ESTIMATION OF DELAY AND VEHICLE STOPS AT SIGNALIZED INTERSECTIONS USING ARTIFICIAL NEURAL NETWORK

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Abstract:

Delay and number of vehicle stops are important indicators that define the level of service of a signalized intersection. Therefore, they are usually considered for optimizing the traffic signal timing. In this study, ANNs are employed to model delay and the number of stops estimation at signalized intersections. Intersection approach volumes, cycle length and left turn lane existence were utilized as input variables since they could easily be obtained from field surveys. On the other hand, the average delay and the number of stops per vehicle were used as the output variables for the ANNs models. Four-leg intersections were examined in this study. Approach volumes including turning volumes are randomly generated for each lane of these intersections, then the traffic simulation program was run 196 times with each generated data. Finally, average delay and the number of stops per vehicle were obtained from the simulations as outputs. In this study, various network architectures were analyzed to get the best architecture that provides the best performance. The results show that the ANNs model has potential to estimate delays and number of vehicle stops.

1 Introduction

Many criteria such as delay, number of stops, capacity, speed, and degree of saturation, etc. are used to determine the level of service (LOS) at an intersection. Among these criteria, delay and number of stops are the most important ones because they directly show the amount of lost time and fuel consumption. Additionally, they are indicators of the degree of frustration and discomfort of the drivers. Delay and number of vehicle stops are measured to evaluate the performances of an intersection under different control, demand and operating conditions. Therefore, accurate predictions of delay and vehicle stops are important measures of effectiveness (MOEs). Delay basically consists of three components which are uniform, non-uniform and initial queue delay.

Uniform delay, which assumes perfectly uniform arrivals and stable flow, occurs resulting from interrupted traffic flow by traffic signals at intersections.

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Whereas non-uniform delay, which assumes non-uniform arrivals, incorporates effects of random arrivals and oversaturated traffic conditions. Initial queue delay, on the other hand, accounts for the additional delay incurred due to an initial queue. This queue is due to the unmet demand from the previous time period. If there is no queue at the end of previous time period, then initial queue delay is zero.

Delay at signalized intersections can be estimated by either employing analytical models or artificial intelligence techniques. To estimate delay at signalized intersections, a number of analytical models have been proposed and developed based on different assumptions of accounting for various traffic conditions. Stochastic steady state delay models, which were investigated by Webster [1], Tanner [2] and Miller [3], and deterministic delay models, which were investigated by May and Keller [4], Neuberger [5] and Pignataro el al. [6], have been commonly used in the estimation of delay at signalized intersections for under saturated and oversaturated traffic conditions, respectively. However, both types of delay models are entirely incompatible when degree of saturation is equal to 1.0. While the first models predict infinite delay, the latter models estimate zero delay at this particular degree of saturation. In order to provide more realistic delay estimations and overcome the deficiencies in both models, time-dependent delay models have been developed such as by Burrow [7], Catling [8], Brilon, Wu [9], Akcelik [10,11], Teply [12] and proposed by Highway Capacity Manual [13-15]. These models are basically a mix of steady state and deterministic models utilizing the coordinate transformation techniques described by Kimber and Hollis [16, 17]. The coordinate transformation method is applied to the steady state curve that shifts it into a deterministic line by making the steady state curve asymptotic to the deterministic line.

Even though analytical models are more practical to estimate delay, they have some deficiencies because of the nature of traffic flow. In reality, the demand in traffic flow is not stable and changes in time but analytical models do not reflect fluctuations in traffic stream. Therefore, artificial intelligence techniques such as ANN, fuzzy systems and a combination of both methods, called ANFIS, have been used for delay estimation at signalized intersections [18-20].

