Development of Online Vissim Traffic Microscopic Calibration Framework Using Artificial Intelligence for Cairo CBD Area

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Abstract

This paper makes a notable contribution to Transportation Planning in urban areas by considering the application of a key transportation Planning software package for the traffic conditions in the Central Business District of Cairo. For urban areas with heterogeneous and very congested traffic conditions and uneven driving behavior such development can be very useful. The paper shows how a microscopic simulation model using a Multilayer Feedforward neural network (MFNN) to calibrate online the VISSIM package driving parameters' values based on predictions of travel time and traffic flow on the network elements. The two-step calibration procedure is faster and more applicable for on-line models than the approaches followed in current literature that require time-consuming iterations for model calibration. Also, this research uses combined Artificial Intelligence models (Long-Short Term Memory based Recurrent Neural Networks - LSTM-RNNs) and Multilayer Feedforward neural network (MFNNs) and calibrates them based on the driving behavior and traffic condition on successive time intervals. In this way, the prediction of the future traffic condition is based on actual traffic conditions on the past intervals and the actual driving behavior.

1. Introduction

The role of traffic simulation models' application has rapidly increased in recent years. Macroscopic, mesoscopic, and microscopic traffic simulation models have been calibrated and validated with the aim of judiciously replicating the actual observed field conditions for online applications (Bartin et al., 2018; Figueiredo et al., 2014; Khaled., 2005).

There are three types of traffic simulation models classified by the level of detail: macroscopic, microscopic, and mesoscopic. Macroscopic models aggregate the characteristics of the vehicles and consider the whole traffic stream on each link as one unit. Dealing with large road networks and broad geographic areas, they enable analysis of the large-scale performance of road networks. Microscopic models use the demand that is output from macroscopic models. They consider vehicles' characteristics separately, analysing time and distance headways for each vehicle and the usage of small road networks among other factors. Microscopic models allow for the presentation of actual traffic on streets, intersections, interchange configurations, intersection control processes, and even pedestrian movements. The mesoscopic level stands between both the micro- and macro- levels; bridging the inconsistencies between them. In mesoscopic models, traffic is considered in terms of platoons of vehicles as opposed to individual vehicles in microscopic models or as a stream of vehicles in macroscopic models. (Adebisi, 2017; ITE, 2014).

The calibration of microscopic simulation models is essential to account for the detailed interactions between vehicles in a network, and to model the congested locations intensively. In online models, calibration, heterogeneous driver behaviours, and traffic conditions are captured and simulated continuously by feeding in real-time field measurements, thereby replicating the actual state of traffic (Papathanasopoulou et al., 2016). Importantly, the demand and supply parameters are updated on a real-time basis to better reflect field conditions (Antoniou et al., 2009).

This paper presents a case study located in Egypt that focuses on the road network in the Cairo CBD area. In this area, traffic congestion plays a crucial role affecting all surrounding road networks. The study applies an online calibration framework and aims to validate microscopic simulation models.

The use of artificial intelligence facilitates numerous estimation and prediction problems. This is manifested in the use of ANNs for microscopic model parameters calibration (Ištoka et al., 2013). Results from this model show that ANNs is highly capable of calibrating microscopic model parameters, given measurable traffic indicators, such as travel time, queue length, the maximum number of vehicles stopping at the entrances of roundabouts, or a combination there of. On the other hand, the proposed algorithm application process has shortcomings represented in its time-consuming iterations needed to find the optimal set of parameters' values. It is therefore infeasible when used on a real-time basis for online models, where model parameters need to be calibrated quickly.

Other considerable research work has been done to calibrate microscopic traffic simulation models using various algorithms and heuristics, both online and offline. These approaches could be summarized in Trial and Error (TAE) (Hourdakis et al., 2003), Generalized least squares (GLS) (Toledo et al., 2004), Artificial Neural Networks (ANNs) (Ištoka Otković et al., 2013), Genetic Algorithms (Chiappone et al., 2016; Mathew & Radhakrishnan, 2010), Simplex Algorithm (Kim & Rilett, 2002), SPSA Algorithm (Zhang et al., 2008), and Transfer Function model (Qin & Mahmassani, 2004).

