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Comparison an artificial intelligence-based model and other models: signalized intersection delay estimates

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Abstract ***- This paper presents an adaptive neuro-fuzzy inference system (ANFIS), which has been adapted as an alternative to other classical models for estimating the vehicle delays at signalized junctions. Rules, fuzzification, and inference were modeled by ANFIS. In this model, a hybrid algorithm was used for training and tests. The artificial network used three input variables representing simulation of the time, the number of approaching vehicles in the green duration, and the number of queuing vehicles in the red duration. The results of neuro-fuzzy networks were also compared with Observation, Webster, HCM, Multiple Regression Analyses, and Signal Simulation Model (SSM) results. It was found that ANFIS, Regression, and SSM results are show the most agreement with the observation values.***

Key Words: neuro-fuzzy, artificial intelligence, signalized intersection, vehicle delay.

I. INTRODUCTION

One of the most difficult engineering problems is to design an optimum transportation plan to deal with traffic jams and complex problems caused by urbanization. Road transportation and vehicle delays at traffic junctions affect the entire traffic system and constitute a major concern in every country of the world. A delay is a time loss that is not within the realm of control by the vehicle (or driver). The vehicle delays occur because vehicles have to wait for other vehicles and pedestrians at signalized intersections and pedestrian crossings, and have to reduce their speeds when passing near them. This delay depends on parameters such as traffic flow in the roads, behavior of the driver, the geometric type of intersection, and whether or not there is an obstruction. Generally, the main goal is to minimize the number of stops across the entire transportation system, while also minimizing delays at the level of each intersection. The amount of delay should be estimated as accurately as possible in order to minimize vehicle delays and to evaluate alternative junction projects. Recently, artificial intelligence techniques (*AI*), which design and solve complex problems in order to enable computers to exhibit intelligent behavior, have been used efficiently in transportation engineering. Simões et al. Were present a microscopic stochastic simulation model that emulates the traffic movements at signalized intersections with semi actuated signal operation [1].

The artificial neural network (*ANN*) method emerged as a result of imitating the human brain operation system. It is widely used in construction and transportation engineering as well as in physics, mathematics, and electrical and computer engineering. The practical usage of *ANN* is generally based on fast recognition and classification of information, which can be in various structures and forms. It is a parallel-distributed information processing system [2]. This system is composed of processing elements that are interconnected and unidirectional, and can adjust itself to yield different results whenever the varying input and the desired output are given to the system. The literature on artificial intelligence systems is fairly wide [3-8].

System modeling based on conventional mathematics is not well suited for dealing with ill-defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy *if-then* rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Fuzzy set theory and fuzzy logic were established in 1965 by Zadeh in order to deal with the vagueness and ambiguity associated with human thinking, reasoning, cognition, and perception [9-10]. After Zadeh's work on fuzzy sets, many theories in fuzzy logic were developed, and fuzzy modeling or fuzzy identification has been applied successfully to a number of applications [11-12].

Adaptive Neuro–Fuzzy Inference Systems (*ANFIS*), developed in the early 90s by Jang [13-14]. Incorporate the concept of fuzzy logic into the neural networks in order to facilitate learning and adaptation. In neuro-fuzzy system control, the parameters of the fuzzy controller are adjusted using a neural network. Neuro-fuzzy systems profit from both the linguistic, human-like reasoning of fuzzy systems and the powerful computing ability of neural networks.

Vehicle delays that occur at junctions affect the entire traffic system. The main factors in these delays are the path choice of the drivers and the distribution of traffic over the road network. In order to minimize vehicle delay on the roads and to evaluate the alternative junction construction projects, the amount of delay should be estimated with high accuracy. There are various mathematical and empirical models to estimate vehicle delays at signalized junctions, including highway capacity manual HCM (HCM-85, HCM-94, HCM-97 and HCM-00) delay formula and Webster's delay formula.

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Artificial intelligence (*AI*) techniques can provide a fundamentally different approach to estimation of vehicle delays at signalized junctions as compared with classical methods. *AI* techniques have been applied to various civil engineering problems: a knowledge-based decision support architecture to advanced traffic management [15], study a traffic intersection with vehicle-actuated traffic signal control [16], travel time prediction in urban networks [17], an intelligent technique to traffic network incident detection [18], Urban signalized intersections are usually among the worst spots in a transportation network to incur congestion and pollution, where vehicles are obliged to stop, accelerate or decelerate, thereby generating delay [19], etc.

