Arab J Sci Eng (2015) 40:3459–3468
DOI 10.1007/s13369-015-1816-5

RESEARCH ARTICLE - CIVIL ENGINEERING

Calibration of PARAMICS Model: Application of Artificial Intelligence-Based Approach

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Received: 25 March 2015 / Accepted: 6 August 2015 / Published online: 4 September 2015

Abstract The advent and significant improvement in computing technology in the last decades has led to immense popularity of traffic microscopic simulation models in addressing different transportation engineering issues. This paper focuses on the challenges of calibration of microscopic model incorporating the driving behavior for the local traffic conditions in the Kingdom of Saudi Arabia (KSA). One of the state-of-the-art microscopic simulation models, PARAMICS was used for the calibration study. This study proposes machine learning model-based calibration methodology for the PARAMICS model. The developed artificial neural network (ANN) model performs adequately in modeling the queue length as a function of mean target headway and mean reaction time. The selected values of the calibration parameters were finally obtained using the genetic algorithm, which ensures minimum difference with the measured values of queue lengths and the ANN output (i.e., queue lengths). The queue lengths obtained through the ANN- and GA-based approach were used as the input parameters for the PARAMICS model. The conformance of the PARAMICS and the ANN model outputs indicates the validity of the proposed calibration methodology.

Keywords Artificial neural network · Genetic algorithm · Microscopic model calibration · Microscopic simulation model · PARAMICS model · Saudi Arabia

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1 Introduction

Simulation has gained an increasing popularity and is being used as an efficient tool for studying transportation problems. It is a powerful tool for analyzing complex systems of a large number of sequential calculations and provides the user with statistical measures of effectiveness which are essential to solve traffic engineering problems. Recent advancements in computation have augmented microscopic simulation models that allows user to get visualized demonstration of target traffic scenarios. Examples of state-of-the-art microscopic traffic simulation models are VISSIM, MITSIM, AIMSUN, and PARAMICS.

Microscopic simulation traces individual vehicles right from entry into the network until it departs. In addition, appropriate microscopic simulation model can be used to represent the lateral and longitudinal movement of an individual vehicle. Such models rely mainly on the use of car-following, lane-changing, and gap-acceptance rules to better describe longitudinal and lateral movements of individual vehicle. However, because of the diverse driving behavior in real traffic, these models incorporate many necessary parameters which make it difficult to calibrate. The model parameters may also be exceedingly sensitive, and there is a higher chance of obtaining misleading results. Therefore, proper calibration is required when using microscopic simulation models for local traffic conditions [1,2].

Saudi Arabia has one of the highest fatality risk levels in the world in terms of traffic crash fatalities with around 29 deaths per 100,000 people. In numbers, more than 6450 people get killed, and more than 36,400 get injured due to traffic crashes in Saudi Arabia annually [3]. These rates are considerably high when compared to many other countries. Many researchers have already investigated on these issues and found that driving behavior is the primary cause of crashes at signalized urban intersections [4]. The time headway and reaction time are two important characteristics of driving behavior. Al-Ghamdi [5] studied driving behavior at signalized intersections in Saudi Arabia and found that the mean of discharge headways is shorter in Riyadh (capital of Saudi Arabia) than in other cities.

This study used PARAMICS microscopic simulation model to analyze an urban arterial road network of the city of Al-Khobar. PARAMICS, a microscopic urban and freeway traffic simulation software, is used to model the vehicle movement and individual driving behavior on road networks. Modeler is the core of PARAMICS software that is a stochastic, microscopic, time step, and behavior-based simulation module. A stochastic model results in unique statistical output each time they are run using a set of input data in contrast to deterministic models that produce identical results in each run. Generally, in PARAMICS, three interacting traffic flow models control the movement of each vehicle, which are: car-following model, gap-acceptance model, and lane-changing model. Now, the challenge lies in selecting the appropriate parameters and their values to calibrate the PARAMICS model.

The driver reaction time and mean target headway are two main user-specified parameters in the car-following and lane-changing models that commonly affect the overall driver behavior in the simulation environment. Network characteristics, traffic demand, overall simulation configuration, and driver behavior factors are considered by Grades et al. [6] as the four key elements while using PARAMICS to evaluate freeway improvement strategies on Interstate 680 in San Franscisco Bay area. Lee and Ozbay [7] simulated a one-mile segment of Interstate 5 in Orange County, California, in PARAMICS and found differences between California drivers' behavior and the default values in PARAMICS. Pinna [8] used generic algorithm for selecting the input parameters while calibrating and validating the PARAMICS model for a highway traffic network between the sites of Veenendaal and Maarsbergen in the province of Ulrecht. Zhe et al. [9] developed a procedure for the calibration and validation of PARAMICS for freeway modeling. They have identified the parameters of PARAMICS that need to be calibrated using 2^{k-p} fractional factorial design by toll data. Prusty et al. [10] calibrated and validated PARAMICS for a heterogeneous traffic interacting with high pedestrian flow in the city of Mangalore, India. This study concluded that PARAMICS' car-following algorithm is effective in reproducing vehicle and pedestrian flow in complex and heterogeneous traffic. In a recent study, traffic flow and queues have been used as a measure of effectiveness to calibrate and validate the PARAMICS model [11].

