To reduce the difference between empirical capacity functions and simulated data, objective functions were defined. The results of this study indicated that GA performed well and can be recommended for calibrating microsimulation models. Besides selecting a single method for calibration purposes, the proposed methodology in the study [20], was based on a combination of artificial neural networks (ANN) and GA. ANN was used to identify the correlation between the input parameter values and vehicular speed. And then, a trained ANN model was used to determine calibrated parameters through GA. The findings of this study demonstrated that the suggested methodology is less time-consuming for the calibration of microscopic traffic models in contrast to other widely used methods. In the study [4], the performance of the manual method and three metaheuristics (the GA, SA, and TS) algorithms were compared for calibrating microsimulation models. The findings of this research indicated that all three algorithms performed better than the manual method. The different metaheuristic algorithms, namely GA, TS and combinations of GA and TS, were employed and evaluated in the study [3]. According to the results of this study, TS performs very well, and the combination of algorithms distinctly demonstrated better performance and was recommended for calibration purposes. Although automated procedures are widely used in recent studies, there are studies in which a trial-and-error approach is utilized. In the study [21], calibration of VISSIM models at three-legged unsignalized intersections was conducted using the trial-and-error method, considering traffic flow as a measure of effectiveness. In the study [22], the calibration process was conducted using a trial-and-error approach. The traffic volume and queue delay were considered comparison parameters between field observations and simulation outputs.

It is clear from the literature review that automated procedures based on evolutionary search, like GA, are the most widely used techniques for calibrating microscopic simulation models. Intersections are facilities that play a crucial role in the safe and efficient operation of traffic networks. Traffic movements are typically prioritized at unsignalized intersections. Stop or yield signs are placed to control the hierarchy of movements. These days, urban regions are facing the challenge of restricted space for devising traffic solutions, particularly in the city center. The employment of mini-roundabouts rather than larger roundabouts is increasing as a result of environmental constraints. Mini-roundabouts are typically identified by their small diameter and offer the majority of the advantages of conventional roundabouts [23,24]. As a result of their reduced geometric characteristics, mini-roundabouts have a limited field of application, usually restricted to urban environments. Therefore, they are more effective in low-speed and low-volume traffic. In general, the benefits of a mini-roundabout can be described as improved road safety through lower vehicle speeds, reduced delays and queuing, and improved road space [25]. Despite the aforementioned benefits, much attention was not given to the complex modeling and calibration of microsimulation models of mini-roundabouts and unsignalized intersections in the literature. This study proposes the calibration of microscopic simulation of urban road network including closely located multi-mini-roundabouts and unsignalized intersection using an open-source simulation tool called SUMO.

Besides the introduction and literature review section, this study is structured into three sections. The next section presents calibration methodology, including selection of study area and data collection, simulation model, and detailed calibration procedure. The third section gives the results of this study. In the last section, the results are summarized, the limitations of the study are listed, and future research directions are also given.

2. METHODOLOGY

The methodology of this study can be divided into several steps. The first step is to record the running traffic of a selected urban network using videography technique and extract relevant data for analysis. The second step is to model the road geometry and integrate the necessary input into a simulation environment called SUMO. The third task is to conduct microsimulation of urban road network with default settings. As a final step, the simulation model is calibrated to reflect field conditions using a trial-and-error method. The detailed descriptions of steps involved in this study are presented in the following subsections. The flow chart below depicts the main phases of the proposed methodology.

Within the scope of this study, an urban network that includes two mini-roundabouts and one unsignalized intersection consecutively located in the city of Istanbul, Ataşehir, was selected. The study area was selected due to strategic factors such as its proximity to İstanbul Finance Centre, business centres and its suitability for the subject of research. Figure-2 indicates the satellite image of the study area.

Geometric details, comprising the number, length, and width of lanes and the diameter of roundabouts, were collected to create a network model in the simulation environment. Collecting traffic data and speed survey from the field were conducted using videography technique. Traffic data required for this study was gathered during a specific time period (from 3 p.m. to 6 p.m.) that captures peak hour on weekdays with favorable visibility conditions. Turning movements at each intersection were retrieved from recorded video at 15-minute intervals, taking into account all vehicle classes. The vehicle classes were considered passenger cars, buses, trucks, motorcycles, and minibuses in this study. The created network, including each length of intersection in SUMO, is given in Figure 3. The diameter of mini-roundabouts is approximately 5 meters.