Besides delay, another performance indicator for a signalized intersection is the number of vehicle stops since they have an associated cost in terms of fuel consumption and wear out on vehicle. It is clear that there are two ways for a driver to get stopped at a traffic signal. First, the driver can arrive at the red interval. Second, the driver arrives at the green light and joins back of a queue that has not been serviced yet. The second case occurs during the saturated green interval. In other words, the driver has to stop unless he arrives during the unsaturated green interval. If the signals of the intersections on an arterial are well coordinated with each other, a driver will arrive at the green interval and will pass through the intersections without stopping. On the other hand, if intersections are operated with poor signal coordination the number of stopped vehicle at the intersections will increase. Therefore, stop rate is used as a performance measure to evaluate coordinated signal systems.

Stop rate is defined as a ratio between the numbers of stopped vehicles to the numbers of served vehicles. The probability of stopping P(s), as known stop rate, is equal to the proportion of the cycle length occupied by the red interval and the saturated green interval and it is computed by using Equation 1. The average number of stops is obtained when approach volume is multiplied to the probability of stopping.

$$P(s) = \frac{(1-\dfrac{g}{C})}{(1-\dfrac{gX}{C})} \tag{1}$$

In which, g: effective green time (sec), C: cycle length (sec), X: the degree of saturation

In the literature, some analytical vehicle stop models have been developed by using queuing and different theories. [1, 10, 21-23]. In queuing theory, incurred average number of stops by vehicles approaching a signalized intersection is calculated by Equation 2. This equation gives the exact number of stops and is valid only for both uniform and random arrivals for under saturated conditions.

$$N_{QT} = \frac{r}{C} * \frac{s}{(s-q)} \tag{2}$$

Where, N_{QT}: number of stops, s: saturation flow (vec/h), r: red time (sec), q: arrival flow (veh/h).

A comprehensive study was performed by Rakha et al. to develop an analytical model to estimate the number of vehicle stops at oversaturated intersections. In the model, signal timings, approach arrival rate, approach saturation flow rate and analysis period were used as input variables to estimate the number of vehicle stops.

As mentioned above, there exist many parametric delay models in literature while non-parametric delay models have remained comparatively limited. Among them, Murat and Baskan [19-20] used a non-parametric ANN approach to estimate the total delay in just one approach of an intersection. However, delay occurring in all of the four approaches were considered in this study. Therefore, instead of accounting for delay in only one approach of the intersection, average delays were considered at all of the approaches of the intersection as whole. Moreover, different from previous studies, the ANN model studied in this paper is a new one that does not only consider the delays but also the stop rates, which is another essential indicator for assessing the LOS of an intersection.

This paper is organized in the following way. ANN is explained in the next section. In section 3, the models to estimate delay and the number of stops are developed by using methodology given in Section 2. The performances of the developed models are compared in Section 3. Finally, the conclusions are discussed in Section 4.

2 Artificial neural network model

ANNs are a class of flexible nonlinear models that can discover patterns adaptively from the data. Theoretically, it is shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and can estimate any complex functional relationship. Empirically, numerous of successful applications have established their role for pattern recognition, forecasting, control and design [24-27]. ANNs consist of three layers, namely, the input, the hidden and the output layers. The input layer consists of all input factors. Information from the input layer is then processed in the course of one or more hidden layers. One or more hidden layers act as intermediate layers between the input and output layers. The neurons join by weighted connections, then, the output vector computes in the output layer. An artificial neuron whose fundamental element of ANNs incorporates weights, summing function, bias, and activation function. The structure of an artificial neuron is illustrated in Fig.1. An artificial neuron is a basic operating unit to constitute an ANN.

In a neural network, the first important stage is the training step in which an input is introduced to the network together with the desired outputs.

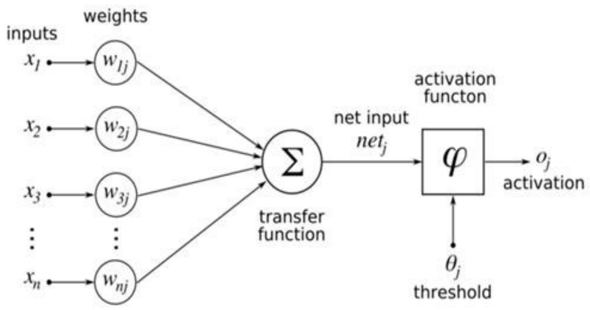

Figure 1. An artificial neuron.

