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Keyword:	Microscopic simulation model, PARAMICS, Microscopic model calibration, Adaptive neuro-fuzzy inference system (ANFIS), Saudi Arab

Calibration protocol for PARAMICS microscopic traffic simulation model

– application of neuro-fuzzy approach

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Abstract

This study investigated the challenges of calibration of the PARAMICS microscopic simulation model for the local traffic conditions in the Kingdom of Saudi Arabia (KSA). It proposed an adaptive neuro-fuzzy inference system (ANFIS) based calibration protocol for the PARAMICS model. The developed ANFIS model performs adequately in modeling the queue length as a function of two key calibration parameters, namely mean headway time and mean reaction time. The selected values of the calibration parameters obtained through the ANFIS modeling approach were used as the input parameters for the PARAMICS model. The error indices such as mean absolute errors and mean absolute percentage errors of the developed ANFIS model in predicting the queue lengths varied between 1.11 and 1.24, and between 3.44 and 4.06, respectively. The conformance of the PARAMICS output and the measured queue length indicates the validity of the proposed calibration protocol.

Keywords: Microscopic simulation model, PARAMICS model, Microscopic model calibration, Adaptive neuro-fuzzy inference system (ANFIS), Saudi Arabia

Introduction

Microscopic simulation traces individual vehicles within the network and individual vehicle movements that can be drawn for both lateral and longitudinal movements. It mainly uses car-following, lane-changing and gap-acceptance models to represent longitudinal and lateral movements of individual vehicles. However, because of the diverse driving behaviour in real traffic, simulation models have to incorporate many necessary parameters. Therefore, it becomes incumbent to calibrate the model for local traffic conditions (Dowling et al. 2004).

Zhe et al. (2009) proposed a protocol for the calibration and validation of PARAMICS for freeway modeling. They selected the important parameters of PARAMICS using fractional factorial design and calibrated it with the help of the detailed vehicle-by-vehicle toll data. Prusty et al. (2014) calibrated and validated PARAMICS for heterogeneous traffic conditions in the city of Mangalore, India. JMP (2013) used traffic flow and queues as a measure of effectiveness to calibrate and validate PARAMICS.

Researchers have used Artificial Neural Network (ANN) and Genetic Algorithm (GA) to calibrate Microscopic simulation models. Ma et al. (2002) used combinatorial parametric optimization to automate the tedious job of trial and error based microscopic calibration model. They had integrated the global search technique and Genetic Algorithm (GA) with micro-simulation model PARAMICS to manipulate the control parameters of PARAMICS, that minimized the discrepancy between simulated output and real field data. Otcović et al. (2013) used ANN to calibrate micro-simulation model VISSIM. A database of 1379 combinations of model input parameter values and the simulated travel time in VISSIM is used for neural network learning. The use of Neural Network achieved very close results in travel time prediction. Zhang et al. (2014) has developed a three-layer feed-forward ANN model to emulate an improved version of a well-known higher-order continuum traffic model. This ANN model worked sufficiently to reproduce the simulation results (Zhang et

al., 2014). Saprykin et al. (2015) proposed the utilization of a ward neural network in processing microscopic traffic data to the mesoscopic level. The use of artificial neural network allowed the minimum loss of information while transferring data from microscopic to mesoscopic level. Ratrout et al. (2015) proposed an ANN-GA based microscopic simulation model calibration methodology. The developed ANN model performed adequately in modeling the queue length as a function of mean target headway and mean reaction time.

This study proposes an artificial intelligence based approach for calibrating the PARAMICS microscopic simulation model. PARAMICS is a microscopic urban and freeway traffic simulation software, which is used to model the movement and behaviour of individual vehicles on road networks. Modeler is the core of this software that is a stochastic, microscopic, time step, and behaviour-based simulation model. In PARAMICS, three interacting traffic flow models control the movement of each vehicle, which are (i) car-following model, (ii) gap-acceptance model, and (iii) lane-changing model. The mean target headway and driver reaction time are two important user-specified parameters in the car-following and lane-changing models. These parameters may significantly influence the overall driver behaviours of the simulation. The mean headway time (MHT) and mean reaction time (MRT) are two key parameters in calibrating the PARAMICS model (Table 1). The calibrated values of the previous studies indicated that MHT and MRT vary from 0.50 to 1.65, and 0.42 to 1.00, respectively, for a number of studies (Table 1).

This study proposed an adaptive neuro-fuzzy inference system (ANFIS) model based calibration protocol for the PARAMICS model. The ANFIS-based modeling approach has become popular in developing non-linear relationships for dynamic and nonlinear systems because of its ability in handling large quantity of noisy data (Noori et al., 2009). The ANFIS models have been successfully adopted in wide range of science and engineering fields including CO prediction (Jain and Khare, 2010), SO₂ prediction (Yildirim and Bayramoglu,

2006), hydrodynamic modeling (Razzak et al., 2012), air quality modeling (Rahman et al., 2013), rapid five-day biochemical oxygen demand (BOD_5) estimation (Noori et al., 2013), and traffic flow prediction (Rahman, 2010).