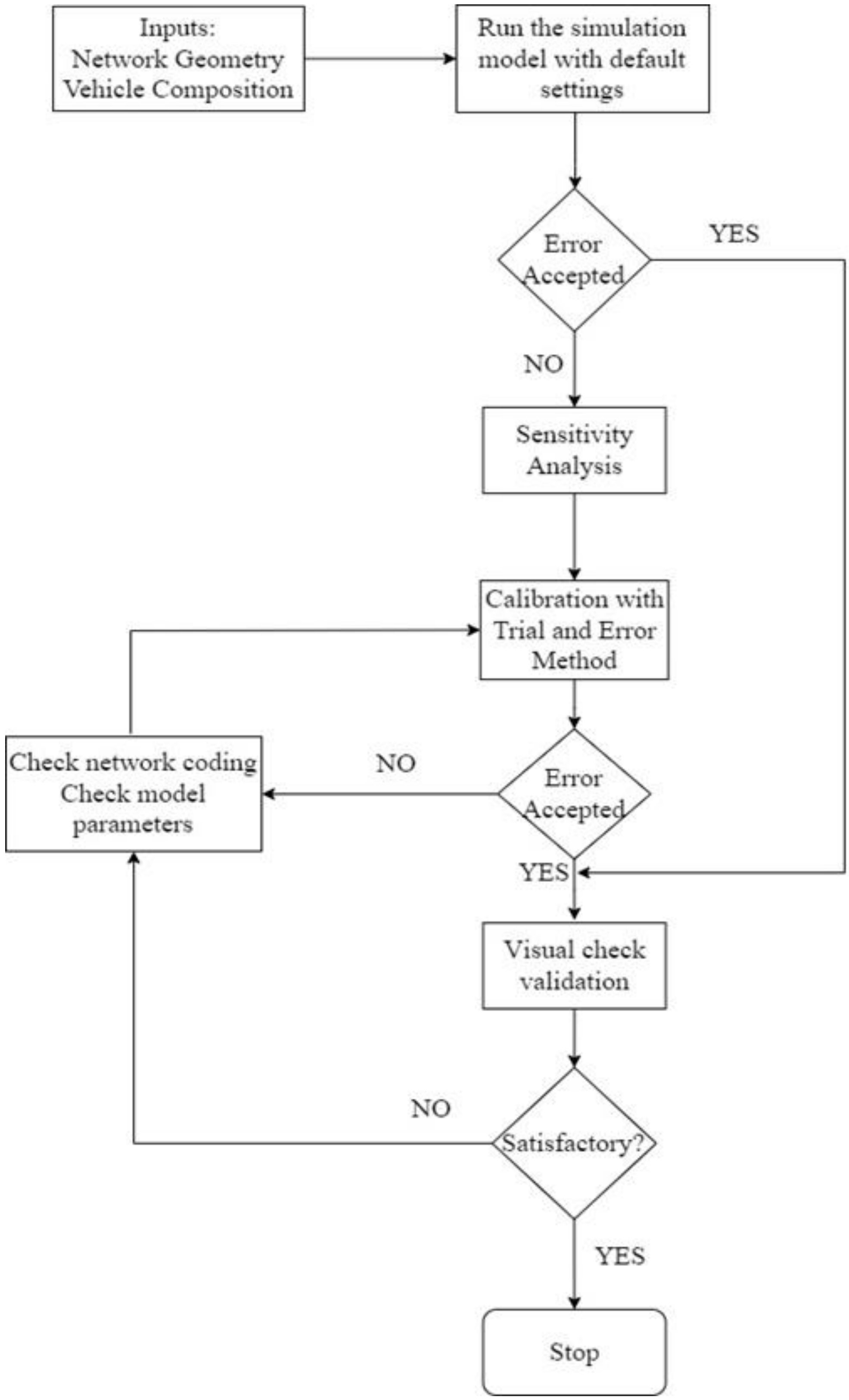

Fig. 1. The methodology of calibration process

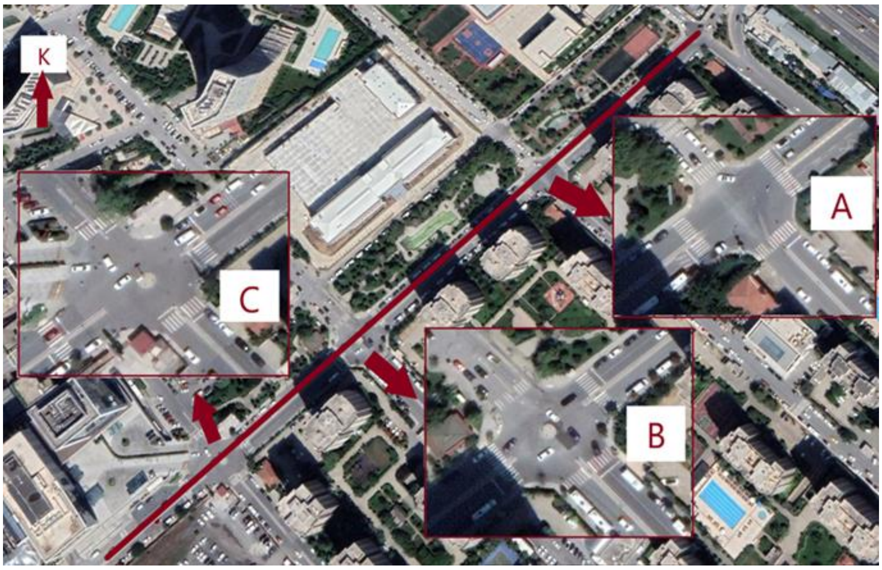

Fig. 2. Satellite image of the study area from Google Earth

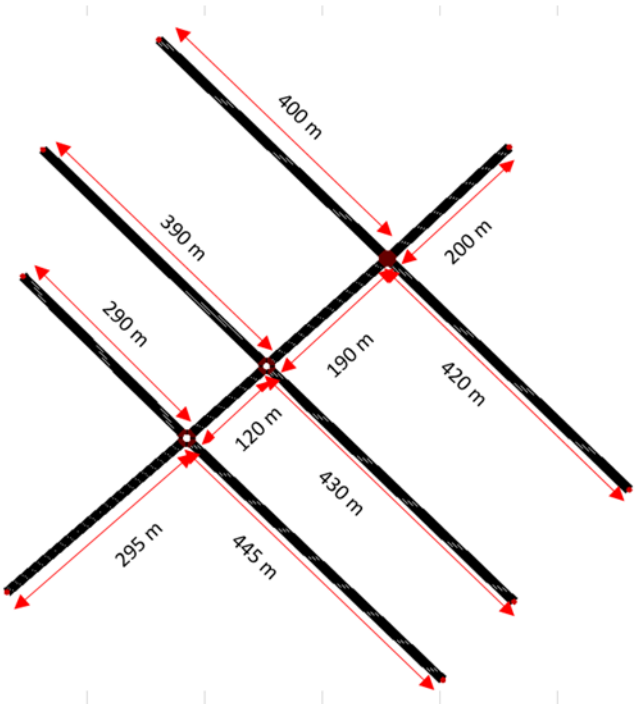

Fig. 3. The created network in SUMO

2.1. Simulation Model

In this study, SUMO is utilized as a simulation tool. SUMO is an open-source traffic simulation tool that can manage large networks. It offers a comprehensive collection of tools for scenario building. It is primarily advanced by the Institute of Transportation Systems at the German Aerospace Center [26]. SUMO enables various internal tools, including NETCONVERT, NETEDIT, and TRACI, for modelling networks and traffic demands.

The road geometry of the selected urban network, priority rules of junctions, and speed limits were applied using the NETEDIT tool in the present study. In SUMO context, road networks consist of edges and junctions. Edges contain a collection of lanes, involving their position, shape, and speed limit. Network models also involve right-of-way rules and connections between lanes at junctions.

Traffic counts, related to turning traffic based on considered vehicle classes for each intersection obtained from recorded video, were processed to create traffic demand in the simulation environment. In this regard, the "routeSampler.py" script of SUMO was utilized to match vehicle counts and time intervals. This tool works based on integer linear programming (ILP), which is used to formulate the problem of selecting multiple routes that match all traffic counts. The possible routes file and turn-count data file were given as input to "routeSampler.py" tool. The use of this tool is to calibrate the traffic simulation model that has recently emerged in the literature [1, 27-28].