The purpose of the training is to minimize the global error level, such as the mean square error (MSE), mean absolute percent error (MAPE), and root mean square error (RMSE). Artificial neural networks typically start out with randomized weights for all their neurons. This means that they do not know anything and must be trained to solve the particular problem for which they are intended. When a satisfactory level of performance is reached, the training is ended and the network uses these weights to make a decision. Multi-layer perception (MLP) networks model is usually preferred in engineering applications because many learning algorithms might be used in MLP. One of the commonly used learning algorithms in ANN applications is the back propagation algorithm (BP), which is also used in this research. The idea of the back propagation algorithm is to reduce the errors, which presents the difference between the observed and expected results until the ANN learns the training data. An activation function is a mathematical function used to transform the activation level of a neuron into an output signal, and to get increased computational power from multiple neurons. This function must be a differentiable and continuous one. Linear, sigmoid and hyperbolic tangent functions are the most common activation functions used in the literature. The activation function is used as a boundary for the output. These boundary levels usually change from zero to one [0, 1] or from minus one to plus one [-1, +1] according to the type of the activation function used.

3 Artificial neural network design

3.1. ANN inputs and outputs

In this study, two different ANN architectures were designed to estimate the average delay per vehicle (ANN-D) and stop-rate (ANN-S). The input layers of ANNs given in Fig. 2 were formed by the three variables.

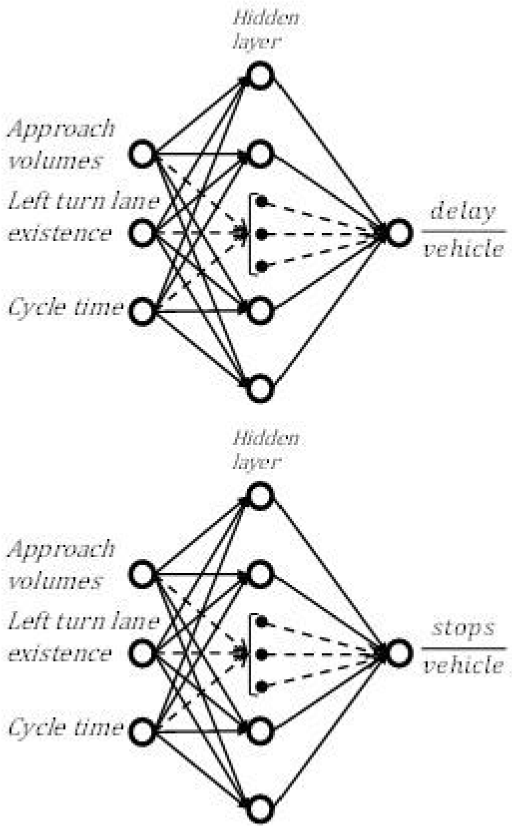

Figure 2. ANN architectures used for analysis.

The approach volumes represent the lane volumes (8 through and if exist 4 left turn lanes totaling 12 lanes), left turn lane existence indicates availability of the left turn lane (1 if exists, otherwise 0 totaling 4 inputs) and cycle time is the optimum cycle length for the corresponding volumes (total of 1 input). The latter was obtained via the Synchro Traffic Analysis and Optimization Program with respect to given traffic conditions. As a result, the input layer was defined as three input variables representing actually 17 input values.

ANNs need a qualified and sufficient amount of data for training process. For this reason, three types of intersections were considered and 196 different approach volumes were generated for each intersection type as shown in Fig. 3.

The approach volumes were generated in range from 100 to 1000 veh/hr, while left and right-turn rates were generated from 0% to 50%, randomly. The cycle lengths with respect to these volumes including left and right turns were optimized by the Synchro Traffic Analysis and Optimization Program as mentioned earlier. The outputs such as delays, stop rates, fuel emissions etc. were obtained from its microscopic simulation tool, SimTraffic [28].