To calibrate such models, appropriate model parameters' values are determined based on measurable traffic performance indicators, such as the work of (Ištoka Otković et al., 2013) which calibrated the model parameters based on measurable performance indicators. In that research, a prediction function is generated using ANNs that estimates the performance indicators for any given set of model parameters' values. Then, the optimal set of parameters' values are extracted by performing many iterations of this prediction function, until it outputs performance indicators that match measured indicators in the field. The prediction function is generated in many cases for different types of traffic performance indicators including travel time, queue length, number of vehicles stopping at roundabout entrances, or combinations of these four indicators. Results have shown that using travel time on its own as a performance indicator generates better rates of prediction. Similar research work is performed by (Park et al., 2006), in which a network of urban streets consisting of 12 actuated signalized intersections is modeled and calibrated using ANNs. VISSIM and CORSIM microsimulation software was used for modeling. The calibration and validation procedures were performed based on travel time measurements and queue length at the studied intersections. The study results showed that the proposed algorithm could adequately calibrate the simulation models to replicate realistic network performance. Furthermore, for online model calibration tasks, prediction of network indicators, such as travel time, traffic flow, and average speed, must be available on a concurrent temporal basis. Yeon (2019) used recurrent neural networks (RNNs) for average speed prediction for 15 seconds (Shafqat et al., 2019) also used RNNs to predict short-term traffic flow.

This paper contributes to the existing literature by introducing a novel direct real-time calibration framework for microscopic simulation models using Multilayer Feedforward neural network (MFNNs). To the best of our knowledge, this is the first research which calibrates directly online the Vissim driving parameters' values, based on predictions of travel time and traffic flow on the network elements, thereby helping to produce parameter values that simulate the expected traffic conditions in the next time interval.

The two-step calibration procedure is considered significantly faster, and thus, more applicable for online models than the approaches followed in the literature which require time-consuming iterations for model calibration. Moreover, this research is the first to train combined AI models (i.e., Long-Short Term Memory based Recurrent Neural Networks (LSTM-RNNs) and Multilayer Feedforward neural network (MFNNs)) together, based on the driving behavior and traffic conditions during successive time intervals. Significantly then, the prediction of future traffic conditions is based on the traffic conditions of the past intervals and the current driving behavior.

The paper is divided into sections: Section 2 introduces the problem statement and describes the objectives. Section 3 presents the implemented methodology. Section 4 presents the results, and Section 5 concludes with the findings of this research.

2. Problem Statement

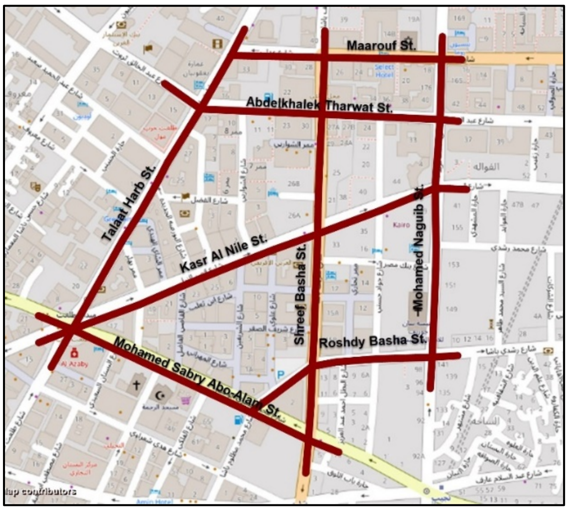

Fig. 1: Road network of the selected study area in Cairo CBD, Egypt

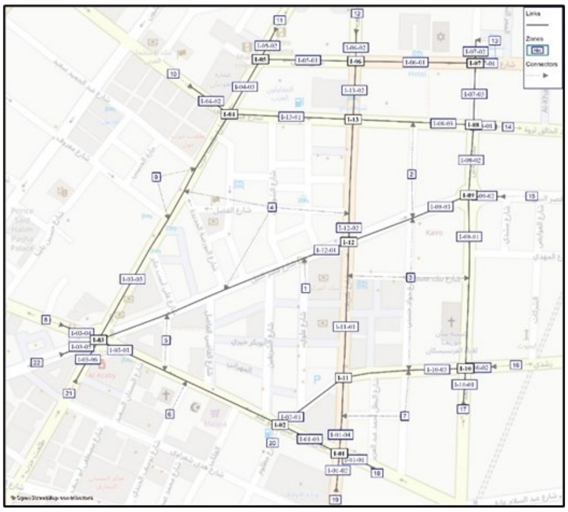

Fig. 2: Coded network of the study area

Traffic in greater Cairo is heterogeneous in terms of driving behaviour and mixed traffic composition. Drivers in a heterogeneous traffic system try to utilize any space available on any part of the road; regardless of the lanes and road rules, and in places where the network elements could be considered as below average. Pedestrians may cross at any location and at any moment. All these features are considered challenges for traffic modelers when trying to mimic prevailing field conditions and capture the heterogeneity of the driving behaviors in such countries (Papathanasopoulou et al., 2016).