The key parameters selected for this calibration study are mean headway time and mean reaction time. In order to develop the ANFIS model, a set of values of MHT and MRT were used for the given network to produce the queue length, which was obtained through PARAMICS. The values of MHT and MRT, and queue length were considered as inputs and output, respectively, for the proposed ANFIS model.

Study Area and Calibration Process

Study site

The site is a moderately congested corridor network in the city of Al-Khobar, Kingdom of Saudi Arabia (Fig. 1). The network includes a three-mile section of the urban arterial with three major intersections. The intersections are operated with different signal timing plans.

Input data

The basic input data are related to network geometry, driver behaviour, vehicle characteristics, transportation analysis zones, travel demands, traffic control systems, and traffic detection systems. The study network in PARAMICS was built using satellite image, the road geometry, and infrastructure maps.

The traffic flow data were collected for one and a half hours with an interval of 15 minutes. 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. Probe vehicles were used to collect the travel time. In this study, the queue length at the intersections (both eastbound and westbound) was considered as the main measures of effectiveness.

Calibration protocol

This study proposed an ANFIS based approach for searching the values of the calibration parameters, which minimize the relative error between the observed measures of effectiveness and PARAMICS simulation model output. The selected calibration parameters are mean headway time (MHT) and mean reaction time (MRT) and Queue Length (QL) is the observed measure of effectiveness. During the model development process, a set of values of MHT and MRT were used for the given network to produce the queue lengths of the westbound; both eastbound and westbound and eastbound traffic of the intersections 1, 2 and 3 respectively (Fig. 1). The values of MHT and MRT, and four queue lengths were considered as inputs and output, respectively, for the proposed ANFIS model. The developed ANFIS model can be used extensively for a number of values within a particular range of inputs of MHT and MRT to produce the desired queue lengths which will meet the field data. The steps of the proposed calibration protocol are provided below.

- Step 1 Development of the PARAMICS model with the help of basic input data including network geometry, driver behaviour, vehicle characteristics, transportation analysis zones, travel demands, traffic control systems, and traffic detection systems.
- Step 2 Determination of suitable calibration parameters such as mean headway time and mean reaction time.
- Step 3 Generation of the PARAMICS output for a number of values of the selected calibration parameters.
- Step 4 Development of the ANFIS model using the calibration parameters as input and the measure of effectiveness such as queue length as output.
- Step 5 Validation of the developed ANFIS model through testing dataset considering the appropriate performance measures.

- Step 6 Comparison of the output of the ANFIS model (considering a number of values of the calibration parameters) with the observed measures of effectiveness.
- Step 7 Determination of the appropriate calibration parameter values based on the ANFIS output and the corresponding PARAMICS output.
- Step 8 Comparison of the PARAMICS output for the appropriate calibration parameter values (obtained in Step 7) with the observed measures of effectiveness.

ANFIS modeling approach

In the ANFIS model building approach, a Fuzzy Inference System (FIS) is embedded into a framework of the artificial neural network (ANN) (Jang 1993). The architecture and functions of a typical Takagi-Sugeno type (Takagi et al. 1985) ANFIS model with two inputs (x and y) and one output (Fig. 2) follow.

First layer

The node of this layer produces membership grades of input variables, which varies within 0 and 1. It stores the parameter of a Gaussian membership function (μ). The function is written as follows:

$$O_i^1 = \mu_{R_i}(x) \quad \dots [1]$$

and

$$O_{i+2}^1 = \mu_{S_i}(y) \quad \dots [2]$$

$$\mu(x) = \exp\left\{-\frac{1}{2}\left(\frac{x-a}{b}\right)^2\right\} \quad \dots [3]$$

where $i = 1, 2$, x and y are the inputs, R_i and S_i are known as linguistic labels, a and b are the mean and variance of the membership function, respectively.

Second layer

The node of this layer performs connective operation through a T-norm such as “AND” within the rule antecedent and determines the corresponding firing strength. The node output of this layer can be written as follows:

$$O_{1,i}^2 = \mu_{R_i}(x) * \mu_{S_i}(y) = w_{1,i} \text{ and}$$

$$O_{2,i}^2 = \mu_{R_i}(x) * \mu_{S_i}(y) = w_{2,i} \quad \text{for } i = 1, 2 \quad \dots [4]$$

Third layer

The node of this layer performs normalization in order to obtain relative strengths of the rules, and the output of this layer is as follows:

$$O_i^3 = \frac{w_i}{\sum w_i} = \bar{w}_i \quad \text{for } i = 1, 2 \quad \dots [5]$$

Fourth layer

The output of this layer is obtained by multiplying the normalized firing strength of the rule with the corresponding rule output of Takagi-Sugeno type fuzzy inference system. The output of the node is as follows:

$$O_i^4 = \bar{w}_i z_i \quad \dots [6]$$

where $z_m = \alpha_k + \beta_k x + \gamma_k y$, α , β , and γ are constants, and $i = 1, 2$.

