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CONTROLLING TRAFFIC FLOW IN MULTILANE-ISOLATED INTERSECTION USING ANFIS APPROACH TECHNIQUES

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Abstract

Many controllers have applied the Adaptive Neural-Fuzzy Inference System (ANFIS) concept for optimizing the controller performance. However, there are less traffic signal controllers developed using the ANFIS concept. 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 aim of this research is to develop an ANFIS traffic signals controller for multilane-isolated four approaches intersections 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-isolated 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, Green phase module, Next phase module, Multilane-isolated intersection.

1. Introduction

Adaptive traffic signal control has been one of recent application of intelligent

Nomenclatures

Ex	Green time extension
Q	Vehicle queue length
W_t	Waiting time

Greek Symbols

λ	Arrival Rate
σ	Standard deviation

Abbreviartions

AI	Artificial Intelligence
ANFIS	Adaptive Neural-Fuzzy Inference System
ES	East Bound
FCC	Fixed-Cycle Controller
FIFO	First In First Out
FIS	Fuzzy Inference System
FTC	Fuzzy Traffic Controller
i.i.d	Independent and Identically Distributed
M	Memoryless
NB	North Bound
SB	South Bound
VAC	Vehicle-Actuated Controller
WB	West Bound

control techniques that is focused in this study. This will expose researcher to the basic traffic control problems, the conflicting matters, like different traffic flows in the same intersection, which demands compromise in competing space allocation.

The most desired factor in a traffic controller at an intersection is that it should be adaptive to any changes in the traffic flow. Traffic flow levels depend on time, where at peak hours the level is higher as compared to in the morning. Generally, durations of red or green phase are dependent on the traffic pattern at intersection and determined by computer program. However, these traffic controllers are not adaptive due to the settings can only be altered manually or by computer commands sent by the traffic control centre. This problem is solved by using intelligent controller, which is capable of signaling adaptively at an intersection. Linguistic and inaccurate traffic data can be utilized in designing traffic signal timing plans for intelligent controller.

Based on previous work, a major research based on AI techniques is the application of fuzzy control method on intersection control [1-18]. Based on literature survey, the control strategy proposed in many fuzzy traffic controller applied to isolated intersection is Extension green time [1-10] and phase sequence techniques [11-13]. These two techniques are part of the decision making module for fuzzy logic controller. The technique of Extension green time is to Extend the green time if there is still higher demand in the current phase compared with other phases. The aim of the phase sequence techniques is to arrange signal time and phase sequencing of traffic flow so that the delays of vehicles can be decreased and the capacity of intersection can be increased. Other authors used both techniques as control strategy to the controller [14-18]. The combination of both techniques gives a flexible control strategy based on current situation and optimum signal timing for controlling traffic flow especially when involving intersection with multilane model. However, the fuzzy controller only good in the decision making process but not in the learning data. The fuzzy controller is not suitable for controlling the traffic flow which is always changing every time during peak hours.

Adaptive Neural-Fuzzy Inference System (ANFIS) that integrates the best features of fuzzy systems and neural networks has been widely applied in many areas especially Control Engineering. 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. ANFIS techniques are quite popularly used as a controller for traffic signal control [19-25]. 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 [14-18] which are the phase sequence and phase length Extension. These both techniques are alterable to optimize traffic flows at the intersections.

From the review [19-25], 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 ANFIS rules-based system 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 multilane-isolated traffic intersection control by ANFIS traffic controller is implemented using a MATLAB software and the comparison with fuzzy traffic controller and traditional controller have 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.

2. Multilane-Isolated Intersection

A dynamic model for multilane-isolated intersection using queuing theory [26] is used as a case study to test the proposed controller. The typical four-legged isolated intersection is shown in Fig. 1. There are 8 movements in this intersection which consist of one through movement and one right turn movement at each of the four-legged.