The objective of this research is to develop an online calibration framework for a microscopic traffic simulation model in the Central Business District of Cairo (CBD) that consists of 8 corridors and 13 intersections (Fig. 1 and Fig.2). The road network features are successively signalized and non-signalized intersections so that the travel time including intersections delays can be evaluated.

The online calibration framework ensures that the traffic model can continuously replicate observed traffic conditions in terms of driving behavior. The microscopic level of traffic simulation is selected so that all interactions between vehicles and control infrastructure in the network can be represented.

3. Methodology

The research is conducted using the following steps: Starting from field data collection, dynamic OD matrix estimation is followed by microscopic modeling, sensitivity analysis, and finally production of the calibration framework using Artificial Neural Networks (ANNs) occurs.

Several types of data are required in this stage of network coding. Traffic Volume Data are collected via manual classified traffic counts on the AM peak period. Signal timing and phasing data are collected at all intersections. The calibration process of the simulation model requires a measure of goodness upon which the quality of calibration can be evaluated. Travel time data on links are collected using Google API and Python programming tools that can collect such information on a predefined regular basis network links represent each homogenous section of a road (102 links), and nodes represent the points of links intersections (45 nodes) are modeled in the macroscopic traffic model.

It is considered that traffic count data is insufficient to infer a unique OD matrix for a transportation network, because they lead to a list of underdetermined equations which may give numerous origin-destination matrices that replicate the given traffic counts on links. That is because the counted objects are always significantly smaller than the number of origin-destination pairs. Various additional assumptions and *a priori* information about the travel pattern can guide the calculation to reach a unique solution (Cascetta, 1984; Cremer & Keller, 1987).

In this research, as no data are available about any outdated OD matrix for the study area, a process of estimating an

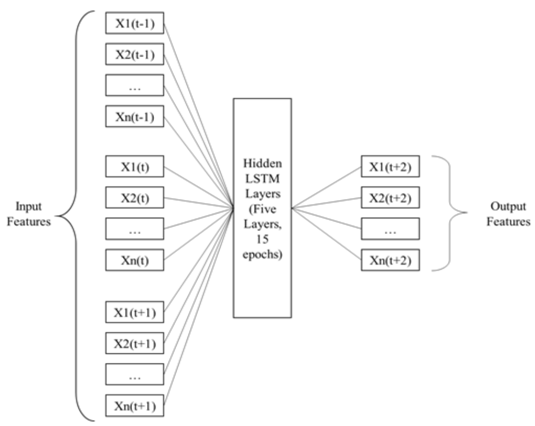

Fig. 3: Structure of LSTM ANNs

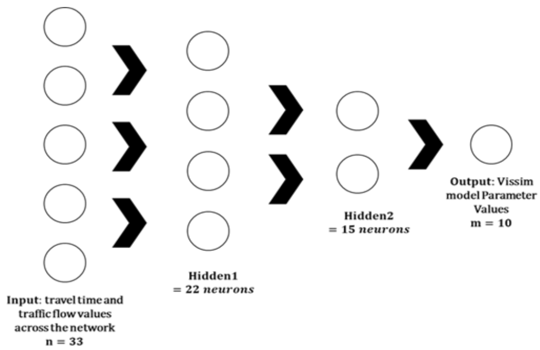

Fig. 4: Structure of MFNNs

initial OD matrix is performed using a best-guess approach based on field observation and the author's experience of travel patterns. The travel pattern between all OD pairs in the study area is translated into the estimated initial OD matrix.

Given the initial OD matrix from available information and assumptions, the estimated origin-destination matrix is then inferred by minimizing the deviation between link volumes from traffic counts, and the estimated link volumes from the estimated origin-destination matrix. This process is iteratively repeated until reaching satisfactory results. While estimating the target OD dynamic matrices, based on this initial OD matrix and the traffic counts, the pattern of the initial matrix is retained as the same.

Dynamic OD matrices estimation is performed using the traffic volumes for each time step of analysis (30 minutes). The process of demand matrix estimation and correction is achieved using the "Least Squares" method inside PTV Visum demand modeling (PTV Planung Transport Verkehr AG, 2017).