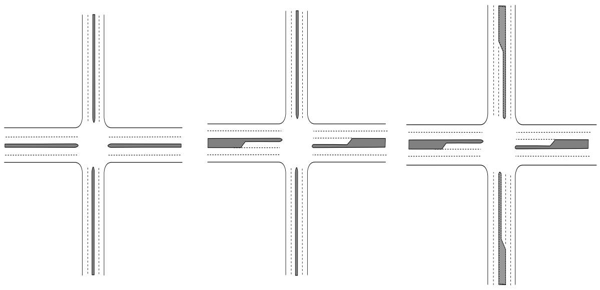

Figure 3. Types of intersections used for analysis.

3.2. ANN architectures

The architecture of ANN has an important role on its performance. Therefore, one of the main stages of designing an effective ANN architecture is to determine the appropriate number of hidden neurons. While the sigmoid transfer function was utilized in hidden layers, the linear function was utilized in the output layer. In this study, the methodology named Best Searcher–ANN (BS-ANN) was developed for this study to determine the number of neurons in hidden layer. The BS-ANN is a heuristic and stepwise technique and has four stages as described in Fig. 4. The BS-ANN works as follows: the first step is an iterative stage which generates the minimum error matrixes (MENMx) based on pre-determined search space. The search space consists of the minimum and maximum range of number of hidden neurons (Nhn).

Although the ANNs have the same architecture, they compute different output values when their connection weights are different. Therefore, in iterative stage 1 of Fig.4, the ANN is started with the minimum number of neurons in search space and it runs for "*k times*" with different random weights, as illustrated in Fig 5.

The "*k times*" in iterative stage-1 is kept relatively lower than the "*k times*" in iterative stage-2 to understand the location of the best performance zone (BPZ), quickly in a large space. After this loop process, the ANN model which generates minimum errors and BS-ANN transfers these errors to MENMx. The errors are calculated with the mean square error (MSE) given in Eq. 3 as performance index. Subsequently, the Nhn is elevated to (Nhn+1) and updated ANN architecture is applied to next cycle. These cycles continue until Nhn reaches the maximum number of the Nhn determined by the user. Finally, the Nhn with the lowest MSE is selected from the MENMx and defined as the best Nhn.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2 \qquad (3)$$

in which t_i is the observed value, o_i is the estimated value, and n is the number of data.

Many studies choose the ANN with the lowest error value used in modeling. Although it seems a plausible assumption, it is not convenient to every situation since ANN's performance also depends on initial weights. Therefore, the best performance zone (BPZ) is determined as the second step. The MSE values in MENMx are arranged from the best to worst. The best of pre-determined amount of Nhn are transferred to the iterative stage 2. In this study, the maximum of three Nhn was considered as an amount of the pre-determined ones.

After the determination of the zones, the BS-ANN_sub run with k=1000 times. It should be noted that having high k value gives an advantage in search of the best performance with different weights, training, validation and testing partitions via the same Nhn.

3.3. Results

Different cycle lengths varying between 40 and 130 sec, optimized by Synchro traffic optimization program, were utilized for traffic scenarios in this research as given in Table 1. The longest cycle length is 130 sec determined for only one case. On the other hand, 60 second cycle length is the most common one determined for hundred cases. It should be noted that all different scenarios were simulated for 15 minutes preceded by a one-minute pre-processing run that is used to initialize the model computations.

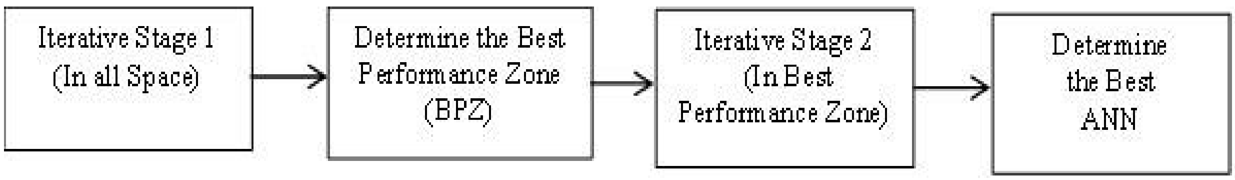

Figure 4. The process of Best Searcher–ANN.