The analyses of different studies on previous literature revealed that mean target headway (MTH) and mean reaction time (MRT) are the main key factors in calibrating the PARAMICS model (Table 1). The calibrated values of MTH and MRT vary from 0.50 to 1.65, and 0.42 to 1.00, respectively, for a number of studies (Table 1).

Currently, the artificial neural network (ANN) and genetic algorithm (GA) are used to calibrate microscopic simulation models and other relevant fields. Ma et al. [13] used combinatorial parametric optimization to automate the tedious job of trial and error based microscopic calibration model. They had integrated the GA with microsimulation model PARAMICS to modify the control parameters of PARAMICS, which minimized the discrepancy between simulated output and real field data. Otković et al. [16] used ANN model to calibrate VISSIM, a microscopic traffic simulation model. A database consisting of 1379 examples were used to develop and validate the ANN model. The ANN model performed adequately in modeling the travel time compared to the output of VISSIM with respect to correlation coefficient, mean absolute error, and maximum absolute error. ANN models are also adopted for modeling car-following drivers' behavior which can be used for calibrating microscopic traffic simulation model [17]. Zhou et al. [18] integrated PARAMICS with Comprehensive Modal Emissions Model (CMEM) and GA to develop traffic signal timings at an intersection which reduce vehicle emissions, fuel consumption, and vehicle delay simultaneously. Zhang et al. [19] developed a traffic pattern recognition model of intersections based on the fuzzy neural network through combining fuzzy inference system and artificial network. Their model was validated with respect to free flow, unstable flow, and compulsory flow using the VISSIM microsimulation software. Ghanim et al. [20] combined GA and ANN to develop a real-time traffic signal controller integrating traffic signal timing optimization and transit signal priority control. The control system was

Table 1 Calibrated parameters of PARAMICS for different traffic conditions

Author(s)	Location of the study	MTH (S)	MRT (S)
Ozbay and Bartin [12]	South Jersey, New Jersey, USA	0.70	0.50
Ma and Abdulhai [13]	Toronto, Canada	0.86	0.71
Gardes et al. [6]	San Francisco Bay, USA	1.65	0.42
Zhe et al. [9]	Guangdong Province, China	0.45	0.43
Jobanputra and Vanderschuren [14]	Cape Town, South Africa	0.50	1.00
Chu et al. [15]	Irvine, Orange County, California	0.78	0.66

successful in reducing transit vehicle delay and improving schedule adherence in VISSIM environment.

This study proposes machine learning model-based calibration methodology for the PARAMICS model. The two main parameters identified for this calibration study were mean target headway and mean reaction time in accordance with the previous literature. In order to develop the ANN model, a set of values of MTH and MRT were used for the given network to produce the queue length. The values of MTH and MRT and queue length were considered as inputs and output, respectively, for the proposed ANN model. Queue length was selected from several measures of effectiveness (MOEs) produced by the model because it is relatively easy to measure such MOEs in the real study network and signalized intersections.

2 Study Area and Calibration Process

2.1 Study Site

The study network is a moderately congested corridor network in the city of Al-Khobar, Kingdom of Saudi Arabia (KSA), as shown in Fig. 1. The network consists of a five-kilometer section of an urban arterial that includes three major signalized intersections.

2.2 Basic Input Data and Coding the Network

Input data needed to run PARAMICS include network geometric features, traffic control system, vehicular characteristics, traffic composition and driver behavior (e.g., reaction time, saturation flow, start-up lost time), analysis zones, and travel demands.

The data collection time for the selected weekday was between 8:30 AM and 09:30 AM with an interval of 15 min. The collected volume data were slightly below the saturation flow. Automatic traffic counter was used to collect the volume data in the selected intersections. The other collected data include turning counts, queue length, and signal timing plan for each intersection.

The simulation was run for one hour in the AM peak of a typical weekday. An ANOVA test was conducted to ensure that the one-hour AM peak traffic represents AM peak of any weekday. Randomly selected seven different weekday mean flow data were compared. The F-value for the ANOVA test for mean flow was 1.16. This value is lower than the F-critical value of 2.12 at 95 % confidence level, which means that the mean of the AM peak traffic flow of these days is not statistically different at 95 % confidence level. In this study, the queue length from the first intersection (Fig. 1) to the downstream intersections for eastbound and westbound traffic was taken as the measures of effectiveness (MOEs).