2.2. Calibration Procedure

The calibration process involves changing model parameters so that simulated data closely matches field data. However, all the parameters may not have a substantial impact on the model output. As a result, it is vital to specify sensitive parameters relevant to the particular traffic scenario. There are various user-adjustable parameters of car-following and lane changing models for the calibration process in SUMO. During car-following, the speed of a following vehicle is computed according to the leader's speed. While car-following model parameters include acceleration, deceleration, time headway, and driver characteristics, lane-changing model parameters include eagerness to speed gain, keep-right likelihood, and gaps in the target lane. The default car-following model in SUMO is the Krauss car-following model. This model relies on a principle that allows the vehicles to drive as fast as possible while confirming maximum safety [29]. The model is a "safe speed" based model, which is calculated using Equation (1):

$$v_{safe} = v_l(t) + \frac{g(t) - v_l(t)t_r}{\frac{v_l(t)+v_f(t)}{2b} + t_r} \tag{1}$$

In equation (1), the terms are listed as following: v_{safe} is the safe speed,v_l(t) is the speed of the leading vehicle at time t, $g(t)$ is the gap between leading and following vehicle, t_r is the reaction time, b is the maximum deceleration and $v_f(t)$ is the speed of following vehicle at time t. Because of the possibility of exceeding the speed limit on the road or the motor capacity of a vehicle, another speed term called v_{des} (desired speed) is considered. It is calculated using Equation (2):

$$v_{des} = min[v_{lim}, v_f(t) + at, v_{safe}] \tag{2}$$

In equation (2), the terms are listed as following: v_{lim} is the speed limit, a is acceleration, t is time. The desired speed is equal to the minimum of these three restraints. Moreover, to increase the realism of human-like driver behavior, a driver imperfection parameter is added in the model. Thus, vehicles with varying desired speed can be accomplished. The default lane-changing model in SUMO is the LC2013 model. In this model, the motivations of lane-changing maneuvers are explained based on strategic, cooperative, tactical, and obligatory reasons [26]. The default values of the lane-changing model are used in this study. The details of Krauss car-following model parameters are given in Table 1. The vehicle-class specific parameters, including minGap, accel, decel, and emergency decel, were taken as default values. The driver characteristics including time-headway (tau) and sigma parameters were calibrated in this study. Before starting the calibration process, Sensitivity Analysis (SA) is a frequently used tool in the scientific community for selecting the optimal set of influential factors from a complicated model. In simple terms, SA is the process of studying how variations in model inputs can lead to variations in model outputs. In the scope of this study, One-At-a-Time (OAT) method was adopted to understand the effect of tau and sigma parameters on speed survey conducted from field data. This method changes one input parameter at a time, while other parameters stay the same [30]

Tab. 1

The parameters of Krauss car following model.

Parameter	Explanation
minGap (m)	It represents the minimum gap when standing.
accel (m/s^2)	It represents the ability of acceleration.
decel (m/s^2)	It represents the ability of deceleration.
emergency decel (m/s^2)	It represents the capability of a vehicle to decelerate in the event of an emergency.
sigma (unitless)	It represents the driver's imperfection. It takes value between 0 and 1 (sigma=0 refers to perfect driving).
tau (s)	It represents the driver's desired minimum time headway.

It was aimed to diminish the discrepancy between the measured and simulated traffic flows during model calibration. In this study, calibration criteria were used based on Federal Highway Administration (FHWA) guidelines [31]. The GEH statistic was chosen as a calibration measure. It is an empirical formula used for comparing the traffic volumes of two sets of data. It is formulated as follows:

$$GEH = \sqrt{\frac{(E-V)^2}{(E+V)/2}} \tag{3}$$

While E represents the simulated traffic volume, V represents the actual traffic volume. The following GEH statistic metrics were evaluated in this study: The GEH statistic of individual link flows must be less than 5 in 85% of situations, and the GEH statistic for the sum of all link flows must be less than 4 [31]. Another calibration measure considered in this study is speed. Using the trial-and-error approach, parameter optimization was carried out by minimizing the difference between simulated speeds and actual speeds measured in the field.