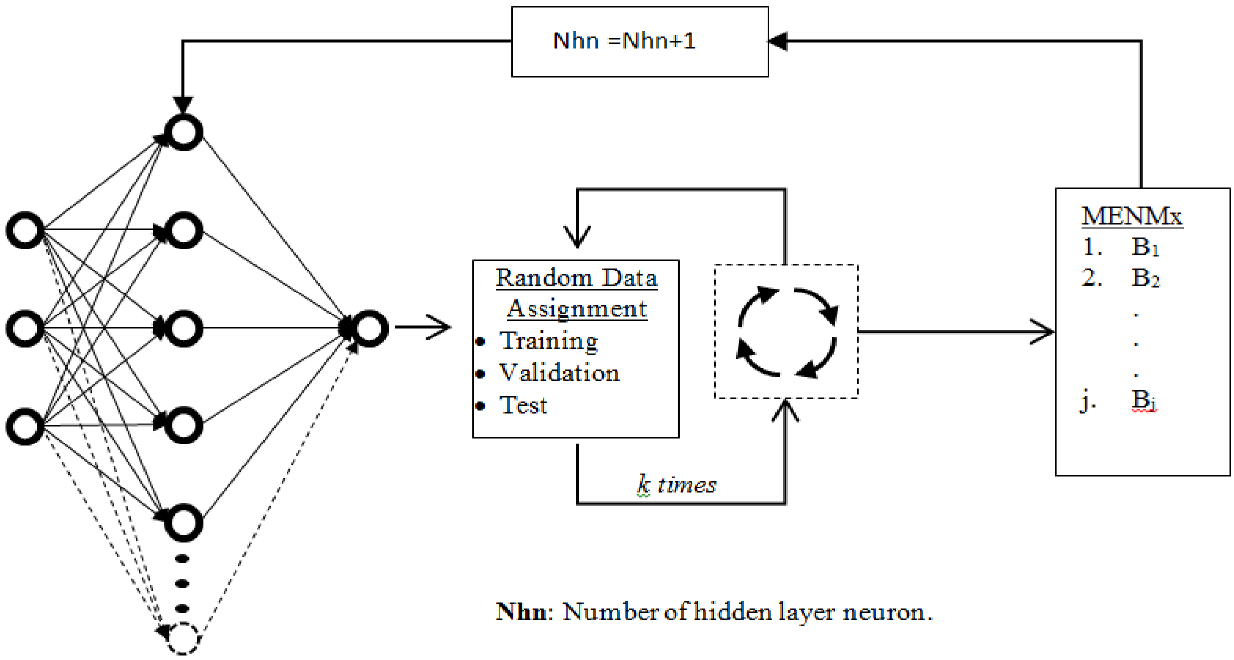

Figure 5. The process of Best Searcher–ANN_Sub.

The Synchro was able to generate multiple useful outputs such as delay and stops per vehicle.

Table 1. Cycle lengths and frequencies

Cycle Length (sec.)	Frequency
40	48
60	100
65	2
80	37
90	9
130	1

For all scenarios, the average delay (μ) calculated was 20.74 seconds per vehicle with a standard deviation (σ) of 12.25 seconds as shown in Fig. 6. Moreover, the numbers of stops per vehicle for each scenario were given in Fig.7. As seen from the figure, the average number of stops was obtained as 0.74 per vehicle with a standard deviation of 0.19. It was seen that the standard deviations for both cases were relatively high due to a large number of data employed in the training stage of the ANNs.

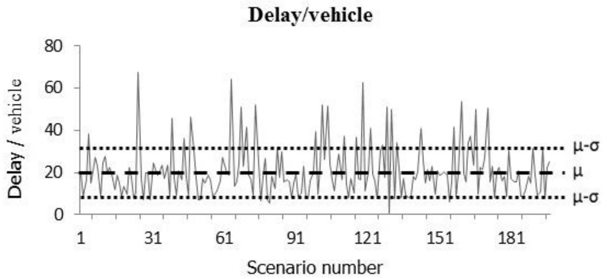

Figure 6. Obtained delay per vehicle for each scenario.

