

Traffic Signal Control Based on Adaptive Neural-Fuzzy Inference System Applied to Intersection

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Abstract— Adaptive Neural-Fuzzy Inference System (ANFIS) that integrates the best features of fuzzy systems and neural networks has been widely applied in many areas. It can be applied to synthesize controllers, which are able to tune the fuzzy control system automatically, and models that learn from past data to predict future behavior. The aim of this research is to develop an ANFIS traffic signals controller for multilane intersection in order to ease traffic congestions at traffic intersections. The new concept to generate sample data for ANFIS training is introduced in this research. The sample data is generated based on fuzzy rules and can be analysed using tree diagram. This controller is simulated on multilane traffic intersection model developed using M/M/1 queuing theory and its performance in terms of average waiting time, queue length and delay time are compared with traditional controllers and fuzzy controller. Simulation result shows that the average waiting time, queue length, and delay time of ANFIS traffic signal controller are the lowest as compared to the other three controllers. In conclusion, the efficiency and performance of ANFIS controller are much better than that of fuzzy and traditional controllers in different traffic volumes.

Keywords—ANFIS controller, multilane intersection, next phase module, green phase module, decision module

I. INTRODUCTION

Many improvements have been made in the past few years in managing and controlling traffic signal in the urban area. The techniques are well known within both the transportation planning and traffic engineering communities. However, most of these techniques failed to give excellent performance and needed more improvement to reduce limitation of current techniques. The Artificial Intelligence (AI) techniques can be applied to the data for approximation on the decision-making behavior of more conventional tools in order to attain real-time control that adapts to varying traffic demands.

Based on previous work, a major research based on AI techniques is the application of fuzzy control method on intersection control [1]-[5]. However, there are less traffic signal controllers developed using the ANFIS controller [6]-[8]. ANFIS traffic signal controller with its fuzzy rule base and its ability to learn from a set of sample data could improve the performance of existing traffic signal controlling system to

reduce traffic congestions at most of the busy traffic intersections in city such as Kuala Lumpur, Malaysia.

The vehicular delays can be improved by a traffic controller developed based on ANFIS because of its changeable membership functions that can be trained based on input – output sampling data to adapt to different traffic conditions in real-time. The traffic system facing with the varying of traffic condition and always changing every time in intersection. This technique is suitable to be applied in the controlling traffic flow in an intersection because the system is categorized as a dynamic model.

In this research, the development of traffic light system based on ANFIS approach is applied to multilane isolated intersection. The controller is developed based on the waiting time of vehicles, vehicles queue length at current green phase, and vehicles queue lengths at the other phases. The control strategy applied in this controller is based on well known decision making used in fuzzy traffic controller which are the phase sequence and phase length extension.

From the review [6]-[8], all the sample data used for training obtained from local authority of traffic transportation and from the field case study. For the case where sample data is difficult to obtain, the authors proposed the concept to generate data from the fuzzy rules and tree diagram. The sample data is generated from this concept is used for training in ANFIS model. The input membership function has been tuned and the output membership function has increased. Using multiple regression method, the rule consequent parameters for each output membership functions have been learned from the training data. The simulation of isolated traffic intersection control by fuzzy traffic controller is implemented using a MATLAB software and the comparison with vehicle-actuated controller has been done.

The paper is organized as follows. In the next section, an overview of the isolated intersection traffic model is described. Section 3 briefly discusses the details of the proposed ANFIS traffic signal controller. Section 4 discusses the simulation results of ANFIS traffic signal controller with comparison to the traditional controller and fuzzy controller on isolated intersection. The conclusion of this paper is summarized in the last section.

II. TRAFFIC MODEL

A dynamic model for isolated intersection using queuing theory [9] is used as a case study to test the proposed controller. The typical four-legged isolated intersection is shown in Figure 1. This isolated intersection has multilane. There are 8 movements in this intersection which consist of one through movement and one right turn movement at each of the four-legged.