There are numerous works that employ fuzzy logic and artificial neural networks to signal control. Pappis and Mamdani were the first to apply fuzzy logic in traffic signal control [20]. Tzes, et al. studied expert fuzzy logic traffic signal control for transportation networks [21]. An investigation on distributed intelligent control of street and highway ramp traffic signals was carried out by Findler, et al., and Lee, et al. conducted a study on the fuzzy-logic-based incident detection for signalized diamond interchanges [22-23]. Trabia, et al. developed a two-stage fuzzy logic controller for traffic signals [24].

Vehicle delays have been studied by a number of investigators. Liu, et al. introduced an adaptive signal control system utilizing an on-line signal performance measure [25]. The proposed method employed real-time delay estimation and an on-line signal timing update algorithm. Performance of the proposed system was evaluated with a high-performance microscopic traffic simulation program, Paramics, and the preliminary results had proven the promising properties of the proposed system. A report by the New England Section Institute of Transportation Engineers Technical Committee presented an independent review of various software packages and methodologies utilized in the analysis of isolated signalized intersections. The methodology and results of the highway capacity manuals (HCM) were compared to these analysis tools: HCS 2.4, HCS 2.4g and 3.1a (Phase II only), SIDRA, SIGCINEMA, SIGNAL94, Synchro, CINCH94, CINCH88, and CIRCULAR 212. A study was presented by Ella Bingham on Neuro-fuzzy traffic signal control. An adjustable fuzzy traffic signal controller was created. The performance of the traffic signal controller was measured by the delay of vehicles [6].

On the other hand, although there are limited works using fuzzy logic on vehicle delay estimation at signalized junctions, the studies which use adaptive neuro-fuzzy inference systems to estimate vehicle delays at signalized junctions is more limited [25,26].

The purpose of this study is to examine the ability of *ANFIS* to accurately predict the vehicle delays at signalized junctions. *ANFIS* is applied to a two-phase controlled intersection of a two-lane street to estimate vehicle delays occurring at two signalized junctions in the province of Erzurum in Turkey. The accuracy of predictions and the adaptability of the neuro-fuzzy system have been examined, and the results of classical vehicle delay methods are compared to those of *ANFIS*. The neuro-fuzzy system was shown to be able to predict the vehicle delays with a significantly higher level of accuracy.

II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

In recent years neuro-fuzzy computing has emerged as a practical technology, with successful application in many fields of artificial intelligence for realizing human intelligence in machines. There are several approaches to integrate neural networks and fuzzy inference systems that very often depend on the application. Takagi and Hayashi made a pioneer augmentation in development of neuro-fuzzy technology in the last decade [27]. Similarly, Jang developed *ANFIS* (Adaptive Neuro–Fuzzy Inference Systems) in the early 90s [3,13]. *ANFIS* is a new inference system, which incorporates Sugeno-type fuzzy inference systems into adaptive neural network structures [28]. As the name suggests, *ANFIS* combines the fuzzy qualitative approach with the neural networks adaptive capabilities to achieve a desired performance. *ANFIS* is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. The learning or training phase of a neural network is a process to determine parameter values that will sufficiently fit the training data.

Takagi, Sugeno and Kang fuzzy inference systems (*TSK*) make use of a mixture of back propagation to learn the membership functions, and least mean square estimation to determine the coefficients of the linear combinations in the rule’s conclusions. A first-order Sugeno fuzzy model is used as a means of modeling fuzzy rules into desired outputs:

$$\text{if } x_1 \text{ is } A_i \text{ and } x_n \text{ is } B_j \text{ then } f_i=p_i x_1+q_i x_n+r_i \qquad (1)$$

where ri, pi and qi are design parameters to be determined during the training stage. In the presentation, a circle indicates a fixed node whereas a square indicates an adaptive node. An adaptive node means that the parameters are changed during adaptation or training. This architecture is a five-layered, feed-forward neural structure, and the functionality of the nodes in these layers is summarized as follows [29].

Layer 1. No computation is done in this layer. Each node in this layer, which corresponds to one input variable, only transmits input values to the next layer directly. The link weight in layer 1 is unity. Each node i in this layer generates a membership grade of a linguistic label. For instance, the node function of the i-th node might be

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$$O_i^1 = \mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (2)$$

where O_i^j denotes the output of the *i*-th node in layer *j*, *x* is the input to node *i*, and A_i is the linguistic label (small, large, etc.) associated with this node, and a_i, c_i is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2. Each node in this layer calculates the firing strength of each rule via multiplication:

$$O_i^2 = w_i = \mu A_i(x) x \, \mu B_i(y), \quad i = 1,2. \quad (3)$$

Layer 3. The *i*-th node of this layer calculates the ratio of the *i*-th rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \; i = 1,2. \quad (4)$$

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4. Every node *i* in this layer is a square node with a node function

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i), \quad (5)$$

Where $\overline{w}_i$ is the output of layer 3, and is the parameter set. Parameters in this layer will be referred to as *consequent parameters*.