In PARAMICS, driver data expressed as a single driver unit (SDU) [15] are represented by driver aggressiveness and awareness factor. These factors were kept to the default value of the model. Another factor called driver familiarity is by default assumed to be 85 % as most of the drivers are familiar with the network, and there are no alternative routes to travel from one zone to another. The coded network in PARAMICS using the modeler module consists of eight zones and 32 nodes. The time step used for the simulation is 3 as recommended by the model developer help guidance [21].

The PARAMICS model uses an origin–destination (OD) matrix to define the travel demand and vehicle paths in the study area. From the perspective of traffic demand input data, the PARAMICS model is categorized into path-based simulation models where the simulation models concentrate on reproducing network trip-making behavior. Since this information was not readily available, it was obtained from the observed traffic volumes and turning movements using the Estimator module of PARAMICS. The model utilizes the GEH statistic (a specialized Chi-square statistic) to compare the observed and modeled flows. Starting with a user-defined

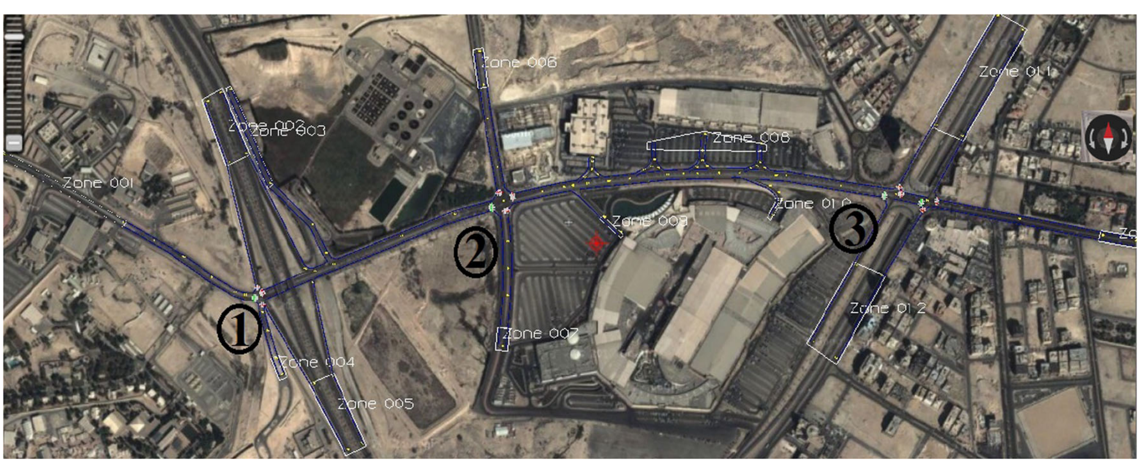

Fig. 1 Study network for calibration in PARAMICS at the urban arterial of Al-Khobar City, KSA (Drawn on Google Map)

initial pattern matrix, flows are recalculated iteratively until a targeted GEH value is reached.

$$\mathrm{GEH} = \sqrt{\frac{(M - O)^2}{(M + O)/2}} \quad (1)$$

where M is the modeled flow and O is the observed flow [22]. In this study, the iterative process was continued until at least 85 % of the link volume with turning volumes has a GEH (named after the inventor Geoffrey E. Havers) values of 5 or below as suggested in the UK Highways Agency's Design Manual for Roads and Bridges [22].

2.3 Calibration Methodology

Model calibration is the process by which the network elements, model parameters, and trip patterns are adjusted in order to obtain a model capable of reproducing observed traffic characteristics such as queuing, travel time, traffic volumes, routing, turn proportions, driving behavior, and vehicle characteristics. This study proposes a GA- and ANN-based approach for searching the values of the main parameters, which minimize the relative error between observed data and the PARAMICS output. Similar to the manual calibration, mean target headway (MTH) and mean reaction time (MRT) are the two key parameters selected for this calibration attempt. In order to develop the ANN model, a set of values of MTH and MRT were used for the given network to produce the queue lengths of the eastbound and westbound traffic of the middle intersection and the inbound approaches of the terminal intersection in the network (Fig. 1). The values of MTH and MRT were the input, while queue lengths were considered as output for the proposed ANN model. The developed ANN model can be used extensively for a wide range of inputs of MTH and MRT to produce the desired queue lengths which will meet the field data. The methodology of this research contains the following steps in the same order as given below:

Step 1 Develop the PARAMICS model using basic input data such as network geometric features, traffic control system, vehicular characteristics and proportions and driver behavior (e.g., reaction time, saturation flow, start-up lost time), analysis zones, travel demands.