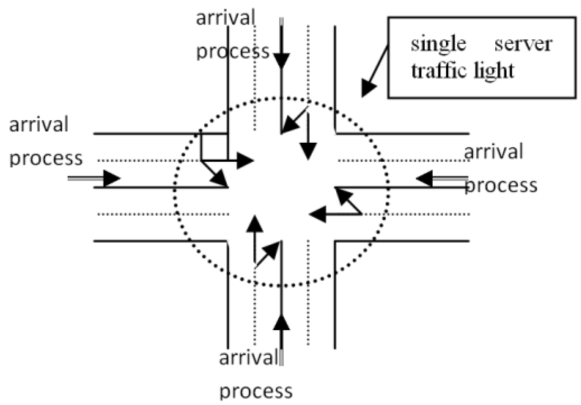


Fig. 1. Isolated Traffic Intersection.

Based on model from [26], a multilane-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.

The 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.

3. Traffic Signal Controller

This section presents the development of an intelligent traffic light system as applied to the multilane-isolated intersection. There are three modules associated with this controller; namely Next Phase module, Green Phase module, and Switch module. Figure 2 shows the schematic diagram of the controller.

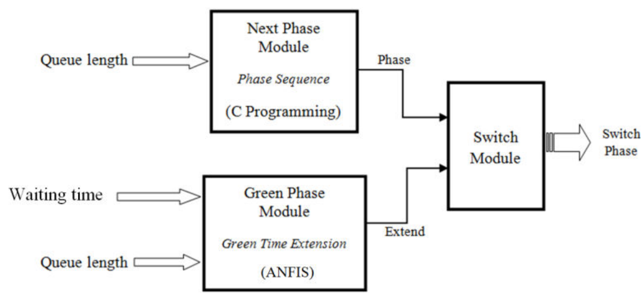


Fig. 2. A Schematic Diagram of the Proposed Traffic Signal Controller.

• 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.

• 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 [27]:

If Input 1 = x and Input 2 = y, then Output is z = ax + by +c (1)

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

In order to evaluate the possibility that the green phase should extend, the traffic flow refers to the following two inputs: waiting time, W_t and vehicles queue length, *Q* is chosen as the input variables for the ANFIS traffic signal controller. The fuzzy rules of this module also resemble the waiting time, W_t and vehicles queue length, *Q* as antecedents and generate Extension time, *Ex* as an output.

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 Fig. 3.

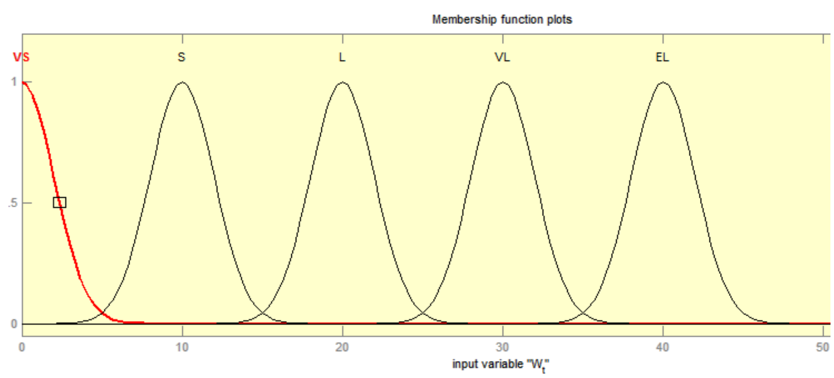


Fig. 3. Input Membership Functions of Vehicles Waiting Time, W_t.

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 Fig. 5.

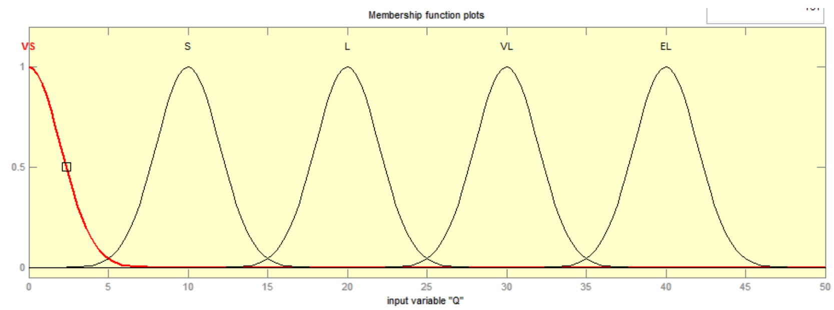


Fig. 4. Input Membership Functions of Vehicles Queue Length, *Q*.