3. RESULTS AND DISCUSSION

The case study was simulated using SUMO's default model for car following and lane changing. In order to extract relevant data, detectors were placed on each leg of the intersection. There are a total of 40 detectors on the selected network, and Figure 4 depicts an example of the positioning of detectors. This study utilized three hours of traffic data with a 15-minute interval. In addition, a 15-minute warm-up and cool-down period were included in the simulation model. No data was gathered during the warm-up and cool-down periods.

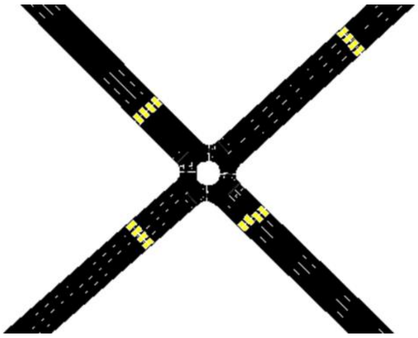

Fig. 4. An example of the positioning of detectors on the network

GEH statistic was calculated for each edge and the results satisfied the requirements as shown in Table 2.

Tab. 2

GEH statistic of each edge

Edge Name	Field Counts			Simulated Counts			GEH Statistic		
	15.00-16.00	16.00-17.00	17.00-18.00	15.00-16.00	16.00-17.00	17.00-18.00	15.00-16.00	16.00-17.00	17.00-18.00
E2	363	351	394	363	344	382	0,00	0,38	0,61
-E2	117	93	72	120	93	72	0,28	0,00	0,00
-E0	1098	1195	1072	1093	1197	1061	0,15	0,06	0,34
E0	104	52	57	105	53	58	0,10	0,14	0,13
-E3	86	82	79	75	81	63	1,23	0,11	1,90
E3	983	1103	1103	980	1090	1094	0,10	0,39	0,27
-E40	457	483	486	380	421	427	3,76	2,92	2,76
E4	800	863	783	786	859	772	0,50	0,14	0,39
E8	329	300	428	331	300	426	0,11	0,00	0,10
-E80	390	391	343	382	391	343	0,41	0,00	0,00
-E9	538	518	481	540	516	484	0,09	0,09	0,14
E9.19	543	598	632	538	586	640	0,22	0,49	0,32
-E10	436	462	416	439	458	418	0,14	0,19	0,10
E1.17	713	671	647	709	668	638	0,15	0,12	0,36
E7	220	221	306	220	223	305	0,00	0,13	0,06
-E70	209	179	200	210	178	199	0,07	0,07	0,07
-E6	200	225	260	200	224	260	0,00	0,07	0,00
E60	467	472	529	472	469	524	0,23	0,14	0,22
-E5	584	568	523	591	562	523	0,29	0,25	0,00
E5.22	605	572	591	598	573	579	0,29	0,04	0,50

Speed is the other calibration measure considered in this study. The calibration of car following model parameters using a trial-and-error approach was employed to diminish the discrepancy between the simulated speeds and field-measured speeds. For collecting speed data, two reference points were selected on the network and passing time between these points was recorded using a stopwatch method. The appropriate study length and having a good visibility view were considered in the selection of the proper location of the speed study. A total of 30 field-measured speeds were compared to the corresponding simulated speeds during the calibration process using the mean absolute percent error (MAPE) concept. MAPE value was calculated using the equation below:

$$MAPE = \frac{1}{n} x \sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \quad (4)$$

In Equation (4), terms are listed as following: n is the total number of observations, A_i is the observed value, F_i is the simulated value. Figure 5 demonstrates the comparison of field-measured speeds and simulated speeds. The MAPE value is calculated as 10.52%, which satisfied the acceptable target (15%) according to the FHWA calibration guideline [31].