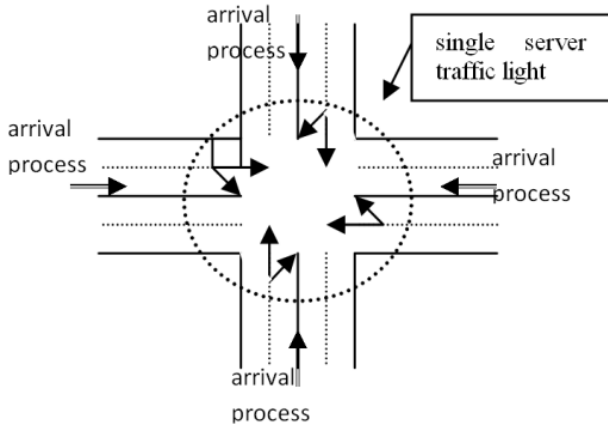


Figure 1. Isolated traffic intersection.

Based on model from [9], an isolated traffic intersection framework is modeled based on an M/M/1 queue theory. Here “M” stands for a “memory less” (that is, exponential) distribution of inter-arrival times. The “M” in the second position stands for a “memory less” distribution of “i.i.d.” service times. The “1” in the third position stands for “one server”. Thus, a single intersection has a single server, traffic signal, which provides service to a single signal phase at a time. The vehicles queue has the FIFO discipline.

The service mechanisms which comprise of customers, queues, and servers are the three main concepts in queuing theory. Customers joining the queuing system are generated by an input source according to a statistical distribution in which the distribution describes their inter-arrival times. The inter-arrival times are the times between arrivals of customers. The basis on which customers are selected to be serviced by the server, which consists of service mechanism, at various times is called queue discipline.

As discussed in [9], traffic arrival and service times at a given intersection are considered as independent random variables, with known distributions. Due to the random nature of traffic arrival, the Poisson distribution usually makes a good fit for the memory-less nature of the exponential distribution which has been widely accepted by researchers in fitting randomly distributed service times, such as those at signalised intersections.

Vehicles arrive at a single-server facility according to a Poisson process with mean arrival rate λ (vehicles per unit time). Equivalently, the inter-arrival times between vehicles are independent and identically distributed with mean $1/\lambda$. Vehicles, therefore, enter the system according to a Poisson process with arrival rate λ .

The service time is defined as the interval used to discharge the individual vehicles from the intersection as traffic light stays green. This should not be confused with the total service time of a given signal phase, which is the effective green time or green phase length. The departure process is the time to cross the intersection (service times) and is arbitrarily and independently distributed.

III. TRAFFIC CONTROLLER

In this section, a detail description of traffic signal controller has been presented. There are three modules in the traffic controller which are Next Phase Module, Switch Module and Green Phase Module. Figure 2 shows the schematic diagram of the controller.

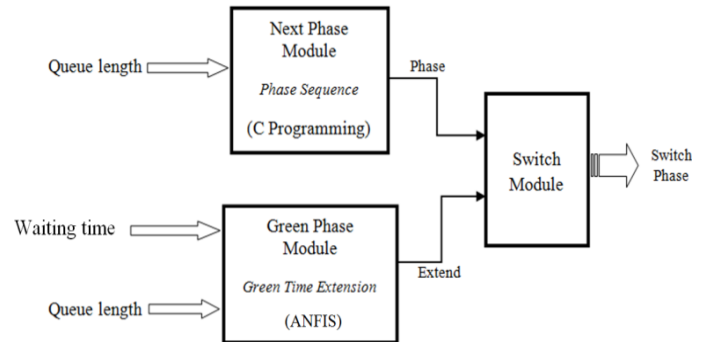


Figure 2. A schematic diagram of the proposed traffic signal controller.