PTV Vissim software takes into consideration several constraints of lane distribution, vehicle type composition, and signal control which helps in analyzing and testing the interactions between systems in the road network, such as adaptive signal control and route recommendation (PTV Planung Transport Verkehr AG, 2018). Vissim is used to apply the proposed calibration framework. Geometric network characteristics and features are coded into the model, such as the network links' geometry, traffic control types at intersections, priority rules and reduced speed areas, traffic flow values, and routing decisions.

Default values of driving behavior parameters from the Vissim manual are initially used. Initial performance verification and error checking of the developed model are performed to evaluate the model. Vissim models have multiple driving behavior parameters that need to be calibrated. It is also necessary to perform a sensitivity analysis to identify which parameters are effective to save

Table 1: Traffic volume Data for the Study Area (vehicles/hr/lane)

Approach Code	Time Interval 7:30 to 8:00 AM	Time Interval 10:00 to 10:30 AM	Approach Code	Time Interval 7:30 to 8:00 AM	Time Interval 10:00 to 10:30 AM
I-01-01	94	68	**I-06-01**	323	234
I-01-03	162	118	**I-06-02**	278	202
I-01-04	124	90	**I-07-01**	225	163
I-02-01	795	577	**I-07-03**	166	120
I-03-01	173	125	**I-08-02**	290	211
I-03-03	470	341	**I-08-03**	460	334
I-03-06	314	228	**I-09-01**	405	294
I-04-02	338	245	**I-09-03**	304	220
I-04-03	544	394	**I-10-01**	364	264
I-05-01	405	294	**I-10-03**	177	128
I-11-01	282	205			
I-12-01	406	294			
I-12-02	231	168			
I-13-02	253	183			

Table 1: Mean Travel Time (sec.) on Different Paths

Path code	Time Interval 7:30 to 8:00 AM	Time Interval 10:00 to 10:30 AM	Path code	Time Interval 7:30 to 8:00 AM	Time Interval 10:00 to 10:30 AM
Path1	168	205.0	**Path5**	193	291.0
Path2	107	144.2	**Path6**	67	89.5
Path3	101	132.7	**Path7**	82	95.0
Path4	123	181.2	**Path8**	63	63.3

simulation and computational processing burdens. The Analysis of Variance (ANOVA) test is utilized to identify Vissim significant model parameters to be calibrated. Artificial Neural Networks (ANNs) are used to build a prediction function that can estimate the values of these parameters so that when they are used in the model, it produces results that mimic actual observed behavior. The role of the ANNs is to figure out the relationship between driving behavior parameters and the model's performance so that the ANNs can be used as an estimator for the driving behavior parameter values when using actual field observations.

The ANNs model is trained using a generated dataset from the model. To build such a dataset, it is necessary to input a large set of parameters values combinations and run the simulation model. 1000 combinations of model parameters were calculated using Latin Hypercube Sampling (LHS) technique, which is a stratified random sampling technique that ensures taking samples from identified parameter ranges, while maintaining all possible combination cases covered. The output model performance measures are collected from the simulation model. Both input and output data constitute the training and validation database to be used in building the ANNs model.

ANNs models are implemented in a two-step framework. In the first step, long-short term memory based recurrent neural networks (LSTM), with five hidden LSTM layers and 15 epochs (Fig. 3), are used to predict travel time and traffic flow for a 30-minute time interval based on the previous five-time intervals. In the second step, multilayer feed-forward neural networks (MFNNs), with a number of two hidden layers with 22 and 15 neurons in the first and second layers respectively (Fig. 4), perform the direct estimation of Vissim driving behavior parameters based on predicted travel time and traffic flow values from Step 1.

The output-calibrated parameters are then used in the simulation model, and the model travel time results are compared with the values fed into the LSTM model, before being compared with the actual values of travel time collected using the online tool. Therefore, the two steps

Table 2: Final Set of Significant Model Parameter

N	Input Parameters	F-Statistic	F critical	Significance
P1	Min Look Ahead Distance - m	4.01	2.46	True
P2	Number of Interaction Objects	434	2.46	True
P3	Average Standstill Distance - m	208	2.46	True
P4	Additive part of desired safety distance (Wiedemann 74) - m	180	2.46	True
P5	Multiplicative part of desired safety distance (Wiedemann 74) - m	63	2.46	True
P6	Waiting Time Before Diffusion - sec	13	2.46	True
P7	Safety Distance Deduction Factor	14	2.46	True
P8	Collision Time Gain - sec	52	2.46	True
P9	Lateral Distance Standing - m	142	2.46	True
P10	Lateral Distance Driving - m	100	2.46	True

together constitute a framework for traffic volume and travel time prediction and the calibration of Vissim driving behavior parameters on a real-time basis.