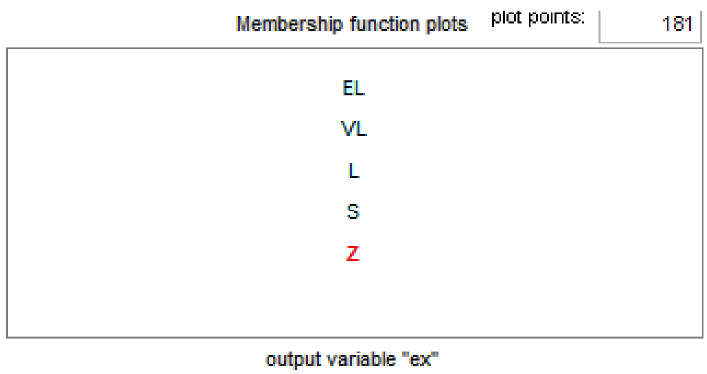


Fig. 5. Output Membership Functions of Extension (Ex).

The fuzzy rules based are developed using “IF-THEN” statement based on humans thinking. The fuzzy rules the controller is shown in Table 1.

The traffic controller develops based on ANFIS First order Sugeno-Type. 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.

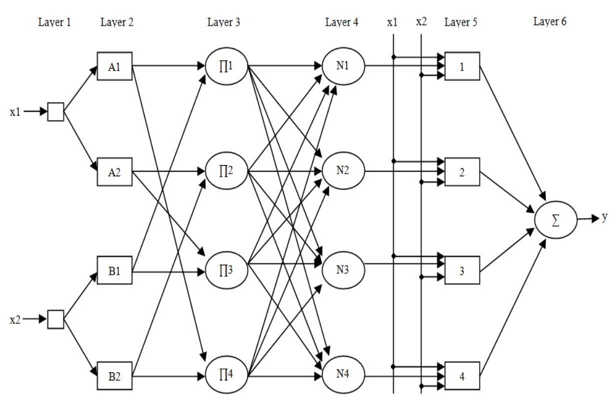


Fig. 6. Structure of ANFIS [27].

Table 1. Fuzzy Rules.

IF	W_t	Condition	Q	Condition	Output (Ex)
R1	VS	AND	VS	THEN	Z
R2	VS	AND	S	THEN	Z
R3	VS	AND	L	THEN	S
R4	VS	AND	VL	THEN	S
R5	VS	AND	EL	THEN	L
R6	S	AND	VS	THEN	Z
R7	S	AND	S	THEN	S
R8	S	AND	L	THEN	S
R9	S	AND	VL	THEN	L
R10	S	AND	EL	THEN	L
R11	L	AND	VS	THEN	S
R12	L	AND	S	THEN	S
R13	L	AND	L	THEN	L
R14	L	AND	VL	THEN	L
R15	L	AND	EL	THEN	L
R16	VL	AND	VS	THEN	S
R17	VL	AND	S	THEN	S
R18	VL	AND	L	THEN	L
R19	VL	AND	VL	THEN	VL
R20	VL	AND	EL	THEN	EL
R21	EL	AND	VS	THEN	L
R22	EL	AND	S	THEN	L
R23	EL	AND	L	THEN	L
R24	EL	AND	VL	THEN	VL
R25	EL	AND	EL	THEN	EL

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:-

a) Layer 1:Input Layer

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

b) Layer 2:Fuzzification Layer

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

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

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, $y^{(2)}_{W_t i} = 1$ and $y^{(2)}_{Qi} = 1$.

c) 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,

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{3} \tag{3}$$

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

From Eq. (3), the output of rule neuron *i* in Layer 3 where *i* = 1, 2, 3, … , 25 is 1.

d) 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,

$$y_i^{(4)} = \frac{x_{ii}^{(4)}}{\Sigma_{j=1}^{n} x_{ji}^{(4)}} = \frac{\mu_i}{\Sigma_{j=1}^{n} \mu_j} = \overline{\mu}_i \tag{4}$$

where $x_{ji}^{(4)}$ 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 1, the output of neuron based on output membership function is summarized in Table 2.