A. Next Phase Module

In this module, simple C programming language is written in embedded MATLAB function block to control the phase sequence based on the current queue length at each of the four routes in East, South, West, and North, respectively. The module selects one candidate for the green phase based on traffic conditions of all phases. The phase that has the longest queue length among the four phases is selected. There are four phases in this module which are phase 1(East Bound), phase 2(South Bound), phase 3(West Bound), and phase 4 (North Bound).

The lengths of the queue at each of the four directions are compared using *if-else* statement. The value of queue lengths from the sensors at East, South, West, and North directions are fetched into this module. Then, the queue length in the East direction is compared with the other three queue lengths in South, West, and North directions. If the queue length in the East direction is the longest then phase 1, which is corresponding to green light in the East direction, is selected. Else, the comparisons of length between queues proceed until the longest queue length is detected.

B. Green Phase Module

The traffic conditions of the green phase are observed by the Green Phase Module. Green light extension time of the green phase is produced by this module according to the condition of observed traffic flow. The extension green time of current green phase is determined by the FIS system in

ANFIS traffic signal controller. The FIS system used in this module is Sugeno-Type.

First order Sugeno-Type FIS is used in ANFIS traffic signal controller. For first order Sugeno-Type FIS, the output membership functions are linear which have a typical rule in the form as shown below [10]:

$$\begin{aligned} &\text{If Input 1} = x \text{ and Input 2} = y, \\ &\text{then Output is } z = ax + by + c \end{aligned} \quad (1)$$

where a , b , and c are rule consequent parameters which are determined using least square estimation method.

Two inputs: waiting time, W_t and vehicles queue length, Q is chosen as the input variables for the ANFIS traffic signal controller. The basic structure of FIS controller consists of input membership functions, fuzzy rules set and output membership function.

The vehicles waiting time has the range between 0 and 50 seconds which includes fuzzy sets, such as very short (VS), short (S), long (L), very long (VL), and extremely long (EL). Each of the elements in fuzzy sets corresponding to each Gaussian membership functions: VS, S, L, VL, and EL, respectively, that has standard deviation (σ) of 2 and the constant for the membership functions of VS, S, L, VL, and EL are 0 seconds, 10 seconds, 20 seconds, 30 seconds, and 40 seconds, respectively. The input membership function of vehicles waiting time, W_t , is shown in Figure 3.

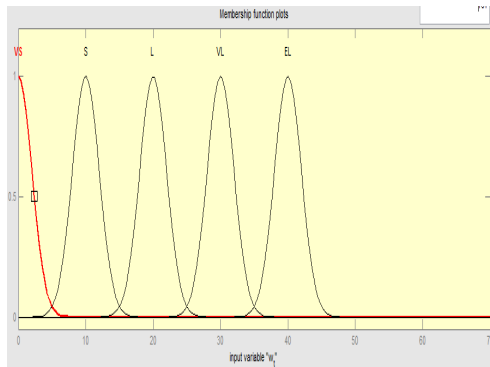


Figure 3. Input membership functions of vehicles waiting time, W_t .

For the second input that is vehicles queue length, Q , it is assumed that the range of queue length is between 0 and 50 vehicles and it includes fuzzy sets: very short (VS), short (S), long (L), very long (VL), and extremely long (EL). Each of these Gaussian membership functions has standard deviation (σ) of 2 and the constant for the Gaussian membership functions of VS, S, L, VL, and EL are 0 vehicle, 10 vehicles, 20 vehicles, 30 vehicles, and 40 vehicles, respectively. Figure 4 shows the input membership function of vehicles queue length, Q .

The output fuzzy variable, extension which means the extension time of green light has fuzzy sets: zero (Z), short (S), long (L), very long (VL), and extremely long (EL). It consists of five output membership functions which are Z, S, L, VL, and EL where these membership functions are Gaussian membership functions with standard deviation, σ

equals 2 and constant, c equals 2.5. The membership function is shown in Figure 5 below.