Layer 5. The single node in this layer is a circle node labeled $\sum$ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = overal\ output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

From the *ANFIS* architecture, it is observed that given the values of the premise parameters, the overall output *f* can be expressed as linear combinations of the consequent parameters:

$$\begin{aligned} f &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \end{aligned} \quad (7)$$

The task of the training or learning algorithm for this architecture is to tune all the modifiable parameters to make the *ANFIS* output match the training data. A training method such as back-propagation, or a hybrid learning rule which combines the gradient method and the least squares, is employed to find the optimum value for the parameters of the membership functions and a least squares procedure for the linear parameters on the fuzzy rules, in such a way as to minimize the error between the input and the output pairs [8,30].

III. OTHER DELAY MODELS

Formally, delay is defined as the uncontrolled time loss of a vehicle. Delay is the most frequently used measure of effectiveness for junction operations. It can be quantified in many different ways; the most frequently used forms are the stopped delay, approach delay, and control delay.

Stopped delay is explained as the time a vehicle is stopped at a junction. Average stopped delay is the total stopped delay experienced by all vehicles arriving during a designated period divided by the total vehicle volume. The stopped-vehicle count technique is the most common approach to measure stopped delay. Stopped delay is easier to measure in the field than either the control delay or approach delay [31]. and therefore, it has been the traditional performance measure used to determine the level of service at signalized junctions.

Approach delay is explained as the difference between the time used by any vehicle to travel a fixed distance from a pre-specified point upstream of a junction to the junction stop bar, and the free-flow time associated with that distance [32]. Approach delay is often obtained from stopped delay.

Control delay is explained as the total delay due to the signalized junction, and it includes deceleration delay, stopped delay, and acceleration delay. Collection of such delay information tends to be very laborious, time-consuming, and expensive [33]. For these reasons, control delay is rarely measured. Many studies about delay problems in the signalized junction have been performed, and were reported in several equations by now. These equations are summarized in the following paragraphs.

A. Webster's Delay Formula

A probabilistic delay equation, which was developed by Webster, is the oldest and the most popular one of the suggested vehicle delay equations [34]. Webster gives average delays equations as follow:

$$d = \frac{C(1-\lambda)^2}{2(1-\lambda.x)} + \frac{x^2}{2q(1-x)} - 0.65\left(\frac{C}{q^2}\right)^{1/3}.x^{(2+5\lambda)} \quad (8)$$

where d is the average delay per vehicle in sec/veh, C is the cycle length in sec, g is the effective green time for each lane in sec, q is the vehicle arrival rate, □ is the proportion of the cycle that is effectively green for the phase under consideration, (that is, effective green/cycle time) (g/C), x is the saturation degree (volume-to-capacity ratio, x=q/□.s), and s is saturation flow in veh./sec. The increase in the delay is a function of saturation degree and the lane capacity. The average delay per vehicle become infinite for *x*=1 in Webster's equation; that is, the equation is applicable for values of *x* not greater than *1.0 (x<1).*

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B. High Capacity Manual (HCM-00) Delay Formula

In analyses of signalized junctions, the employed delay formula based on the average vehicle delays is the HCM delay formula (HCM 2000) [35].
The HCM delay formula is

$$d = d_1 PF + d_2 + d_3 \tag{9}$$

Where d_1 = uniform delay component

d_2 = incremental delay component

d_3 = initial queue delay component

$$d_1 = 0.50.C.\frac{(1-g/C)^2}{1-[\min(1,x)g/C]}$$

and

$$d_2 = 900T\left[(x-1)+\sqrt{(x-1)^2+\frac{8klx}{cT}}\right]$$

where d is the average delay per vehicle in sec, PF is progression adjustment factor *(*a function of arrival type and signal timing*)*, T is duration of analysis period *(hrs)*, k is incremental delay factor dependent on signal controller settings, l is upstream filtering/metering adjustment factor, C is the cycle length in sec, g is the effective green time for each lane in sec, x is the saturation degree, and c is the lane group capacity in vehicles per hour. This formula gives reliable results for the values of x smaller than *1.2* [36].

C. Multiple Regression Analysis

Multiple linear regression analysis is usually used to summarize data as well as to study relations between variables [37]. Stepwise regression is basically a combination of backward and forward procedures and is probably the most commonly used method [38]. In this method, the first variable is selected in the same manner as in the forward selection. If the variables fail to meet the entry requirements, the procedure terminates with no independent variables entering into the equation. If it passes the criterion, the second variable based on the highest partial correlation is selected. If it passes the entry criterion, it also enters the equation. After the first variable is entered, stepwise selection differs from forward selection; the first variable is examined to see whether it should be removed according to the removal criterion as in backward elimination. In the next step, variables not in the equation are examined for removal. Variables are removed until none of the remaining variables meet the removal criterion. Variable selection terminates when no more variables meet entry and removal criteria. The multiple correlation coefficients (R^2) values of the regression equation obtained.