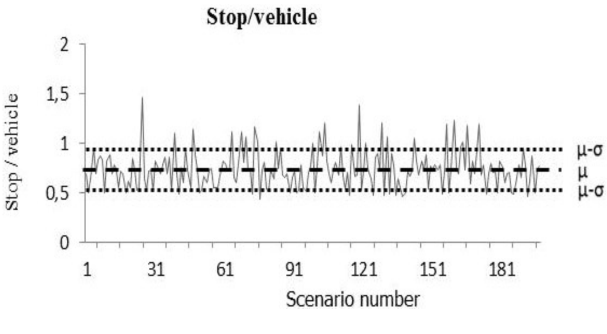

Figure 7. The obtained number of stops per vehicle for each scenario.

The BS-ANN run with k= 25 times and defined max Nhn = 15 to find the number of the hidden layer neurons giving the best ANN architecture. The performance of each of the ANN architecture was measured in terms of MSE given in Eq.3. As seen from Fig. 8, not only the number of the hidden layer neurons increases, but also the error values tended to increase for both ANN-D (delay) and ANN-S (the number of stops).

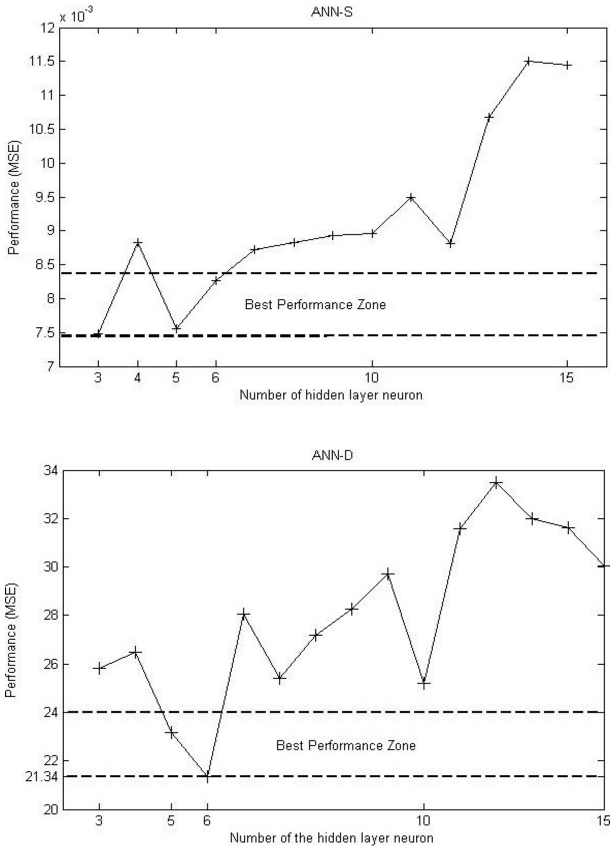

Figure 8. The best performance zones for ANN-D and ANN-S.

Therefore, the BPZ is utilized instead of the maximum Nhn for the zone search. The best architecture for ANN-Ds was (17x6x1), and the (17x5x1) is very close to the minimum error point in the BPZ. On the other hand, the architecture with (17x3x1) was out of BPZ. Similarly, for the ANN-S, the Nhn of the best ANNs was (17x3x1) but the (17x5x1) and (17x6x1) were in the BPZ.

The ANN estimates and SimTraffic Simulation values for delay and the number of stops were graphically shown in Fig. 9 and Fig. 10. The training process was completed with 105 data using the Levenberg-Marquardt back propagation learning algorithm. The hidden layer has 6 neurons and they used the sigmoid transfer function.