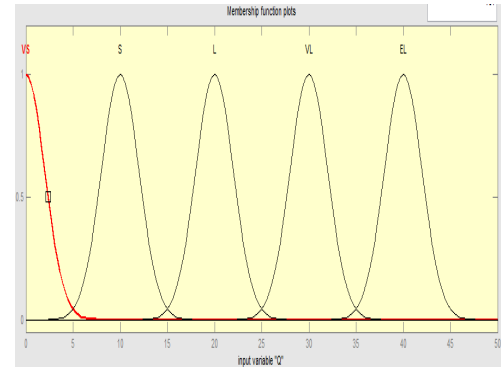


Figure 4. Input membership functions of vehicles queue length, Q .

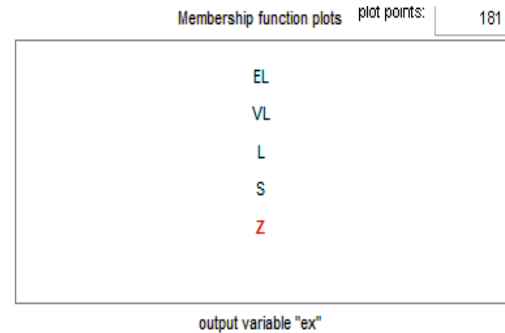


Figure 5. Output membership functions of extension.

The fuzzy rules based are developed using “IF-THEN” statement based on humans thinking. The fuzzy rules the controller is shown in Table I.

TABLE I. FUZZY RULES

IF	Input 1 (W_t)	Condition	Input 2 (Q)	Condition	Output (extension)
RULE 1	VS	AND	VS	THEN	Z
RULE 2	VS	AND	S	THEN	Z
RULE 3	VS	AND	L	THEN	S
RULE 4	VS	AND	VL	THEN	S
RULE 5	VS	AND	EL	THEN	L
RULE 6	S	AND	VS	THEN	Z
RULE 7	S	AND	S	THEN	S
RULE 8	S	AND	L	THEN	S
RULE 9	S	AND	VL	THEN	L
RULE 10	S	AND	EL	THEN	L
RULE 11	L	AND	VS	THEN	S
RULE 12	L	AND	S	THEN	S
RULE 13	L	AND	L	THEN	L
RULE 14	L	AND	VL	THEN	L
RULE 15	L	AND	EL	THEN	L
RULE 16	VL	AND	VS	THEN	S
RULE 17	VL	AND	S	THEN	S
RULE 18	VL	AND	L	THEN	L
RULE 19	VL	AND	VL	THEN	VL
RULE 20	VL	AND	EL	THEN	EL
RULE 21	EL	AND	VS	THEN	L
RULE 22	EL	AND	S	THEN	L
RULE 23	EL	AND	L	THEN	L
RULE 24	EL	AND	VL	THEN	VL
RULE 25	EL	AND	EL	THEN	EL

Rule Consequent Parameters

As mentioned previous section, the traffic controller develop based on ANFIS First order Sugeno-Type FIS. Figure 6 shows the ANFIS architecture that corresponds to the first order Sugeno fuzzy model. The ANFIS has two inputs x_1 and x_2 and one output y . Each input is represented by two fuzzy sets and the output by a first-order polynomial.

For ANFIS controller, the rule consequent parameters can be found by using least square estimate method. These parameters: a , b , and c are calculated by finding the output of each neuron in each of the six layers in ANFIS architecture. At first, the function of each input membership function is determined. Then, the respective function parameters are calculated according to the process discussed below:-

- **Layer 1:Input Layer**

Inputs to this layer are vehicles waiting time, W_i , and vehicles queue length, Q . Gaussian function is chosen as the input membership functions of both input variables W_i and Q .

- **Layer 2:Fuzzification Layer**

The node function is Gaussian function. The Gaussian function is given Equation (2) as shown below.

$$F(x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (2)$$

where σ is the standard deviation and c is the constant of the function. The maximum value of this function is 1 while the minimum value is 0. In calculating the rule consequent parameters, the values of each Gaussian membership functions for both inputs are assumed to be 1. So, $y_{W_i}^{(2)} = 1$ and $y_{Q_i}^{(2)} = 1$.