In the statistical analysis, the data have been evaluated and the correlations between one dependent delay and the TIME, APP and QUE as independent varibles have been analyzed by stepwise regression. Analysis results are given in Table 1.

Regression equation *($Y = a + b_1X_1 + b_2X_2 + ... + b_pX_p$)*	F	R^2
DELAY = 13.039 - 0,00029**TIME** – 0,144**QUE**	10,39[a]	0,231

[a] : significance difference at level p<0,001.

Table 1: Regression equation between DELAY and TIME, APP and QUE

D. Signal Simulation Model

The estimation of vehicle delays at intersections has vital importance in traffic engineering. The prediction of vehicle delays can be performed by empirical, mathematical, or simulation models. It is well known that there are some limitations in the use of empirical and mathematical models, but simulation techniques have no limitations. Simulation can be defined as computer modeling of a system.

The mathematical models related to vehicle delay in signalized intersections are valid for limited conditions that depend on queue theories. It is known that these models do not cover all values of traffic flow at determined conditions. In addition, real values are represented with mean values in all the mathematical models. However, in representing a stochastic system as traffic flow, it is appropriate to use real values instead of mean values.

It is very difficult and expensive to set up the model of a signalized system in the laboratory and to perform the experiments on the real system. Therefore, in this study, a computer simulation model and an imitation of the signalized intersection have been set up in a computer medium. In this aspect, a program, which is called a signal simulation program, has been developed by Gokdag [39].

In the simulation model, although the real system is attempted, for the sake of simplicity irrelevant parameters are not taken into account. Some logical assumptions were made with this aim. The operation rules of simulated model are;

(1) The simulation starts with the red light turning on and at that time it is assumed that there aren't any vehicles in the lane of junction.

(2) It is assumed that the traffic flow is random and the period of the incoming vehicle is driven by a negative exponential distribution.

(3) When a vehicle approaches, it follows the rules of the light: if the green light is on, this vehicle will pass on

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without waiting and if the red light is on, it will stop behind the stop line and will be delayed. Therefore, the number of the vehicles at the queue increases (added one).

(4) It is assumed that the vehicles waiting at the red light disperse equally to the lines of the approaching lane.

(5) The vehicle queue or queues subjected to delay during the red light discharge when the green light turns on. The delay will continue until every vehicle arrives at the stop line. When the green light turns off, if there are any vehicles at the queue, their delay will continue.

(6) Vehicle variations were not taken into consideration in this model. The simulation assumes only one kind of vehicle. As input data, the traffic volume is given as passenger cars.

(7) The accidents that can happen in junction and the effect of pedestrians on the vehicle traffic are not taken into consideration.

(8) The simulation time unit is the second and the time progress method was used.

(9) A double exponential headway distribution function was used for internal vehicle arrival. If it is $S=1$, the flow will be a dependent function or if it is $S=0$, it will be an independent one. The form of the equation will be negative exponential and double exponential, respectively. The dependent and independent flow percentages in the function were calculated by Salter equations [40].

(10) For one-way and double line roads, $S = 0.00158Q - 1.04222$, where S is the rate of dependent vehicle, Q is the traffic volume that is between 660 veh./h and 1295 veh./h.

(11) All the vehicle delays were calculated one-to-one and then were summed up after individual calculations. The average delay per vehicle was found by dividing this total amount by vehicle number.

(12) Input data required for simulation models were the average traffic flow at the approaching lane (veh./h), the number of lines at the approaching lane, the simulation period, the minimum gap between vehicles, and the periods of red, yellow, and green light.

(13) The output data from the simulation model were the list of the input data, the period since the beginning of the simulation, traffic flow (the number of vehicle arrivals at the junction leg), queue (the number of vehicles in the queue), and cumulative totals of vehicle headway and delaying.

The flow diagram of the model is shown in (Fig. 1.). This simulation program was applied to the many signalized intersections in Erzurum in Turkey. Traffic flow and vehicle delays at signalized junctions in Yakutiye and Gez, districts of Erzurum province, were determined by observation. A schematic diagram of the signalized junction, a two-phase controlled junction of two-lanes, is shown in (Fig. 2.). Vehicle delays were calculated by noting the difference between the time each vehicle enters the queue and the time it passes the stop line. Then the total delay was found by summing the individual delays and the average delay per vehicle was calculated by dividing the total delay by the number of vehicles.