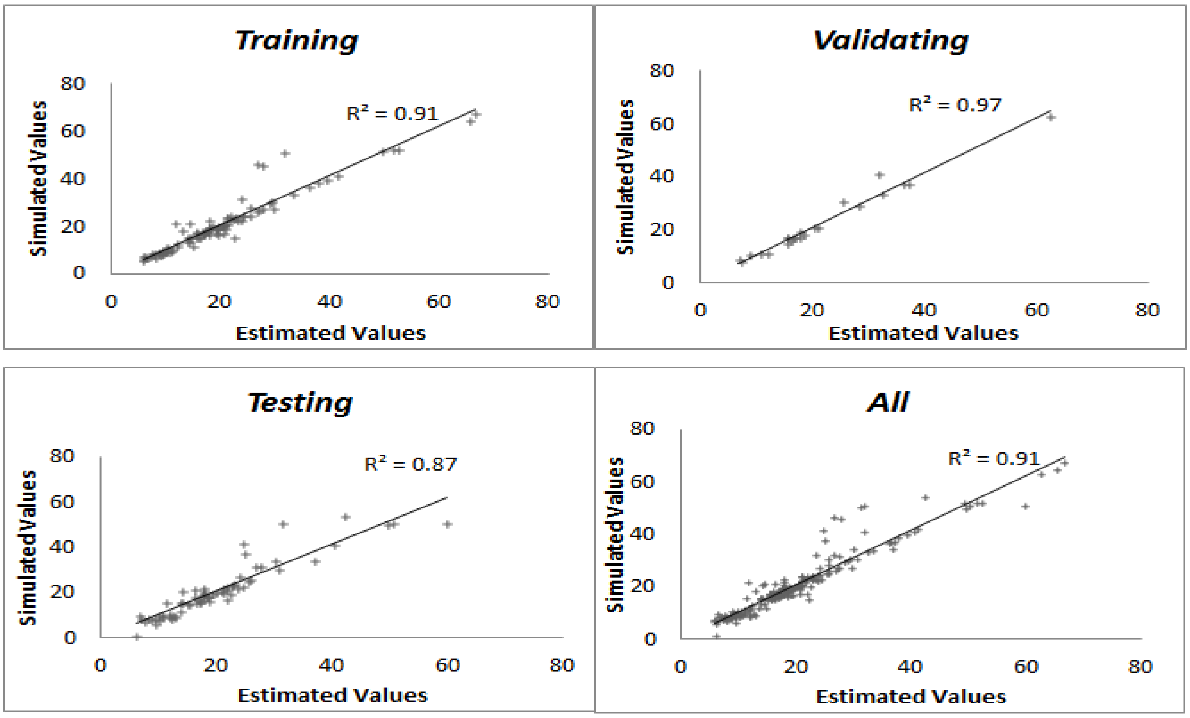

Figure 9. R^2 values for ANN-D.