- **Layer 3:Rule Layer**

Each neuron in this layer corresponds to a single Sugeno-type fuzzy rule. A rule neuron receives inputs from the respective fuzzification neurons and calculates the firing strength of the rule it represents. The output of neuron i in Layer 3 is obtained as,

$$y_i^{(3)} = \prod_{j=1}^n x_{ji}^{(2)} \quad (3)$$

where $x_{ji}^{(2)}$ are the inputs and $y_i^{(3)}$ is the output of rule neuron i in Layer 3.

From Equation (3), the output of rule neuron i in Layer 3 where $i = 1, 2, 3, \dots, 25$ is 1.

- **Layer 4:Normalization Layer**

Each neuron in this layer receives inputs from all neurons in the rule layer, and calculates the normalized firing strength of a given rule. The normalized firing strength is the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. It represents the contribution of a given

rule to the final result. The output of neuron i in Layer 4 is obtained as,

$$y_i^{(4)} = \frac{x_{ji}^{(3)}}{\sum_{j=1}^n x_{ji}^{(3)}} = \frac{\mu_i}{\sum_{j=1}^n \mu_j} = \bar{\mu}_i \quad (4)$$

where $x_{ji}^{(3)}$ is the input from neuron j located in Layer 3 to neuron i in Layer 4, and n is the total number of rule neurons.

From Table I, the output of neuron based on output membership function is summarized in Table II.

TABLE II. THE OUTPUT NEURON IN LAYER 4

Output Membership Function	Output neuron, $\bar{\mu}_i$
Zero(Z)	$\bar{\mu}_Z = 1/3$
Short (S)	$\bar{\mu}_S = 1/8$
Long(L)	$\bar{\mu}_L = 1/9$
Very Long(VL)	$\bar{\mu}_{VL} = 1/3$
Extremely Long(EL)	$\bar{\mu}_{EL} = 1/2$

- **Layer 5:Defuzzification Layer**

Each neuron in this layer is connected to the respective normalization neuron, and also receives initial inputs. Multiple regression is a method used to estimate these parameters. In order to show steps on how to calculate these parameters, consider a linear relationship Equation (5) as shown below.

$$z = a + bx + cy \quad (5)$$

For a given data set $(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_n, y_n, z_n)$, where $n \geq 3$, the best fitting curve $f(x)$ has the least square error, i.e.,

$$\Pi = \sum_{i=1}^n [z_i - (a + bx_i + cy_i)]^2 = \min \quad (6)$$

From Equation (6), a , b , and c are the unknown coefficients while x_i , y_i , and z_i are given. In order to obtain the least square error, the unknown coefficients a , b , and c must yield zero first derivatives.

Based on multiple regression method are discussed above, the rule consequent parameters for output membership functions of Zero (Z), Short (S), Long (L), Very Long (VL), and Extremely Long (EL) are calculated. For each output membership function, the values for both input variables of Q_i and W_{ii} are assigned based on fuzzy rules in Table I.

Generate Sample Data

In actual fact, ANFIS training data can be obtained from real time traffic condition. However, in this research, there are no real time traffic data for the training of ANFIS traffic signal

controller. In this case, the sample data is generating basically based on the 25 fuzzy rules listed in Table 1.

This sample data consists of a total of 2550 input-output sample data. Each sample data has two inputs data which are waiting time (W_i) and queue length (Q), respectively, and one output data which is green time extension (Ex). From the first rule if input W_i is VS and input Q is VS then the output extension is Z. Based on Table 1, the fuzzy set very short, VS for both input variables W_i and Q have values in the range of 0 – 10 seconds and 0 – 10 vehicles, respectively. The fuzzy set of Z for output variable is in the range of 0 – 5 seconds. The sample data for the first fuzzy rule that is RULE 1 in ANFIS is obtained as shown by the tree diagram in Figure 7.