IV. RESULTS AND DISCUSSION

This paper shows how the neuro-fuzzy inference system was adapted to estimate vehicle delays at signalized junctions, rather than other classical models such as Webster, Highway capacity manual (*HCM*), Regression, and Signal simulation model.

Vehicle delay and cycle of light were recorded based on films taken by a camera from different intersections in Erzurum. The Yakutiye and Gez intersections, which are the most crowded intersections in Erzurum, were selected to obtain data. Data were taken at Yakutiye intersection on Mondays and Wednesdays from 05.12.03 to 05.14.03, on Tuesdays and Wednesdays from 05.20.03 to 05.21.03. Observations were taken during the week because traffic density was less on weekends. The camera was used at hours 7:30-8.30, 12:00-13:00, and 17:00-18:00, which are rush hours during the week. The camera was inserted at two intersections at a good angle of vision. The number of vehicles passing through these lanes was counted, the images were transported into a computer, and the observation delays were computed. By measuring the width of the approach lane in the related intersections, a saturation flow was computed. Finally, the red light, yellow light, and cycle durations for each lane were measured by a chronometer.

An adaptive network-based fuzzy inference system was adapted as an alternative to predict vehicle delays at signalized junctions. The network uses three input variables representing simulation of the time (*TIME*), the number of approaching vehicles in the green direction (*APP*), and the number of queuing vehicles in the red direction (*QUE*). The approach adopted in this investigation was to model the vehicle delay, *d*, as a function of three variables, namely *TIME*, *APP*, and *QUE*. *ANFIS* was used to train and validate the neural network and to generate the fuzzy rules. Based on the observation, the time, the number of approaching vehicles in the green direction, and the number of queuing vehicles in the red direction, dimensionless distances were chosen as the input, and the vehicle delay was used as the output. The network employed simulates a fuzzy inference system based on simple fuzzy *if-then* rules and the final output is the aggregated consequence of these rules. A three-input, first-order, Sugeno fuzzy inference system with six rules was used. Six membership functions were chosen for each input, and the membership function parameters were tuned using a hybrid algorithm (mixed least squares and back-

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propagation). All of the membership functions of the input variables were of the Gaussian type, and the premise parameter sub-spaces were determined by using *k*-means clustering of the training data set. In order to verify the generation of the model, all of the data were divided into two categories: half of them for the training set, the other half for the test set. *ANFIS* was trained by half of the values obtained from *SSM* and the other half from *ANFIS* testing. The *ANFIS* was set for training, and the tuning algorithm modified the *ANFIS* parameters to match the training data. After having been verified by the test data set, the vehicle delays were estimated using the above neuro-fuzzy algorithm procedure [30]. The prediction graphics of delays in *ANFIS* with the corresponding inputs and output are shown in (Fig.3.) presents overall input-output surface for vehicle delays.

The predicted vehicle delays in addition to the observed values are shown in Table 2. In general, the matching of the experimental and predicted values in each case is acceptable. These results reveal that errors are very small, and the neuro-fuzzy results are very accurate with respect to the experimental observations. Therefore, the neuro-fuzzy could be used to predict the vehicle delays with a higher level of accuracy**.**

A. Comparison of ANFIS Results with SSM, Regression and Classical Models

The test results of *ANFIS* were compared with Observation, Webster, and HCM, Regression, and SSM methods. Fig. 4 shows this comparison. ANFIS, SSM, and Regression results are the ones closest to the observation values. For instance, when the observation, Webster, HCM, Regression, SSM, and *ANFIS* test prediction delay values were compared for a period of 3400 seconds, the observed average vehicle delay was 12.73 sec., Webster delay was 31.48 sec., HCM-94 delay was 21.10 sec., HCM-00 delay was 29.02 sec., Regression delay was 12.05 sec., SSM delay was 11.62 sec., and *ANFIS* delay was 11.70 sec. The difference between the Webster and HCMxx values and the observation values are found to be large.

Standard deviations of the results, $S_{Webster}$, S_{HCM}, $S_{Regression}$, S_{SSM} and S_{ANFIS}, are used as a very simple statistic to compare performance methods:

$$S_{SSM} = \sqrt{\frac{\sum (observed - SSM_{\text{estimated}})^2}{n-1}} \qquad (10)$$

A lower standard deviation means a better modeling approach, and thus a better estimation capability. When the means of the standard deviations of the fifteen outputs are calculated for the five methods with separate observation, it is found that SWebster= 6.84, SHCM-94=5.84, SHCM-00=7.02, SRegression.= 1.60, SSSM= 1.49 and SANFIS=1.61 vehicle delay. The comparison of the ANFIS with the observation, HCM, Regression, SSM, and Webster shows that:

(1) The maximum standard deviations were obtained with HCM-00.