Step 2 Balance between observed and modeled flows using appropriate performance measures such as GEH statistic.

Step 3 Determine the appropriate calibration parameters such as mean target headway and mean reaction time.

Step 4 Generate PARAMICS output for a set of values of calibration parameters (MTH and MRT).

Step 5 Develop the ANN model considering the calibration parameters as input and the measure of effectiveness such as queue length as output. If needed, multiple-input and multiple-output-based ANN model may be considered.

Step 6 Validate the developed ANN model with the help of testing dataset considering appropriate performance measures.

Step 7 Use an optimization tool such as GA model to determine the appropriate values of MTH and MRT for the given network. The model determines the desired MTH and MRT, which ensure minimum difference with the measured values of queue lengths and the ANN output (i.e., queue lengths).

Step 8 Select the appropriate calibration parameters based on the ANN output and determine the corresponding PARAMICS output.

Step 9 Compare the PARAMICS output with the observed measures of effectiveness for validation.

2.4 Fundamentals of ANN Modeling Approach

This subsection describes the fundamentals of ANN based on the literature. ANNs have been introduced during 1940s following the concept of learning mechanisms of the brain [23] and have got a great development during 1980s because of the advanced training algorithms suitable for large sets of data [24]. They are robust estimators of nonlinear, stochastic and noisy phenomena, such as driving behavior. They consist of inter-connected processing nodes that are structured in layers and added together with weighted connections. The learning algorithm in response to training data provides a given network with the ability of adjusting its connections weights and bias levels. Theoretically, conventional ANNs can approximate any continuous function to any desired degree of accuracy, if sufficient numbers of hidden units (neurons) are available [25].

Generally, the topology of ANNs is described in terms of the order, interconnections, and organization of the nodes within layers of a given network [26]. The appropriate selection of the desired topology is determined depending on the problems. The nodes of a feed-forward neural network are arranged in layers beginning with the input layer and ending with the output layer. In addition, a number of hidden layers in between input and output layers provide most of the network computational power [26].

A feed-forward neural network for a simple problem may consist of three layers: (1) the first layer with two inputs, (2) the second hidden layer with two neurons, and (3) the third layer with one output in Fig. 2. The input layer does not provide any computational ability rather it directs the input to the first hidden layer and the remaining connections carry real-valued weights, which modify the signal strength received

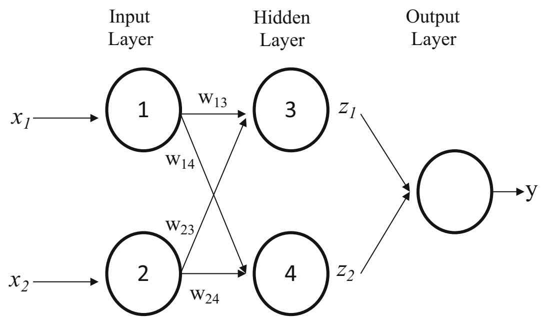

Fig. 2 Typical architecture of a simple feed-forward neural network with two inputs, one output, and one single hidden layer

from other neurons. The node of other layers, i.e., the hidden layer and output layer receive the summation of weighted inputs from the previous layers and bias. The received input and bias are processed by the activation function of the corresponding neuron and directed to the neuron of the next layer or to the environment as output. The output of a neuron of the hidden layer is obtained by:

$$\text{Output of node } j\text{th hidden node, } z_j = f\left(\sum_i w_{ij} x_i + w_{oj}\right) = f(p) = \frac{1}{1+e^{-p}} \quad (2)$$

where w_{ij} is the connection weight from the ith input node to jth hidden node, and w_{oj} is the bias of the jth hidden node. In the above example, a logistic sigmoid function is considered as the activation function of the hidden node.

3 Fundamentals of Genetic Algorithm

This section provides insights into the proposed ANN model obtained through experimental datasets. This evolutionary computation is developed loosely based on the concepts of biological evolutionary theory [27]. The GA is an evolutionary computation method, which has been successfully used in many applications. Holland [28] introduced the GA, which is based on the concept of survival of the fittest strategy. Therefore, the stronger individuals in the population have a higher opportunity of producing offspring. Each individual in the population is considered as a possible solution, made up of a set of individual genes. The GA adopts a stochastic global search technique within the solution space for determining the individual with a maximum fitness value. The steps involving a standard GA are as follows [27]:

Step 1 Generation of an initial population of chromosomes adopting a random method.

Step 2 Computation of the fitness values of each individual of the current population.