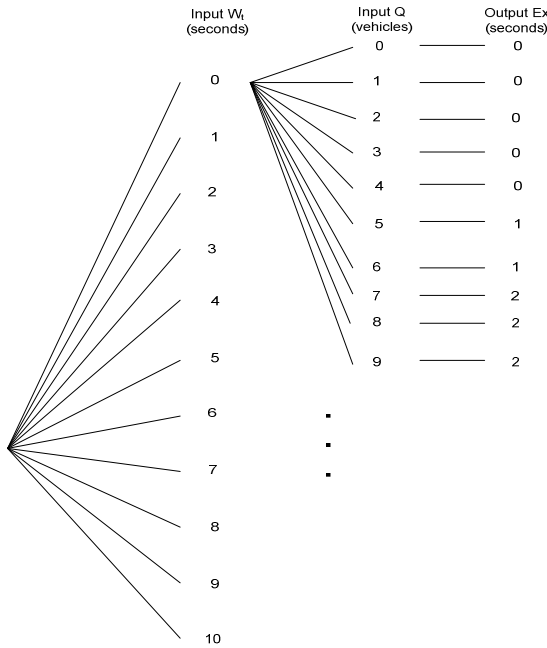


Figure 7. Tree diagram for ANFIS training sample data

By referring to Figure 7, the VS fuzzy set of input waiting time, W_i , is assumed to be 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10. Each element in the VS fuzzy set of waiting time is possible to match to each element in the VS fuzzy set of input queue, Q , which is assumed to have elements 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9. The output extension, Ex , is determined based on human expert knowledge. For example, for 0 seconds waiting time and 0 vehicles on one approach at the intersection, there is no need to assign green light extension time to the green phase since there is no vehicle on the road. So, the extension time is set to 0 seconds for 0 seconds waiting time and 0 vehicles. For 0 seconds waiting time and 1 vehicle, it is unnecessary to extend the green phase because the preset time of green light is enough to let 1 vehicle to depart from the intersection. Similarly, 0 seconds extension time is assumed for 0 seconds waiting time with respective 2, 3, and 4 vehicles. For 0 seconds waiting time with respective 5, 6, 7, 8, and 9 vehicles, the green light extension time is set in accordance with the waiting time, W_i , and queue length, Q , based on human knowledge. For 1 second waiting time, the sample data is obtained similarly as for 0 second waiting time.

Training of ANFIS

The performance of ANFIS traffic signal controller is optimized by training it with a set of input-output sample data to learn the rule consequents parameters and tunes the membership functions. The FIS is trained using the hybrid optimization method. By this method, the membership function parameters are trained to emulate the training data.

C. Switch Module

The Switch Module switches current phase to the appropriate next phase based on the inputs from the outputs of Green Phase Module and Next Phase Module. Basically, this module switches the current phase to the next phase based on the outputs of Next Phase Module. If the other phases have longer queue than the queue of current phase, then, the Next Phase Module will give signal to Switch Module to switch to the phase that has the longest queue. The output from the Green Phase Module to the input of Switch Module will determine the length of the extension time of the next phase based on the conditions observed from other phases.

IV. SIMULATION RESULTS AND DISCUSSIONS

The performance of the developed ANFIS traffic signal controller is evaluated by simulation. The performance of ANFIS controller is compared with fuzzy controller and traditional traffic controller in terms of average queue length, average waiting time and delay time at each of the four approaches at the isolated intersection.