(2) The minimum standard deviations were obtained with SSM.

(3) SSM, Regression, and ANFIS results are the ones closest to the observation values.

V. CONCLUSIONS

This study was conducted to demonstrate the usefulness of an adaptive neuro-fuzzy inference system for the prediction of vehicle delays in signalized intersections. The accuracy of predictions and the adaptability of the ANFIS have been examined. Traffic flow and vehicle delays at signalized junctions in Yakutiye and Gez, districts of Erzurum province in Turkey, were determined by observation. A hybrid algorithm was used for training and testing. The vehicle delay was simulated as a function of the time, the number of approaching vehicles in the green direction, and the number of queuing vehicles in the red direction. The ANFIS were shown to be used to predict the vehicle delays with a higher level of accuracy. The results obtained with the ANFIS are also compared with Observation, Webster, Highway capacity manual HCM, Regression, and Signal Simulation Model. It was found that ANFIS, Regression, and SSM results are the ones closest to the observation values.

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Table 2: Delay input values and results of *Webster, HCM, Regression, SSM*, and *ANFIS* for *Yakutiye* Junction in Erzurum province. (*Junction parameters: C=58, g=27 sec, k=31, s=3150 vec./h, λ=0,466*)

INPUT			OUTPUT						
			Calculated DELAY and Prediction Results						
TIME	**QEU**	**APP**	**Observation**	**Webster**	**HCM 94**	**HCM00**	**Regression**	**SSM**	**ANFIS**
300,00	1,00	26,00	14,10	8,65	6,51	8,66	12,80	12,34	12,80
550,00	1,00	47,00	13,98	8,97	6,7	8,99	12,74	12,00	12,50
780,00	4,00	76,00	15,29	9,44	6,98	9,49	12,24	13,22	11,20
1080,00	2,45	108,00	14,76	10,00	7,33	10,11	12,37	12,86	12,90
1300,00	3,00	130,00	14,66	10,42	7,61	10,6	12,23	12,32	12,90
1560,00	0,00	154,00	13,71	10,9	7,95	11,18	12,59	12,71	12,30
1750,00	1,00	176,00	13,13	11,38	8,31	11,8	12,39	12,3	12,80
2040,00	2,00	213,00	13,06	12,27	9,07	13,04	12,16	12,42	12,50
2250,00	0,00	232,00	13,05	12,81	9,57	13,83	12,39	12,46	12,60
2520,00	2,00	263,00	13,36	13,92	10,66	15,48	12,03	12,19	12,20
2820,00	3,45	292,00	13,38	15,55	12,24	17,74	11,73	12,04	12,50
2940,00	0,45	307,00	13,31	16,92	13,48	19,43	12,13	12,02	12,10
3150,00	2,00	327,00	13,23	20,28	16,04	22,78	11,84	11,97	11,70
3250,00	0,00	334,00	12,73	22,41	17,35	24,44	12,10	11,85	11,90
3400,00	0,00	348,00	12,73	31,48	21,1	29,02	12,05	11,62	11,70

Standard Deviations Results: $S_{Webster}$= **6,84** S_{HCM}=**5,84** S_{HCM}=**7,02** $S_{Regression}$= **1,60** S_{SSM}= **1,49** S_{ANFIS}=**1,61**