Table 2. The Output Neuron in Layer 4.

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

e) 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 Eq. (5) as shown below.

$$z = a + bx + cy \tag{5}$$

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

$$\begin{aligned} \Pi &= \Sigma_{i=1}^{n} \left[z_i - f(x_i, y_i)\right]^2 \\ &= \Sigma_{i=1}^{n} \left[z_i - (a + bx_i + cy_i)\right]^2 \\ &= \min \end{aligned} \tag{6}$$

From Eq. (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. So,

$$\frac{\partial \Pi}{\partial a} = -2\Sigma_{i=1}^{n} \left[z_i - (a + bx_i + cy_i)\right] = 0 \tag{7}$$

$$\frac{\partial \Pi}{\partial b} = -2\Sigma_{i=1}^{n} x_i \left[z_i - (a + bx_i + cy_i)\right] = 0 \tag{8}$$

$$\frac{\partial \Pi}{\partial c} = -2\Sigma_{i=1}^{n} y_i \left[z_i - (a + bx_i + cy_i)\right] = 0 \tag{9}$$

From Eqs. (7), Eq. (8) and Eq. (9),

$$\Sigma_{i=1}^{n} z_i = a\Sigma_{i=1}^{n} 1 + b\Sigma_{i=1}^{n} x_i + c\Sigma_{i=1}^{n} y_i \tag{10}$$

$$\Sigma_{i=1}^{n} x_i z_i = a\Sigma_{i=1}^{n} x_i + b\Sigma_{i=1}^{n} x_i^2 + c\Sigma_{i=1}^{n} x_i y_i \tag{11}$$

$$\Sigma_{i=1}^{n} y_i z_i = a\Sigma_{i=1}^{n} y_i + b\Sigma_{i=1}^{n} x_i y_i + c\Sigma_{i=1}^{n} y_i^2 \tag{12}$$

The coefficients a, b, and c can be found by solving Eqs. (10), (11), and (12) using matrices.

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_{ti} are assigned based on fuzzy rules in Table 1 and shown in Tables 3 to 7 respectively. From this values, the coefficients *a, b*, and *c* can be obtained and shown in Table 8.

Table 3. Values of y_i, W_{ti}, and Q_i for Zero (Z).

y_i	W_{ti}	Q_i	$W_{ti} * y_i$	W_{ti}^2	$W_{ti} * Q_i$	$Q_i * y_i$	Q_i^2
1	5	0	5	25	0	0	0
3	15.5	0	46.5	240.25	0	0	0
5	5	10	25	25	50	50	100

∑	9	25.5	10	76.5	290.25	50	50	100

Table 4. Values of y_i, W_{ti}, and Q_i for Short (S).

	y_i	W_{ti}	Q_i	$W_{ti} * y_i$	W_{ti}^2	$W_{ti} * Q_i$	$Q_i * y_i$	Q_i^2
	6	25.5	0	153	650.25	0	0	0
	7	35.5	0	248.5	1260.25	0	0	0
	8	15.5	10	124	240.25	155	80	100
	9	25.5	10	229.5	650.25	255	90	100
	10	35.5	10	355	1260.25	355	100	100
	10	5	20	50	25	100	200	400
	10	15.5	20	155	240.25	310	200	400
	10	5	30	50	25	150	300	900
∑	70	163	100	1365	4351.5	1325	970	2000

Table 5. Values of y_i, W_{ti}, and Q_i for Long (L) .

	y_i	W_{ti}	Q_i	$W_{ti} * y_i$	W_{ti}^2	$W_{ti} * Q_i$	$Q_i * y_i$	Q_i^2
	11	45.5	0	500.5	2070.25	0	0	0
	12	45.5	10	546	2070.25	455	120	100
	13	25.5	20	331.5	650.25	510	260	400
	14	35.5	20	497	1260.25	710	280	400
	15	45.5	20	682.5	2070.25	910	300	400
	15	15.5	30	232.5	240.25	465	450	900
	15	25.5	30	382.5	650.25	765	450	900
	15	5	40	75	25	200	600	1600
	15	15.5	40	232.5	240.25	620	600	1600
∑	125	259	210	3480	9277	4635	3060	6300