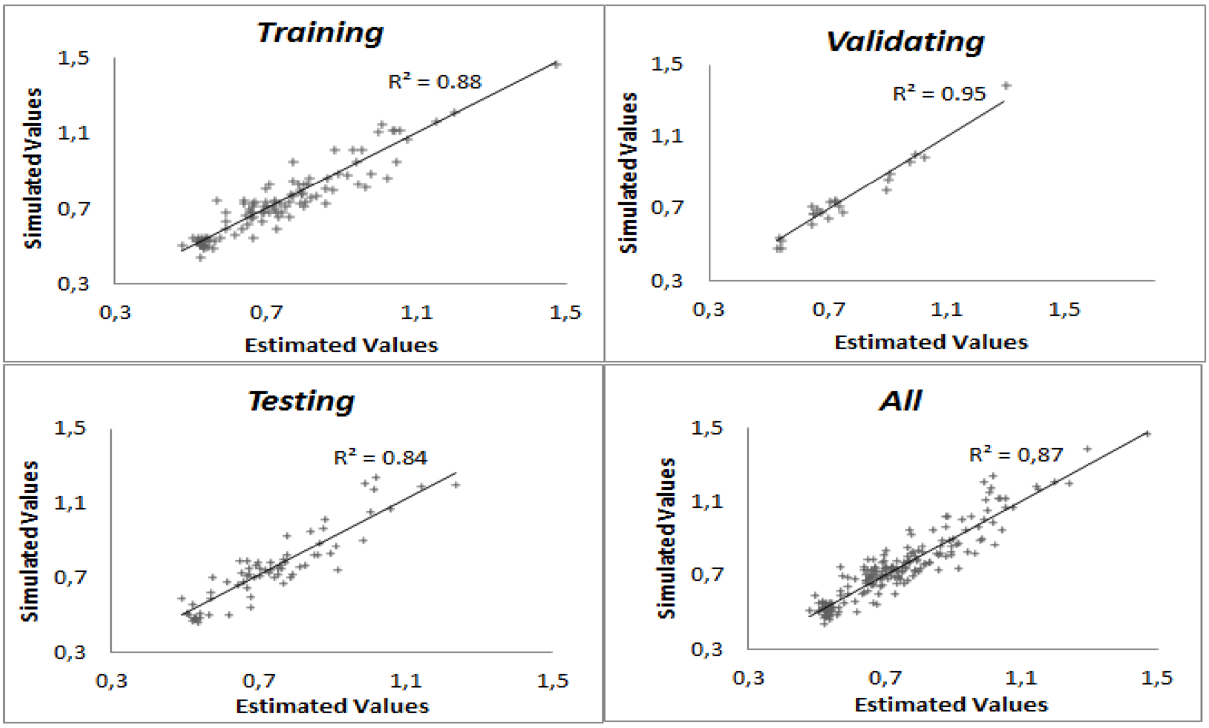

Figure 10. R^2 values for ANN-S.

The output layer had one neuron with a linear transfer function. All calculated R^2 values for ANN-D are higher than 0.90 except for the testing which was 0.87 but it was still high enough to conclude that the ANN-D was working well.

The coefficients of determination, R^2 for the ANN-S were shown in Fig.10. As seen from the Fig.10, all R^2 values of the ANN-S were higher than 0.84. For the ANN-S, the number of the data partitions for testing, training and validation was the same as used for the ANN-D. The R^2 value for validation had the highest value. The R^2 value of 0.84 obtained for testing was calculated.

4 Conclusion

Delays and stops experienced at signalized intersections have a number of potential negative consequences including higher fuel expenses and the loss of valuable time. Therefore, the accurate estimation of delay and stop rates is an imperative for evaluating the performance of signalized intersections. Accordingly, this paper aimed to predict delay and stop rates per vehicle that can be experienced by the most common types of four-leg intersections. For this purpose, two different ANN models were developed. One of them was to estimate the average delay per vehicle, and the other was to predict the average number of stops per vehicle. Intersection approach volumes, cycle lengths and left turn lane existence were used as input variables in both ANN models. Different scenarios were studied in simulation experiments via traffic simulation and optimization program. Simulations results were used for training, testing and validation stages. 70% of the data was used for training while remaining data were employed equally for validation and testing purpose. In order to find the best model, performances under various ANN architectures were analyzed. The best architectures obtained were (17x6x1) for ANN-D and (17x3x1) for ANN-S. The R^2 values of both ANN-D and ANN-S were computed for training, testing, validating and all data. It is found that the performance of ANN-D was slightly better than that of ANN-S according to their calculated R^2 values.

In this study, only the existence of left turn lanes in different combinations was considered and their effects on the delays and stop rates were estimated by the ANNs model. The existence of right turn lanes can also positively affect the delay and stop rates particularly where right turn rates are high. Therefore, future studies can also consider the combinations with different sets including right turn lanes. The results show that the ANN models have potential to estimate delays and number of vehicle stops at signalized intersections. The input variables utilized in this study (volumes, left turn lane existence, and cycle length) can be easily collected from the intersections in the field for the real world applications. Therefore, the collected data can directly be applied to ANN models. Furthermore, with these features, ANN models for estimating delay and stop rates can offer a great advantage over other models.

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