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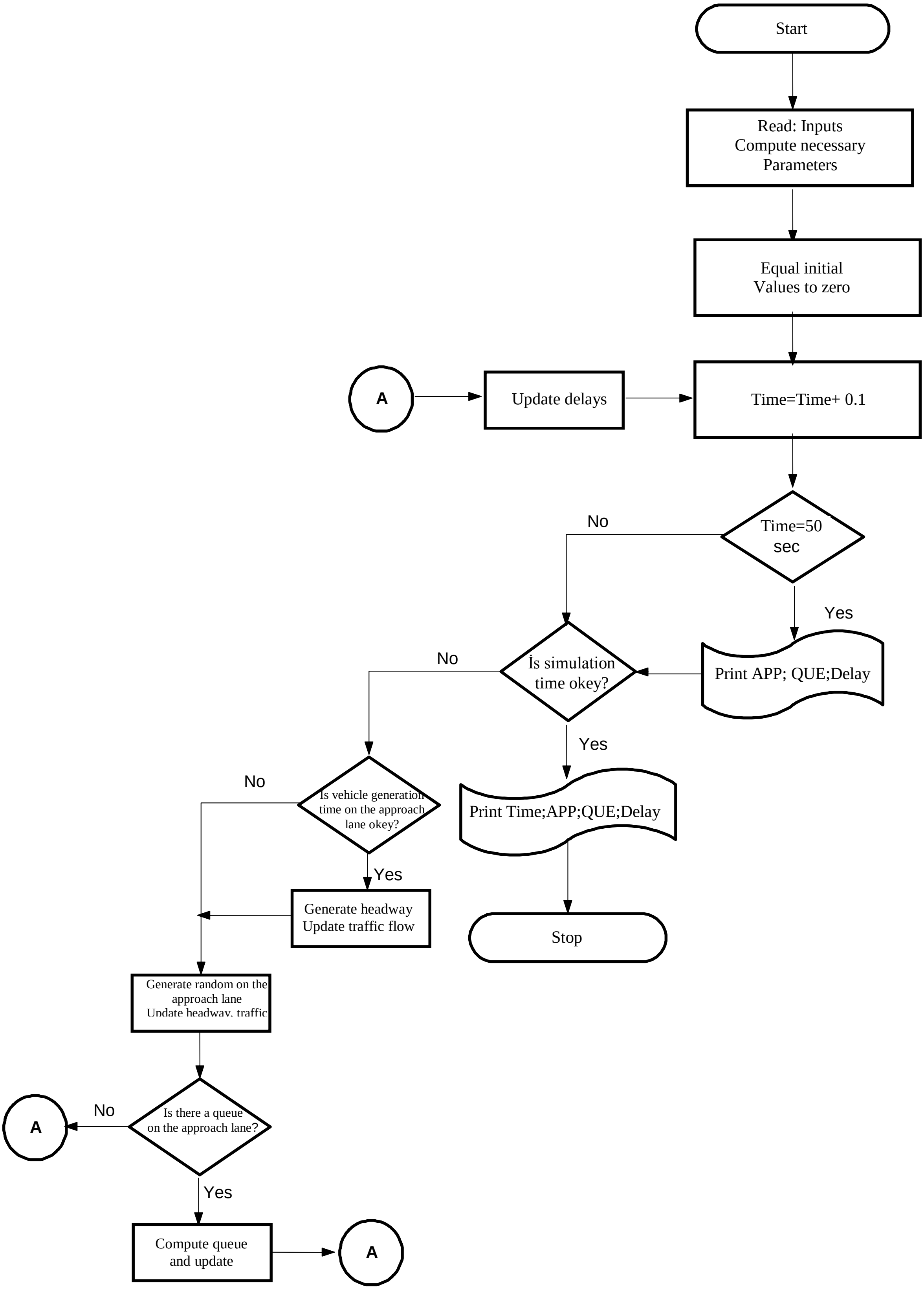

Fig.1: The flow diagram of the *SSM* model

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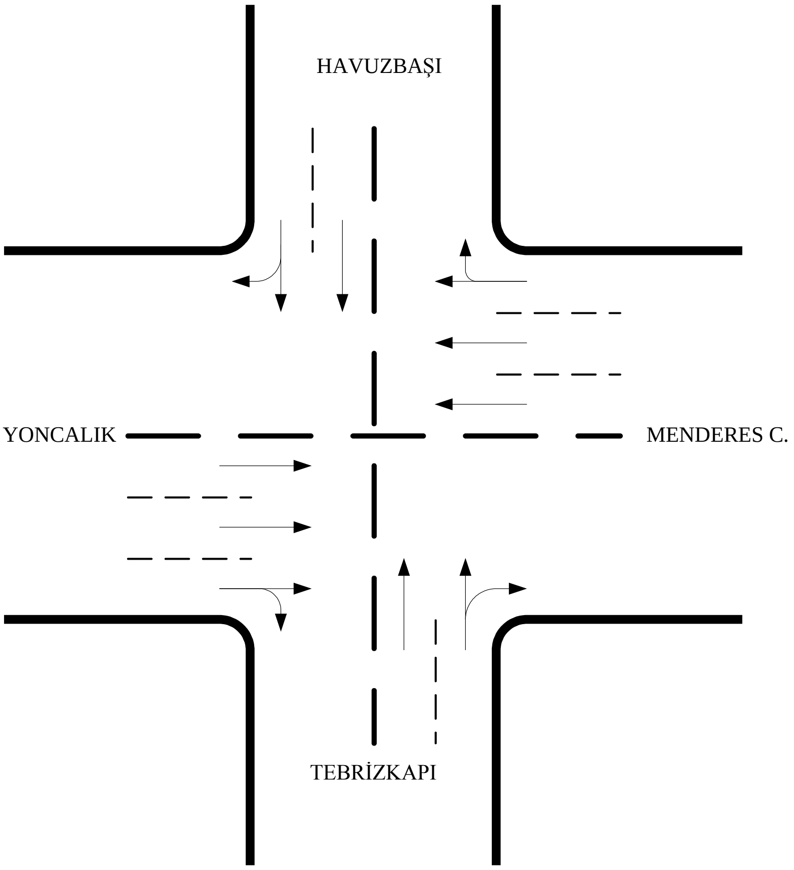