Table 6. Values of y_i, W_{ti}, and Q_i for Very Long (VL).

	y_i	W_{ti}	Q_i	$W_{ti} * y_i$	W_{ti}^2	$W_{ti} * Q_i$	$Q_i * y_i$	Q_i^2
	16	35.5	30	568	1260.25	1065	480	900
	18	45.5	30	819	2070.25	1365	540	900
	20	25.5	40	510	650.25	1020	800	1600
∑	54	106.5	100	1897	3980.75	3450	1820	3400

Table 7. Values of y_i, W_{ti}, and Q_i for Very Long (VL).

y_i	W_{ti}	Q_i	$W_{ti} * y_i$	W_{ti}^2	$W_{ti} * Q_i$	$Q_i * y_i$	Q_i^2

	23	35.5	40	816.5	1260.25	1420	920	1600
	25	45.5	40	1137.5	2070.25	1820	1000	1600
∑	48	81	80	1954	3330.5	3240	1920	3200

Table 8. The Values of Coefficients *a, b*, and *c*.

Output Membership Function	Coefficients		
	a	*b*	*c*
Zero(Z)	0.585365853	1.211064842	-0.037477691
Short(S)	1.709587863	2.829865219	-1.649343564
Long(L)	1.907592977	3.010521466	-1.276088978
Very Long(VL)	0.313081958	1.285728773	0.313081958
Extremely Long (EL)	0.4	0.795	0

• **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.

4. 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_t) and queue length (Q), respectively, and one output data which is green time Extension (Ex). From the first rule if input W_t 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_t 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 Fig. 7.

By referring to Fig. 7, the VS fuzzy set of input waiting time, W_t , 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_t, 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.

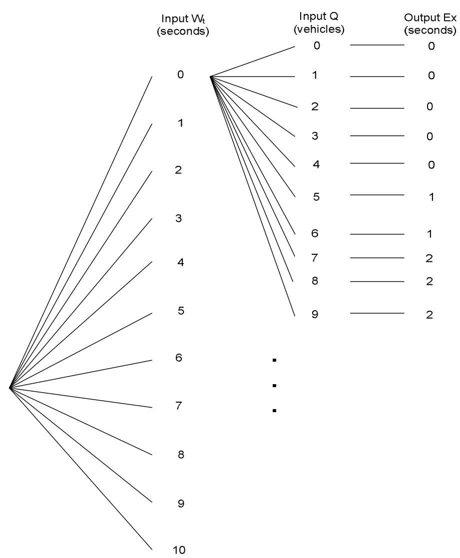


Fig. 7. Tree Diagram for Training Sample Data.

5. 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.

The ANFIS model structure for the trained FIS is shown in Fig. 8. Based on this figure, the ANFIS model structure of trained FIS has a six-layer feedforward neural network, consisting of two inputs and each input has five fuzzy sets. There are 25 rules in the ANFIS model structure. The output is represented by a linear function.

When the training sample data is loaded into the ANFIS model, the plot of training data is obtained as shown in Fig. 9. This plot shows the data that is used for the FIS system to learn the rule consequent parameters and to train and tune the membership functions of the FIS system. As can be seen from the plot, the training data consists of more than 2500 sample data. As shown in Fig. 10, the training error of the trained FIS remained constant between the values of 0.5 and 1 over 50 epochs. The training process of the FIS system is stopped when the epoch number of 50 is reached. After training, the set of generated output is tested with the training data. The training data is compared with the plot of FIS output as shown in Fig. 11. Obviously, the generated FIS outputs approximately resembled the linear functions and the error between the training data set and the FIS output is very small and can be neglected.

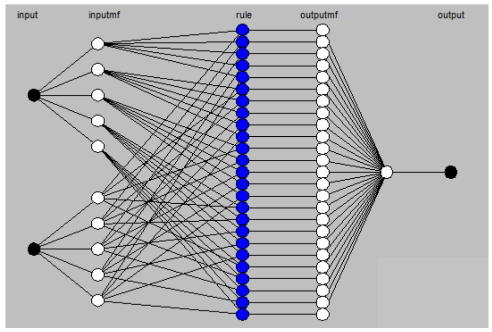


Fig. 8. ANFIS Model Structure of Trained FIS.