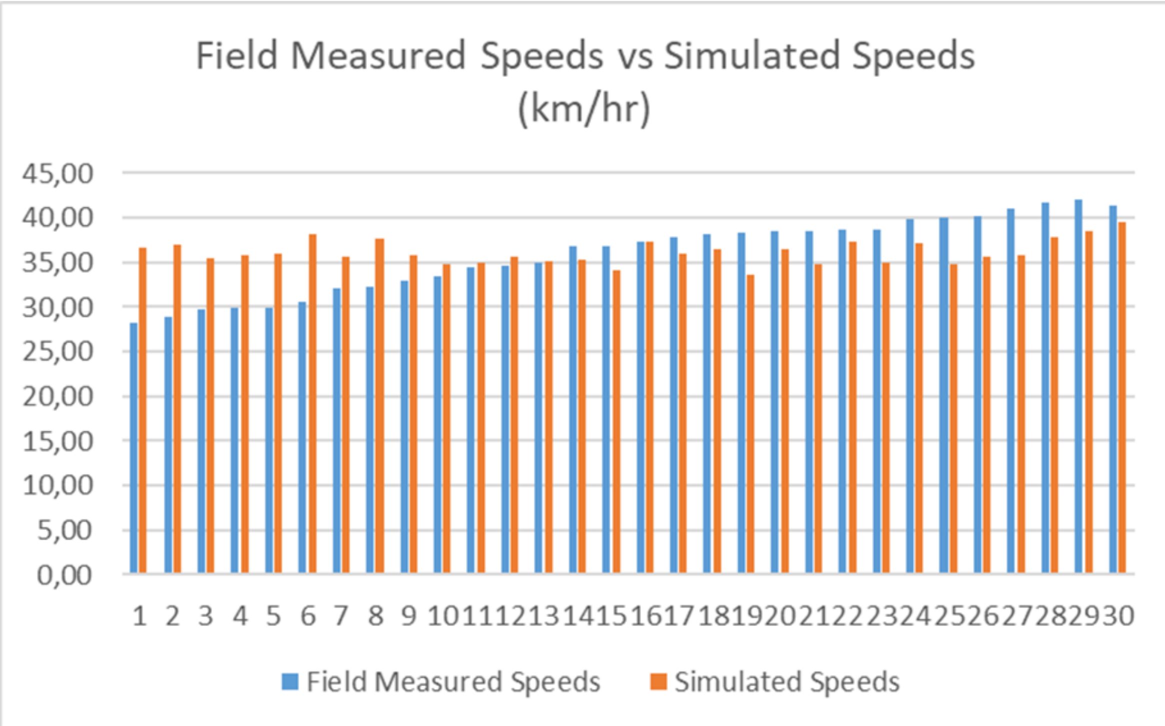

Fig. 5. Comparison of field-measured speed and simulated speeds.

Following the calibration procedure, the calibrated model parameters using a trial-and-error approach were given in Table 3. It was found that the calibrated parameters are higher than SUMO's default values. The higher "sigma" value than its default value indicates that a higher driver imperfection can simulate field conditions more closely. Visual validation technique was conducted by examining the graphical representation of the urban road network in an attempt to detect any unusual behavior.

Tab. 3

Calibrated parameter values

Parameters	Default value	Calibrated value
tau (s)	1.0	1.5
sigma (unitless)	0.5	0.6

4. CONCLUSION

In recent years, the development of simulation models has tremendously aided transportation engineering. Because of the growing concern over traffic management, particularly in metropolitan areas, simulation tools provide an excellent chance to simulate real-world conditions. However, calibrating a simulation model is a highly challenging task. Based on the given literature review, while some studies utilize automated calibration procedures, others employ a trial-and-error approach to calibrate the traffic simulation models. This study presents the calibration of a microsimulation model of an urban road network consisting of two mini-roundabouts and one unsignalized intersection using a trial-and-error procedure. In this study, SUMO is utilized as a simulation environment. The traffic count and speed data from the field are gathered from recorded video of selected urban network. The routeSampler tool of SUMO enables the matching of traffic counts relating to turning counts for each intersection and the corresponding time interval. As a result of traffic volume calibration, it was found that GEH statistics for all links are less than 5, which is acceptable for the FHWA calibration guideline. Furthermore, car following model parameters were calibrated so as to minimize the difference between simulated speeds and actual speeds measured in the field utilizing a trial-and-error approach. The MAPE value was calculated as 10.52%, which satisfied the acceptable target according to the FHWA calibration guideline. Further research will concentrate on using metaheuristic optimization approaches to improve the accuracy and efficiency of calibration procedures for microscopic traffic simulation models of urban road networks. As a limitation of this study, the validation stage was employed visually rather than statistically due to the limited availability of data.

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