Fig.2: A two-phase controlled signalized junctions in *Yakutiye* districts of Erzurum province

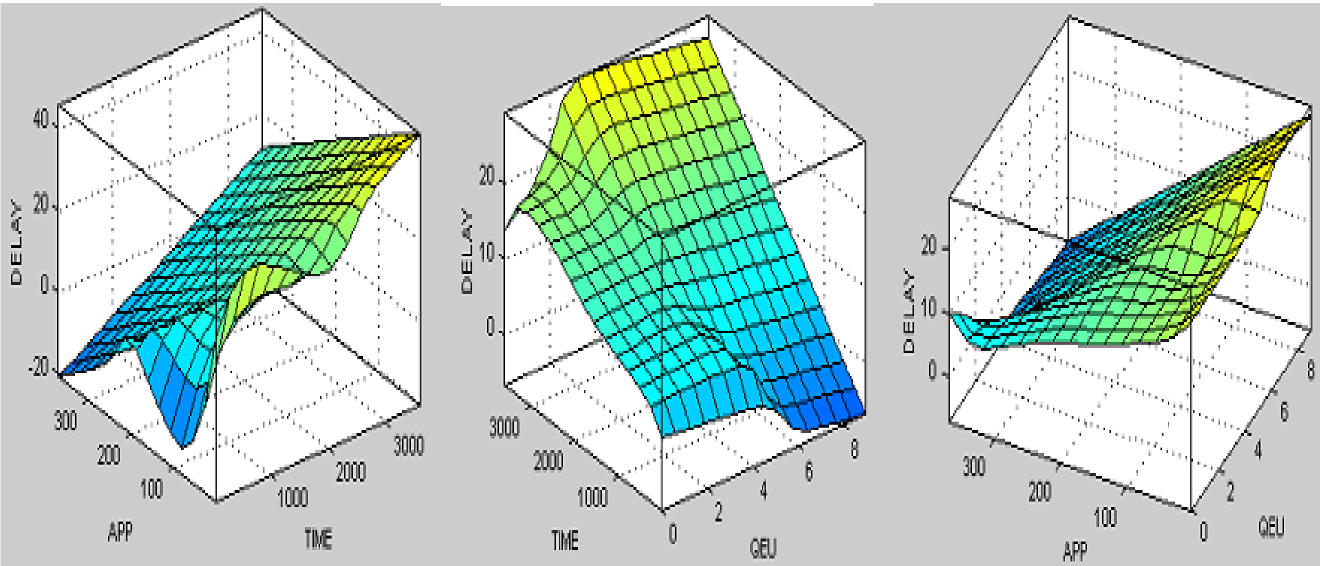

Fig.3: Overall input-output surfaces for delay estimation *(TIME, APP and QUE)*

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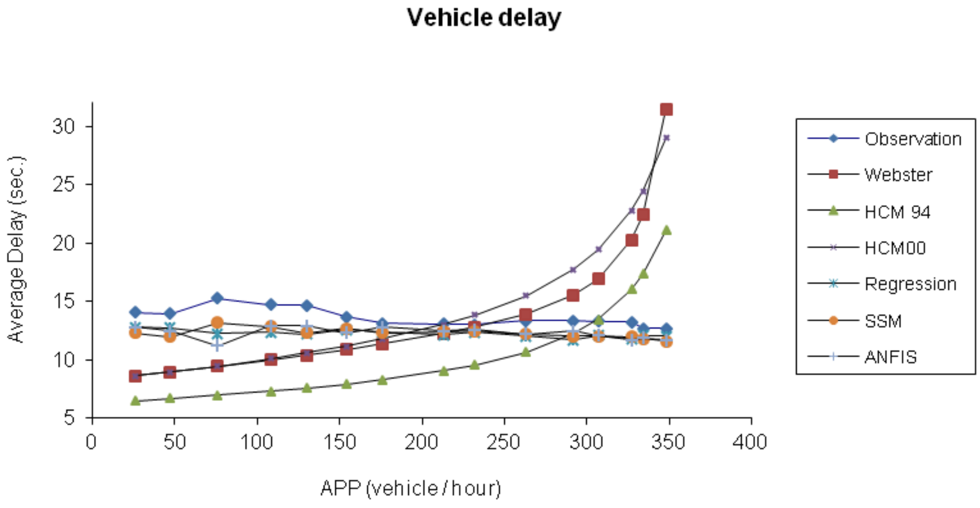

Fig.4: Average delays versus traffic flow