Fifth layer

The node of this layer can be regarded as an addition node. The output is calculated as follows:

$$O^5 = \sum_{i=1}^2 \bar{w}_i (\alpha_i + \beta_i x + \gamma_i y) = \varphi \quad \dots [7]$$

where φ = model output.

In ANFIS architecture, as the mean and variance of the membership functions are fixed, the output of the whole system is a linear combination of the consequent parameters (Ying et al. 2008). Finally, the output can be written as the following matrix format for n numbers of training data:

$$\varphi = BS \quad \dots [8]$$

$$\text{where } \varphi = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_n \end{bmatrix}, S = \begin{bmatrix} \alpha_1 \\ \beta_1 \\ \gamma_1 \\ \alpha_2 \\ \beta_2 \\ \gamma_2 \end{bmatrix}, B = \begin{bmatrix} \bar{w}_1 & \bar{w}_1 x_1 & \bar{w}_1 y_1 & \bar{w}_2 & \bar{w}_2 x_1 & \bar{w}_2 y_1 \\ \bar{w}_1 & \bar{w}_1 x_2 & \bar{w}_1 y_2 & \bar{w}_2 & \bar{w}_2 x_2 & \bar{w}_2 y_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \bar{w}_1 & \bar{w}_1 x_n & \bar{w}_1 y_n & \bar{w}_2 & \bar{w}_2 x_n & \bar{w}_2 y_n \end{bmatrix}$$

The unknown matrix, S , is estimated using the least squares method. The gradient descent technique is considered for tuning the architecture (Jang 1993). The premise and consequent parameters are learnt based on gradient descent and least squares method, respectively. The update formula for each premise parameter (δ) in terms of the overall error (E) is:

$$\nabla \delta = -\eta \frac{\partial E}{\partial \delta} \quad \dots [9]$$

where η = learning rate, $E = \sum_{i=1}^n (T_i - \varphi_i)^2$, T = target, and φ = model output.

Development of ANFIS Model

Four modelling exercises were performed during this study. The description of the models is provided in Table 2. Only seventy percent of the total dataset were randomly selected for developing the model and the remaining thirty percent dataset were used for testing the obtained model.

The ANFIS model shows good performance, but it may produce spurious rules (Jantzen 1998). The appropriate input selection (Noori et al., 2010) and the number of rules affect the

performance of ANFIS models. A fuzzy model with a large number of rules will eventually reduce generalization capability (Yen et al. 1999). This problem is resolved by introducing an initial FIS generated by clustering techniques such as subtractive clustering (SC) and grid partitioning algorithms (Noori et al., 2016). Chiu (1994) developed subtractive clustering, which is a modification of the mountain method. In this method, the possibility of each data point to become a cluster center depends on the density of the surrounding data points. Consider m data points ($X_1, X_2, X_3, \dots, X_m$) with n dimensions which are assumed to have fallen inside a hyper box. The density (ρ_i) of the data point X_i can be expressed as:

$$\rho_i = \sum_{k=1}^m \exp\left(-\frac{\|X_i - X_k\|^2}{\left(\frac{r_a}{2}\right)^2}\right) \quad \dots [10]$$

r_a is a positive number indicating the influence area of a data point, and the data points beyond the radius do not affect the density of X_i . In the following step, the data point with the highest density value becomes the first cluster center. The density of a data point is modified by the following formula:

$$\rho_i = \rho_i - \rho_t \exp\left(-\frac{\|X_i - X_t\|^2}{\left(\frac{r_b}{2}\right)^2}\right) \quad \dots [11]$$

r_b is a positive number indicating the influence area where the density of data point will reduce. ρ_t is the density of the first selected cluster center (X_t) among the data points. After modifying the density of data point, the new cluster center will be selected. The density of all data points will be changed again. This process will be continued until all the data points are within the radii of a cluster.

In the proposed modeling approach, SC was used to develop the initial fuzzy inference system (FIS). The considered radius and iterations improvement were 0.3 and 20, respectively adopted by trial and error approach. In the ANFIS structure, there are twenty

bell-shaped membership functions for each input. The rule base contains twenty rules. The above computations of the ANFIS model and SC were performed in Matlab environment, which provides the gradient descent and least squares method based training algorithms.