Step 3 Preparation of a transitional population by selecting individuals from the current population with the help of the reproduction operator.

Step 4 Generation of the new population by using genetic operators including crossover and mutation to the transitional population, and

Step 5 Completion of the search whenever an individual of the present population meets the current problem requirement in terms of error measures or time, then stop, otherwise go to step 2.

4 ANN Model Development

The modeling exercise considered 210 sets of MTH and MRT values to predict the eastbound and westbound queue lengths. The training dataset consists of randomly selected 70 % of the dataset. The remaining data were used to test the developed model. Generally, the topology of ANN affects the performance of the model significantly. In this study, different numbers of hidden layers and neurons in each layer, transfer functions, numbers of iterations, and training algorithms were systematically evaluated for selecting the appropriate topology. Depending on error measures, the best performing model based on both training and testing dataset is selected. The selected model ensures sufficient learning of the training dataset without compromising the generalization capability of the model.

The transfer function for the hidden layer was tan-sigmoid, which scales down the input into −1 to 1. The weight and bias of the ANN were obtained using Levenberg–Marquardt optimization algorithm [29,30]. The optimization method used mean-squared error (MSE) of the network as error measure. The method was implemented considering the learning rate and goal of the model as 0.0002 and 0.00001, respectively. The number of hidden layer was only one, and the number of neurons in the hidden layer was fourteen. The model was built in MATLAB environment.

5 Results and Discussion

The results of the developed ANN model for the testing dataset were analyzed. The output of PARAMICS and that of ANN model are quite comparable (Figs. 3, 4, 5, 6). The performance of the proposed ANN model is evaluated by considering a number of error measures including mean absolute error (MAE), mean-squared error (MSE), root-mean-square error (RMSE), mean absolute percentage error (MAPE), and coefficient of correlation (CC). The CC varies between 0 and 1, which indicates the degree of statistical cor-