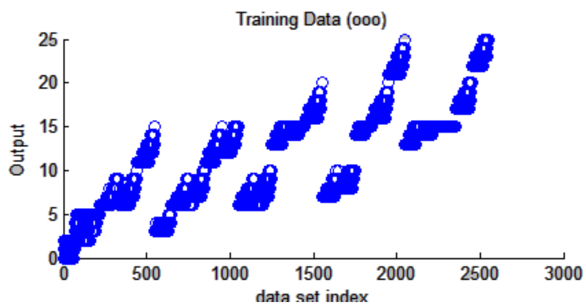


Fig. 9. Plot of Training Data in ANFIS Model.

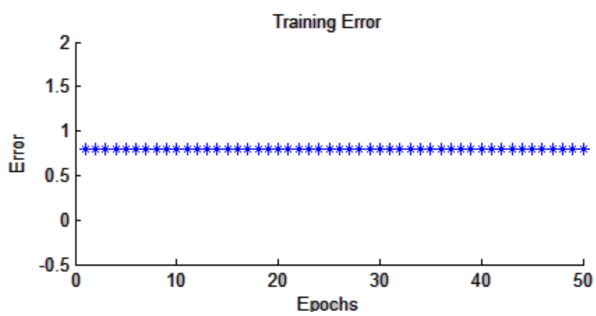


Fig. 10. Training Error of Trained FIS.

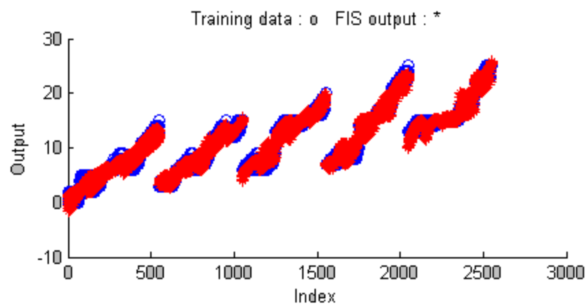


Fig. 11. Plot of Training Data in Comparison with the FIS Output.

The input membership functions have been tuned and the output membership functions have been increased from the initial of five membership functions to twenty-five membership functions so that the FIS system responds smoothly. Each output membership function corresponds to a single fuzzy rule in the rule based of FIS. The rule consequent parameters for each output membership functions have been learned from the training data. The change of the input membership functions of input variables W_t and Q and output membership functions of output variable, *Ex* are shown in Fig. 12, Fig. 13, and Fig. 14, respectively.

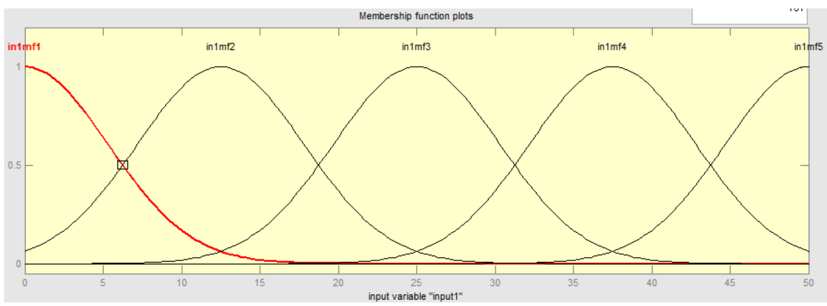


Fig. 12. Input Variable, W_t After Training.