Table III show the comparisons between the performance measures of ANFIS, fuzzy and traditional traffic signal controllers at each of the four approaches. According to the table, ANFIS traffic signal controller results lowest average vehicles queue length, average waiting time and average delay time at all of the four approaches at the isolated intersection while fuzzy traffic signal controller results second lowest average vehicles queue length. Fuzzy and ANFIS traffic signal controller produce good performance measures as compared to the traditional traffic signal controllers because fuzzy and ANFIS traffic signal controller are able to skip the phase where there is no vehicle detected on any approach and assign the right of way to other approach where vehicles are present. This means that green phase will not assign the approach where there is no vehicle so that more green time can be allocated to other approaches that have longer vehicles queue length. By this means, shorter average vehicles queue length on each approach at the isolated traffic intersection can be maintained at all time.

Since fuzzy and ANFIS traffic signal controllers have the capability to assign green time extension based on the average vehicles queue length on each approach at the intersection, both of these controllers should have approximate performance. However, the simulation results show that the average vehicles queue length, average waiting time and delay time of ANFIS controller are lower than that of fuzzy controller. The ANFIS controller outperformed the fuzzy controller because ANFIS traffic controller can adapt to the real time traffic condition at all time. ANFIS traffic controller has the ability to learn from a set of input-output sample data to

tune its input and out membership functions. The membership functions in the controller can be tuned based on the traffic conditions so that optimized performance is achieved. The membership functions of fuzzy controller are fixed and cannot be tuned in accordance with the real time traffic condition data.

V. CONCLUSIONS

The performance of ANFIS traffic signal controller based on waiting time and vehicles queue length at multilane isolated traffic intersection has been tested and compared with conventional controller and fuzzy controller.

The ANFIS traffic signal controller shows good performance during simulation in the multilane isolated intersection model. Based on the simulation results, the average waiting time, queue length, and delay time are the lowest for the 4-ways isolated intersection where ANFIS traffic signal controller is implemented as compared to the other three controllers which are used for comparison with ANFIS controller. The efficiency of ANFIS controller is much better than that of fuzzy, actuated, and fixed controller in different traffic volumes.

The effectiveness of ANFIS controller is superior to the conventional controllers, such as fixed-cycle and actuated controllers, and fuzzy controller due to the ability of ANFIS controller to adapt to different and dynamic traffic conditions. Same as fuzzy controller, the time extendibility is not fixed and it can freely determine the length of the green phase according to traffic conditions at the intersection. Actuated traffic signal controller has the ability to extend the length of green phase but the extension time is fixed while the extension time for ANFIS and fuzzy controller is not fixed but varied according to the traffic condition. The advantage of ANFIS controller over fuzzy controller is that ANFIS has the ability to fine tune the membership functions in respond to traffic conditions while the membership functions of fuzzy controller

are developed based on expert knowledge. So, performance of ANFIS controller is better than that of fuzzy controller in terms of extension time accuracy.

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TABLE III. PERFORMANCE MEASURES

Performance Measure	Phase	Controller				Performance Comparison (%)		
		ANFIS	Fuzzy	Actuated	Fixed	ANFIS vs Fuzzy	ANFIS vs Actuated	ANFIS vs Fixed
Average waiting time	East Bound	17.95	35.99	47.32	63.89	50.13	62.07	71.90
	South Bound	18.86	30.92	44.95	62.68	39.00	58.04	69.91
	West Bound	16.90	28.82	42.60	63.49	41.36	60.33	73.38
	North Bound	19.10	32.46	53.40	64.25	41.16	64.23	70.27
Average queue length	East Bound	3.39	6.73	8.50	11.71	49.59	60.07	71.02
	South Bound	2.87	4.67	6.97	9.83	38.63	58.83	70.81
	West Bound	3.31	5.64	8.26	12.60	41.22	59.89	73.71
	North Bound	4.32	7.10	12.45	14.34	39.19	65.31	69.88
Delay time	East Bound	25.11	43.98	56.15	72.73	42.91	55.28	65.48
	South Bound	27.59	40.33	54.68	72.78	31.59	49.54	62.09
	West Bound	23.93	36.23	50.43	71.71	33.95	52.55	66.63
	North Bound	25.64	39.45	60.61	71.83	35.01	57.70	64.30