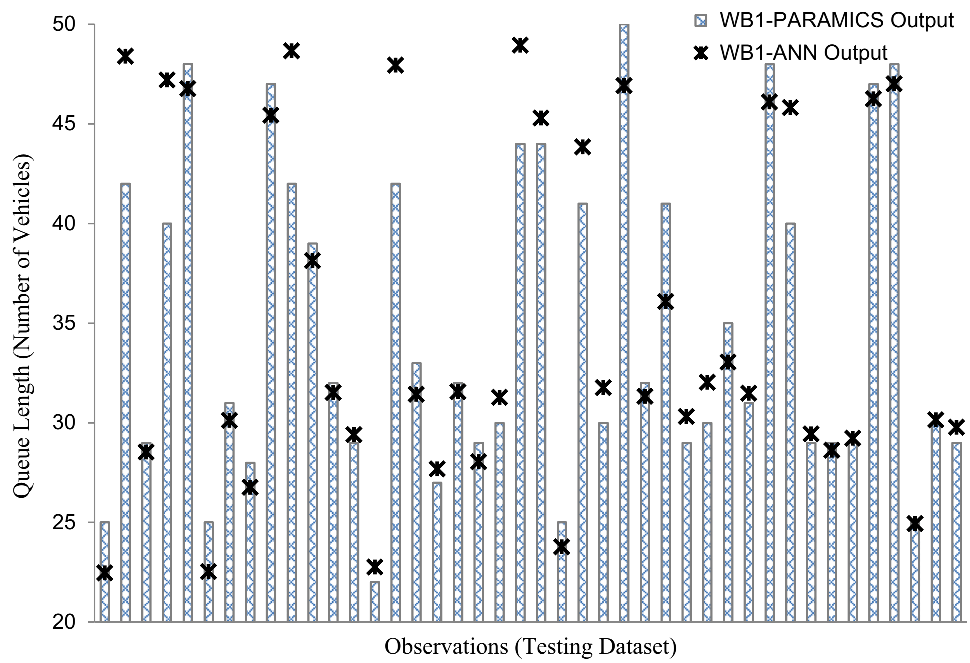

Fig. 3 Output of PARAMICS and ANN model outputs for WB1

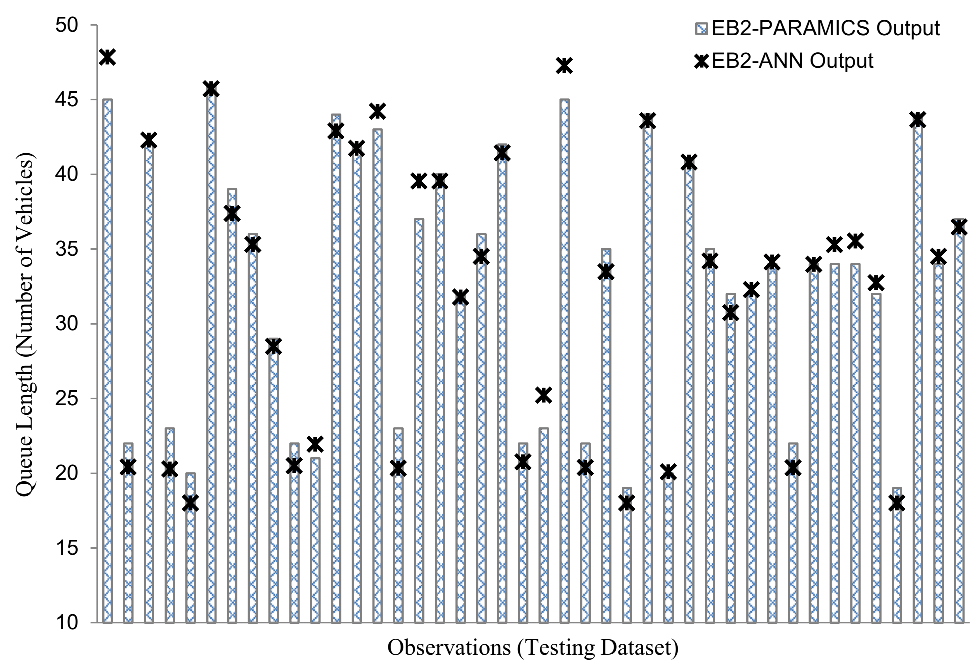

Fig. 4 Output of PARAMICS and ANN model outputs for EB2

relation between the predicted outputs of ANN model and the PARAMICS output. The scatter plot of the PARAMICS and ANN model outputs shows the visual relationship. An identity line passing through the origin and making an angle of 45° with the X-axis is often drawn as the reference. The more the two datasets agree, the more the data points tend to concentrate near the identity line. The data points fall exactly on the identity line when both datasets are numerically identical. The scatter plots of the PARAMICS and ANN model outputs are shown in Fig. 7. The considered error measures indicate that the ANN model is capable of realizing the underlying relationship among the MTH and MRT, and the queue length established in the PARAMICS simulation model (Table 2).