Results and Discussions

The results of the developed ANFIS model for the testing dataset were investigated. The output of PARAMICS and that of the ANFIS model are comparable (Figs. 3 to 6). In order to investigate the performance of the ANFIS model, mean absolute error (MAE), mean squared error (MSE) and mean absolute percentage error (MAPE) error measures and coefficient of correlation (CC) were considered. The CC varies between 0 and 1, indicating the strength of statistical correlation between the predicted outputs of ANFIS and PARAMICS model output. The scatter plots of the PARAMICS and ANFIS model outputs show the visual relationship. An identity line passing through the origin and making an angle of 45° with the X -axis is typically drawn as the reference. The more the datasets agree, the more the data points tend to be near the identity line. When the data points fall exactly on the identity line, both variables are numerically identical. The scatter plots of the PARAMICS and ANFIS model outputs are shown in Fig. 7. The considered error measures indicate that the ANFIS model is successful in realizing the underlying relationship among the MHT and MRT, and the queue length established in the PARAMICS simulation model (Table 2).

In order to find out the appropriate values of MHT and MRT for the given network, an extensive search was performed using 1000 data points for the different combinations of MHT and MRT ranging between 0.5 and 1.7 seconds, and between 0.4 and 1.5 seconds, respectively. The developed model provides the desired values of MHT ($=0.68$) and MRT ($=0.72$), which guarantee minimum difference with the measured values of queue lengths. The obtained values appear adequate for the local traffic conditions (Fig. 8). The maximum

difference between observed queue length and simulated ones (both by PARAMICS and ANFIS) is at intersection 2 in the westbound direction (Fig 8.). One possible reason of these differences might be due to excessive side friction at intersection 2, particularly in the westbound direction because of the high concentration of commercial activity surrounding it. During the traffic data collection, it was also observed that there exists a lot of illegal lane changing at this intersection in green. Vehicles in middle lane stop at the green trying to make left turn and vice versa. Often vehicles attempt to beat the green of the signal and such illegal driving behaviour could not be modelled in PARAMICS and consequently by ANFIS.

Conclusions

This study proposed an adaptive neuro-fuzzy inference system (ANFIS) based calibration protocol for the PARAMICS model. It introduced a novel neuro-fuzzy calibration methodology which can be incorporated with the advanced traffic management system very easily. The developed ANFIS model performs adequately in modeling the queue length as a function of mean headway time and mean reaction time. The considered error measures of the ANFIS model are quite reasonable. The outputs of the ANFIS model for a great number of mean headway time and mean reaction time to determine the appropriate values to match the observed queue length. Finally, the selected values of the calibration parameters obtained through the ANFIS modeling approach were used as the input parameters for the PARAMICS model. The conformance of the PARAMICS output and the measured queue length exhibits the validity of the proposed calibration protocol. Advanced traffic management system can easily be incorporated with the proposed calibration approach. The developed road network specific ANFIS model will allow user to obtain real time traffic performance measures without running the PARAMICS model repeatedly.

The future research may explore the use of other variables (i.e., driver familiarity and aggression) to the PARAMICS simulation model as input and different measures of effectiveness (i.e., point to point travel time, network delay, fuel consumption) as output. If the model is built appropriately, the proposed methodology may work with varying geometry and traffic volume.

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Table 1—Values of calibrated parameters of PARAMICS proposed by different studies		
Author(s)	MHT (sec.)	MRT (sec.)
Ozbay et al. (2003)	0.7	0.50
Ma et al. (2002)	0.8	0.71
Gardes et al. (2002)	1.6	0.42
Lee et al. (2001)	0.6	0.41
Li et al. (2010)	0.4	0.43
Jobanputra et al. (2012)	0.5	1.00
Chu et al. (2004)	0.7	0.66

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Table 2—Error measures of the developed ANFIS model				
	WB1	EB2	WB2	EB3
MAE	1.23	1.24	1.11	1.18
MSE	2.92	2.37	2.83	2.99
MAPE (%)	4.06	3.99	3.63	3.44
CC	0.97	0.98	0.93	0.97

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Figure Captions

Fig. 1—Study network for calibration of PARAMICS at the urban arterial of Al-Khobar city, KSA

Fig. 2—An example of ANFIS architecture

Fig. 3—Output of PARAMICS and ANFIS model outputs for WB1

Fig. 4—Output of PARAMICS and ANFIS model outputs for EB2

Fig. 5—Output of PARAMICS and ANFIS model outputs for WB2

Fig. 6—Output of PARAMICS and ANFIS model outputs for EB3

Fig. 7—Scatter plots of PARAMICS and ANFIS model outputs

Fig. 8—Observed queue lengths, ANFIS model output and PARAMICS simulation model output using calibrated parameters as input

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