4.0 Results

4.1 Data Collection Results

Tables 1 and 2 present the field survey data of traffic volume and the average travel time on each path, respectively. These tables provide the average of collected traffic data on 30 minutes time periods. The first period starts from 7:30 to 8:00 am while the last starts from 10:00 to 10:30 am.

4.2 ANOVA Test Results

Table 3 summarizes the final set of significant model parameters, identified by ANOVA test, which will be used in the calibration procedure, where 10 parameters are identified to have a significant effect on the simulation output at an alpha level of (0.05), and critical F-statistic threshold is (2.46).

4.3 Traffic Volume and Travel Time Prediction Results

Recurrent Neural Networks resulted in a good prediction ability for travel time and traffic volume based on inputs from previous time steps. The evaluation was completed using the GEH formula, which measured the closeness of the values between LSTM model predictions and actual field measurements of traffic volume. LSTM results show that it is applicable to predict traffic volume values on the network that match actual values in the field. For the testing dataset, the GEH value is less than 5.0 for 99% of the network links. This is accepted by the rules of the FHWA, where 85% of the network links must have GEH values less than 5.0 (Kelton & Law, 1991). Figure 5 shows the training and validation of travel time prediction results.

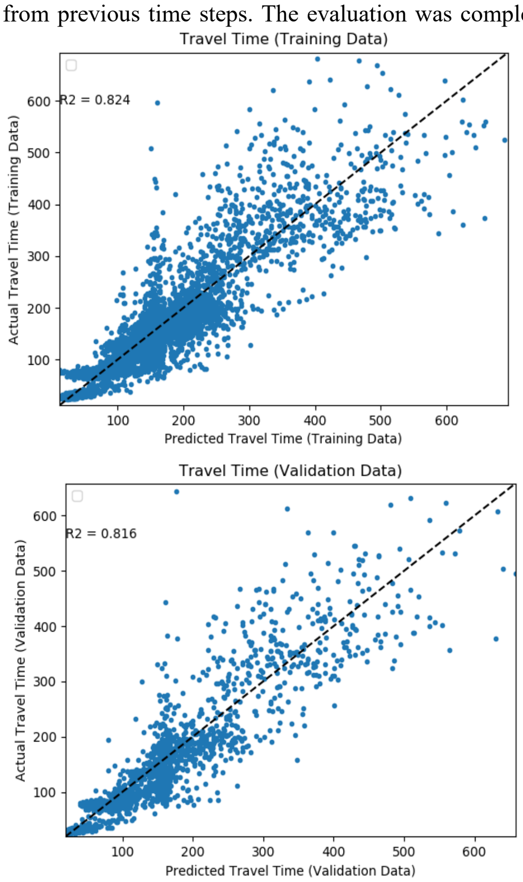

Fig. 5: Training and validation results of Travel Time prediction

4.4 Vissim Parameter Values Estimation Results

Figure 6 shows the results of Multilayer Feed-Forward Neural Networks (MFNNs) functionality for the model training dataset. As shown, the correlation between MFNNs and Vissim results is (0.657). Besides, Figure 7 shows the correlation using the testing dataset (0.654). This level of accuracy can be considered sufficient due to the stochastic nature of the traffic stream itself. The developed algorithm will be self-improving by continuously learning from field data when put into actual operation. The introduced algorithm directly estimates the model parameter values in less than a second without time-consuming iterations, which makes it applicable for calibrating online simulation models of road networks.

4.5 Test Application of the Proposed Framework

The framework is applied for online estimation of Vissim model parameter values based on five previous time steps of travel time data. Table 4 gives the predicted travel time by the framework versus actual measured travel time with a correlation coefficient of 0.9. This shows the powerful ability for RNNs to replicate observed travel time patterns and estimate future values based on it. This table also shows a comparison between actual measured and