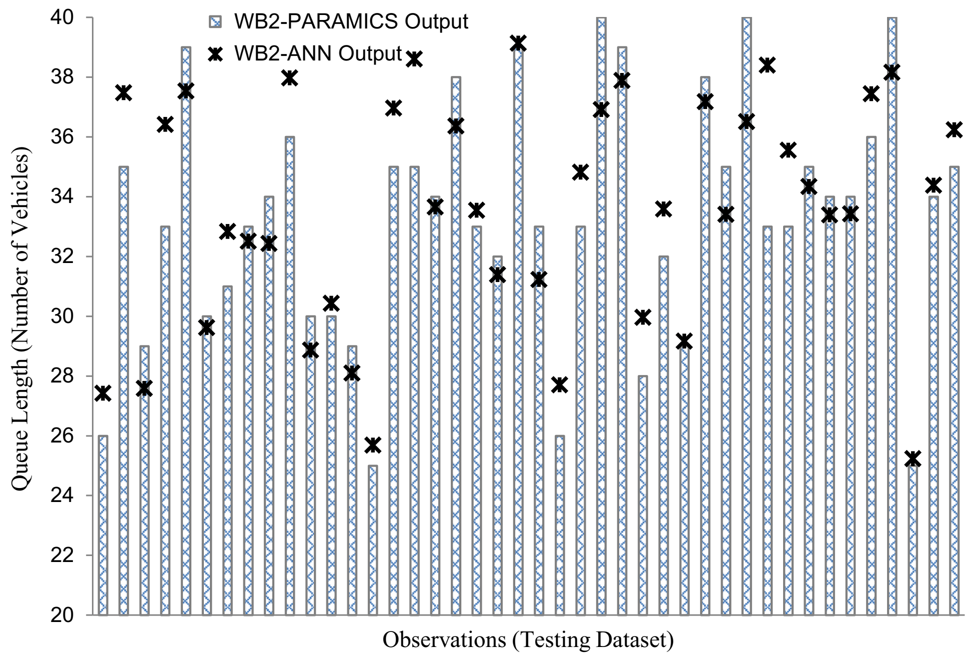

Fig. 5 Output of PARAMICS and ANN model outputs for WB2

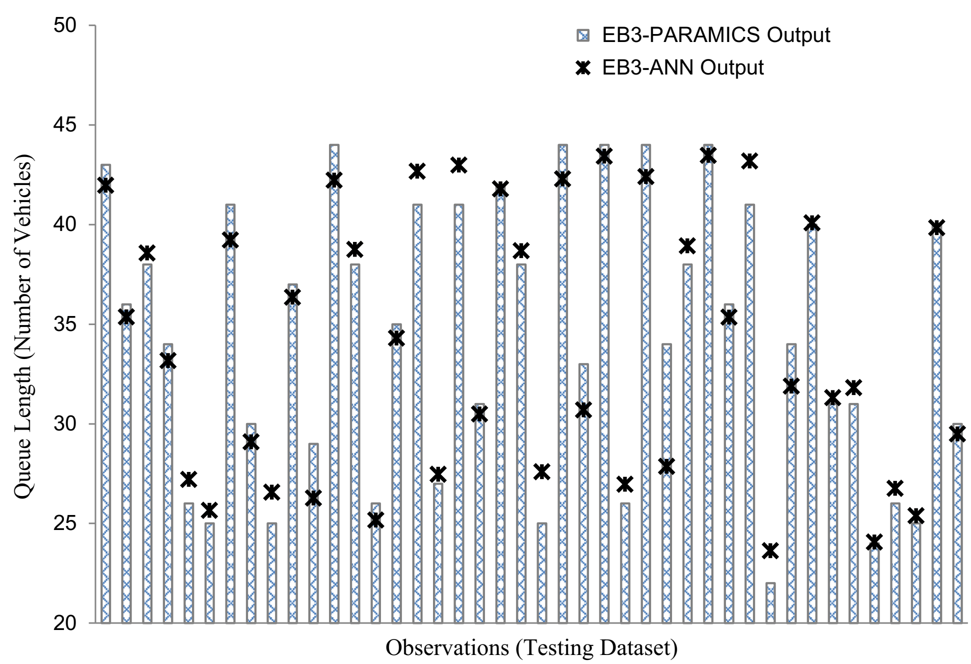

Fig. 6 Output of PARAMICS and ANN model outputs for EB3

In order to find out the appropriate values of MTH and MRT for the given network, GA was used. The developed GA model determined the desired MTH and MRT, which ensure minimum difference with the measured values of queue lengths and the ANN output (i.e., queue lengths). The selected parameters of the GA such as population and generation size and crossover ratio were 1000, 50, and 0.65, respectively. The optimum values of MTH and MRT were 0.683 and 0.789, respectively. These values were used in the developed PARAMICS and ANN model. The queue lengths obtained through GA-based ANN appeared to be adequate for reproducing the local traffic conditions (Fig. 8).

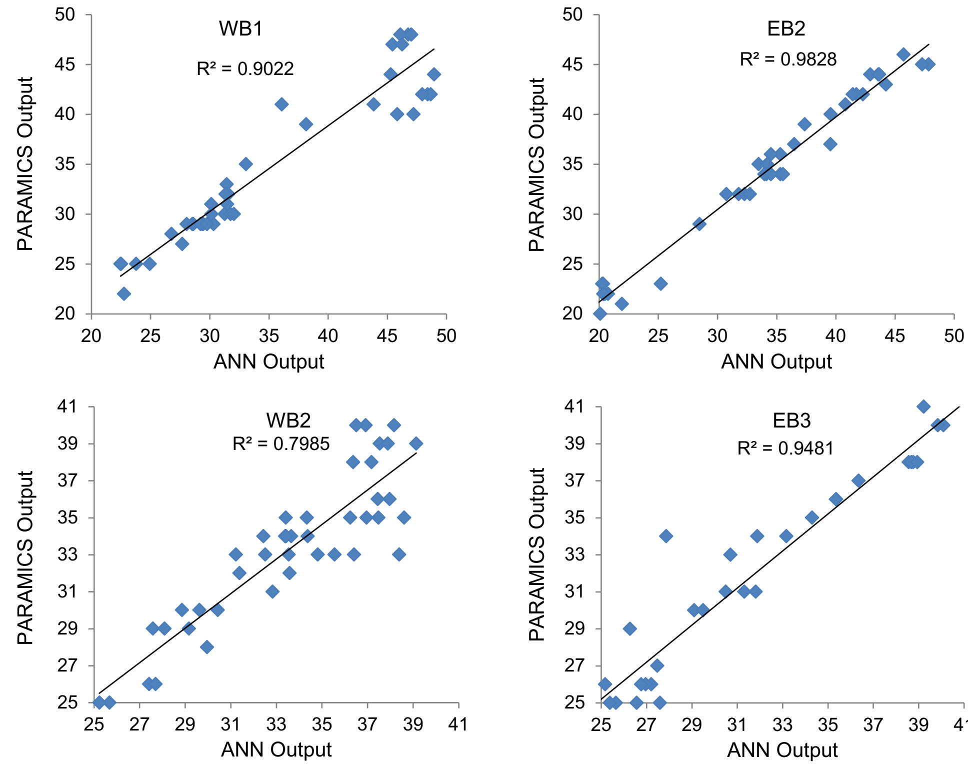

Fig. 7 Scatter plots of PARAMICS and ANN model outputs (i.e., queue length)