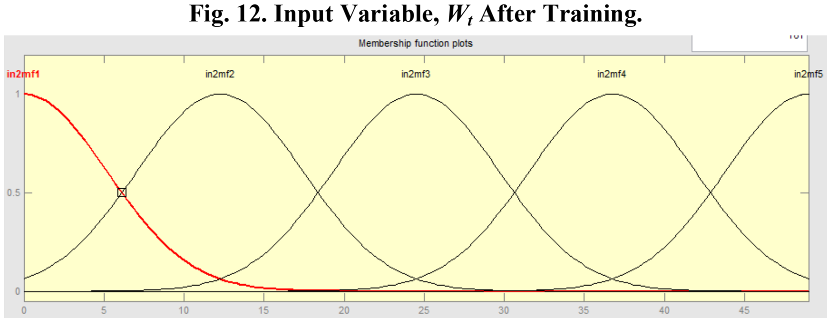


Fig. 13. Input Variable, *Q* After Training.

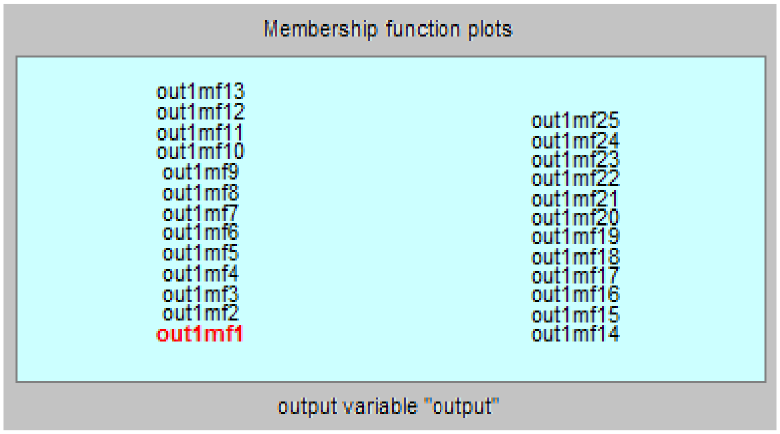


Fig. 14. Output Variable, *Ex* After Training.

6. Simulation Results and Discussions

The performance of the developed proposed traffic signal controller is evaluated by simulation. The simulation is done in three different scenarios, which are low traffic volume (0-1000 vehicles), medium traffic volume (1000-2000 vehicles) and high traffic volume (2000 vehicles above), in multilane-isolated intersection model. 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 multilane-isolated intersection. In this research, the fuzzy controller used for comparison with the ANFIS controller is developed based on ANFIS controller which has the same three modules. The difference is only in the Green Phase module, where the fuzzy controller used is the FIS Mamdani-type.

The simulation results are summarized as in Tables 9 to 11. From these tables, the evaluation results show that in general the proposed controller performs significantly better than the other controllers for almost all performance criteria for each phase of intersection. From the simulation done, for all tests on the multilane-isolated intersection, the ANFIS controller produces lower average waiting time, average queue length and average delay time than fuzzy method, fixed-cycle and vehicle actuated control in all cases.

Table 9. Performance of Traffic Signal Controllers at Low Volume.

Performance Measure	Phase	Controller				Performance Comparison (%)		
		ANFIS	FTC	VAC	FCC	ANFIS vs FTC	ANFIS vs VAC	ANFIS vs FCC
Average waiting time (seconds)	EB	23.17	53.56	61.63	60.43	56.74	62.40	61.66
	SB	21.09	29.06	54.44	57.53	27.43	61.26	63.34
	WB	13.44	28.90	59.3	52.0	53.49	77.37	74.15

				9	0			
	NB	20.21	32.24	60.84	58.80	37.31	66.78	65.63
Average queue length (vehicles)	EB	3.04	6.87	8.06	7.52	55.70	62.28	59.57
	SB	2.20	2.88	5.47	5.85	23.70	59.82	62.46
	WB	1.01	2.07	4.45	3.91	51.45	77.42	74.31
	NB	2.19	3.44	7.00	6.08	36.39	68.80	64.04
Delay time (seconds)	EB	33.32	65.49	73.41	72.49	49.12	54.61	54.04
	SB	33.29	42.16	67.93	71.79	21.04	50.99	53.63
	WB	25.86	44.62	77.25	70.11	42.04	66.52	63.12
	NB	31.67	44.66	74.77	73.22	29.09	57.64	56.75

Table 10. Performance of Traffic Signal Controllers at Medium Volume.

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

Table 11. Performance of Traffic Signal Controllers at High Volume.