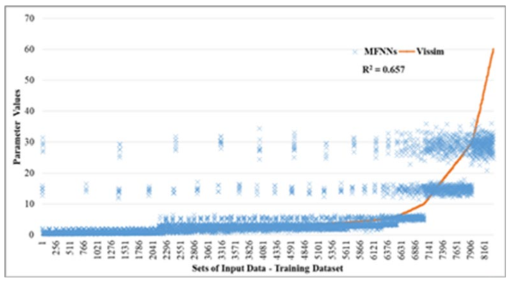

Fig. 6: Training results of Vissim Model Parameters

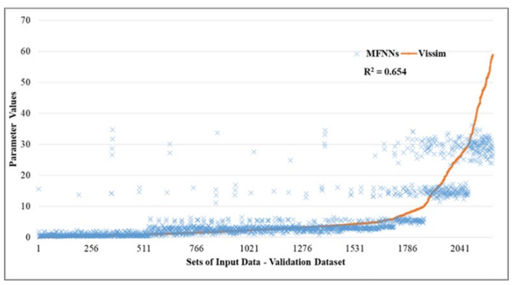

Fig. 7: Validation results of Vissim Model Parameters

simulated travel times where the correlation coefficient is 0.75. As such, the proposed framework showed a good ability to produce simulated travel times. Table 5 shows the results of the parameters' value estimation, which will be used in the Vissim model and in which the resulted travel times will be recorded.

Table 4: Comparison between LSTM, Vissim, and Actual Field measurement of Travel Time

Path	Time Step 6 Travel Time		
	Estimated Values By LSTM	Vissim Model Values	Actual Values
Path1	204.9	187.7	205.0
Path2	144.0	255.4	144.2
Path3	133.0	95.0	132.7
Path4	181.0	170.4	181.2
Path5	291.0	291.7	291.0
Path6	90.1	71.5	89.5
Path7	95.0	80.8	95.0
Path8	63.0	32.5	63.3
R^2 *	0.99	0.75	-

* Compared to Actual Values

4. Conclusion

The paper introduces a framework for online calibration of microscopic model parameters and applies it to the CBD area in Cairo. The research work concerns capturing the effect of dynamic changes in driving behaviour as a response to changes in traffic conditions on the traffic flow characteristics in the CBD. Again, driving behaviour parameter calibration is essential in the overall calibration process as it controls the overall behaviour of the modelled objects. The calibration process is based on calibrating the effective Vissim driving behaviour parameters given measurable traffic indicators from the field.

To identify significant model parameters, network modelling and sensitivity analysis using ANOVA test is performed. Therefore, the calibration process is performed using a two-step framework utilizing Artificial Neural Networks. In the first step, short term traffic volume and travel time are predicted across the network on a real-time basis given historical patterns. In the second step, these estimates are used to calibrate Vissim driving behaviour parameters to mimic actual field conditions. In this proposed framework, the parameters calibration procedure is performed directly using the travel time and traffic volume across the road network. As such, this calibration methodology is considerably faster than other time-consuming processes mentioned in the literature, which require many iterations until eventually finding the optimal parameter values.

Results show that the proposed framework can perform the required tasks with a good level of accuracy. Regarding the framework's first step, the predicted short term travel time and traffic volume could be validated with an R2 of (0.816). This is considered a good accuracy given all the uncertain and stochastic nature of the observed travel time and traffic volume. Regarding the second step, the calibration procedure can mimic travel time observed on the field with an R2 of (0.654). This is considered on the other hand a plausible result comparing to the intelligence of the calibration process.

Table 5: Estimated Parameter Values by the Framework

Code	Parameters	Default (min-max)	Estimated Parameter
P1	Min Look Ahead Distance - m	10 (1-20)	20.32
P2	Number of Interaction Objects	2 (0-4)	3
P3	Average Standstill Distance (Wiedemann 74) - m	2(1-5)	3.59
P4	Additive part of desired safety distance (Wiedemann 74) - m	2(1-5)	3.29
P5	Multiplicative part of desired safety distance (Wiedemann 74) - m	3(1-6)	4.09
P6	Waiting Time Before Diffusion - sec	60(0-60)	37.87
P7	Safety Distance Reduction Factor	0.6(0-1)	0.63
P8	Collision Time Gain - sec	2(1-10)	6.85
P9	Lateral Distance Standing - m	1(0-5)	1.79
P10	Lateral Distance Driving - m	1(0-5)	0.69

Finally, the overall results of this research show that ANNs can be effectively used to calibrate online traffic simulation models. However, other modifications to the calibration procedures or the ANNs models' structures are required to improve the calibration accuracy and better produce models that more accurately mimic reality. Thus, it may be used to enhance the estimation capabilities for current road network conditions. Furthermore, generating proactive traffic management schemes could be a potential extension for this work.

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Keywords

VISSIM, traffic simulation, Cairo traffic, urban traffic simulation, driving behaviour model.