Table 2 Error measures of the developed ANN model

	WB1	EB2	WB2	EB3
MAE	1.98	1.10	1.49	1.17
MSE	7.83	1.83	3.40	2.45
RMSE	2.80	1.35	1.84	1.57
MAPE (%)	5.34	3.84	4.43	3.54
CC	0.95	0.99	0.89	0.97

6 Conclusions

This study proposes machine learning model-based calibration methodology for the PARAMICS model considering an urban arterial network of the Kingdom of Saudi Arabia. The developed ANN model performs adequately in modeling the queue length as output using mean target headway (MTH) and mean reaction time (MRT) as inputs. The considered error measures of the ANN model are quite reasonable. Finally, a GA model was developed to obtain the optimum values of MTH and MRT, which will ensure minimum errors among the observed queue lengths and the ANN model outputs (i.e., queue lengths). The selected values of the calibration parameters obtained through the GA-based ANN modeling approach were also used as the input parameters for the PARAMICS model. The conformance of the PARAMICS output and the measured queue length ensures the validity of the proposed calibration methodology. Therefore, this study attempted to provide a systematic calibration methodology for the PARAMICS model, which requires minimum subjective intervention from the users. This study proposed a novel calibration methodology for PARAMICS and other microscopic simulation models. The proposed approach can be incorporated with the advanced traffic management system very easily. The developed road network specific ANN model can be integrated with advanced traffic management system, and real-time traffic performance measures can be obtained without running the PARAMICS model. Therefore, it will be very suitable for real-life applications. The future research may explore the use of other variables (i.e., driver aggression, familiarity) for the PARAMICS simulation model as input to the machine learning model and different measures of effectiveness (i.e., network delay, travel time, fuel consumption) as output. The proposed methodology may work with varying geometry and traffic volume if the model is appropriately built.

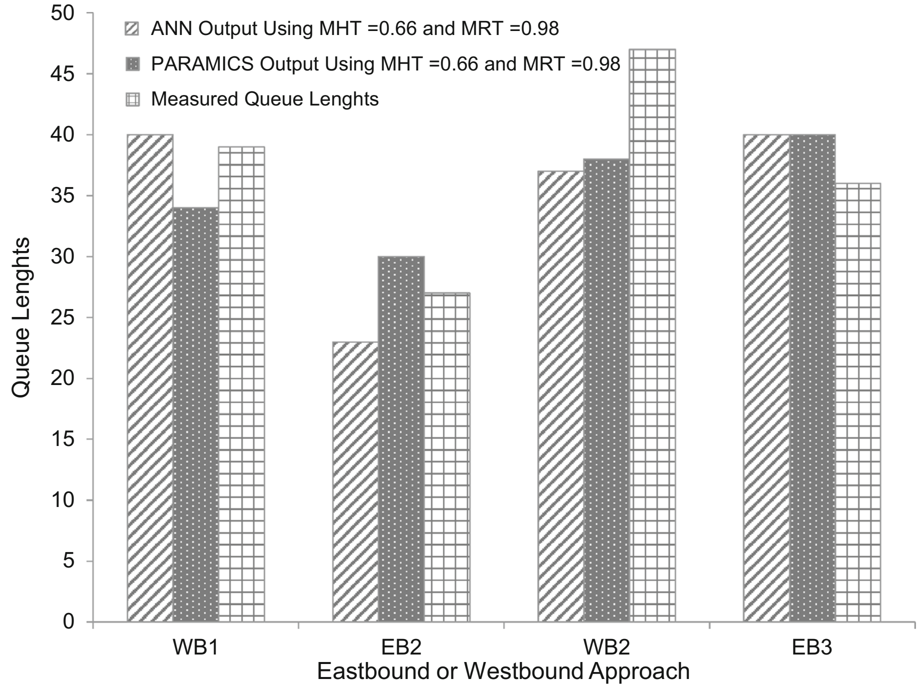

Fig. 8 Measured queue lengths and ANN model outputs and PARAMICS simulation model output using calibrated parameters as inputs

Acknowledgments The authors wish to acknowledge the financial support provided by the Deanship of Scientific Research (DSR) of King Fahd University of Petroleum & Minerals, Saudi Arabia in carrying out this study under the project titled “PARAMICS Model Development for Local Traffic Conditions in Saudi Arabia” (Project No. IN111047).

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