Per-formance Measure	Phase	Controller				Performance Comparison (%)		
		ANFIS	FTC	VAC	FCC	ANFIS vs. FTC	ANFIS vs. VAC	ANFIS vs. FCC
Average waiting time (seconds)	EB	15.08	22.77	36.21	68.71	33.77	58.35	78.05
	SB	15.88	26.25	36.95	70.06	39.50	57.02	77.33
	WB	16.36	27.91	36.08	70.19	41.38	54.66	76.69
	NB	17.87	31.73	46.23	73.08	43.68	61.35	75.55
Average queue length (vehicles)	EB	4.42	6.62	10.66	19.45	33.34	58.58	77.30
	SB	5.07	8.07	11.32	22.23	37.21	55.21	77.19
	WB	4.79	8.14	10.73	20.48	41.13	55.37	76.62
	NB	6.40	11.74	16.93	26.38	45.48	62.19	75.74
Delay time	EB	20.55	28.40	41.87	74.82	27.64	50.92	72.53
	SB	20.86	31.73	42.55	75.70	34.26	50.98	72.44

(seconds)	WB	21.75	33.61	41.80	76.21	35.29	47.97	71.46
	NB	22.48	36.37	51.28	78.13	38.19	56.16	71.23

At low traffic volume, the total number of vehicles flow in and out of the isolated intersection in one hour is assumed to be varied between 0 and 1000 vehicles. The results in tables above shows that, compared to the fuzzy controller, the ANFIS controller produces better results in terms of average waiting time, average queue length, and average delay time. The simulation results show that the average waiting time giving the percentages from 27.43%- 56.74% and the average queue length giving the percentages from 23.70%-55.70% compared to fuzzy traffic controller. The better performances also show in comparison with the traditional controller in terms of average waiting time (VAC: 61.26%-77.37% and FCC: 61.66%-74.15%) and average queue length (VAC: 59.82%-77.42% and FCC: 59.57%-74.31%). The good performance of average waiting time and average queue length cause the vehicles to spend not as much time from the moment it arrives at the intersection until it leaves the intersection. This indicator means that the ANFIS traffic controller shows improvement in average delay time over fuzzy traffic and traditional controller. So, the lower the average delay time of the ANFIS traffic controller, the more throughput or departure vehicles exit the intersection. The simulation graphs for each performance measures at low traffic volume are shown in Figs. 15 to 17.

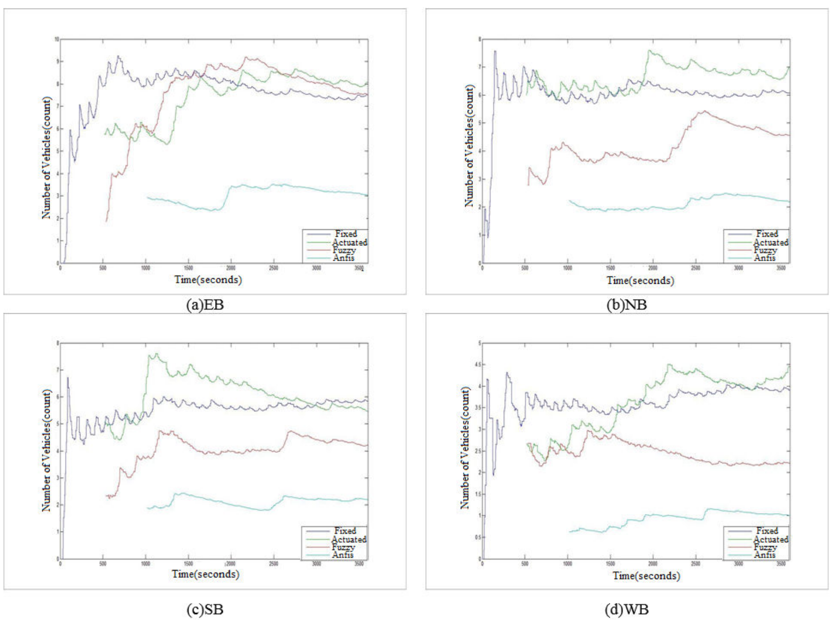
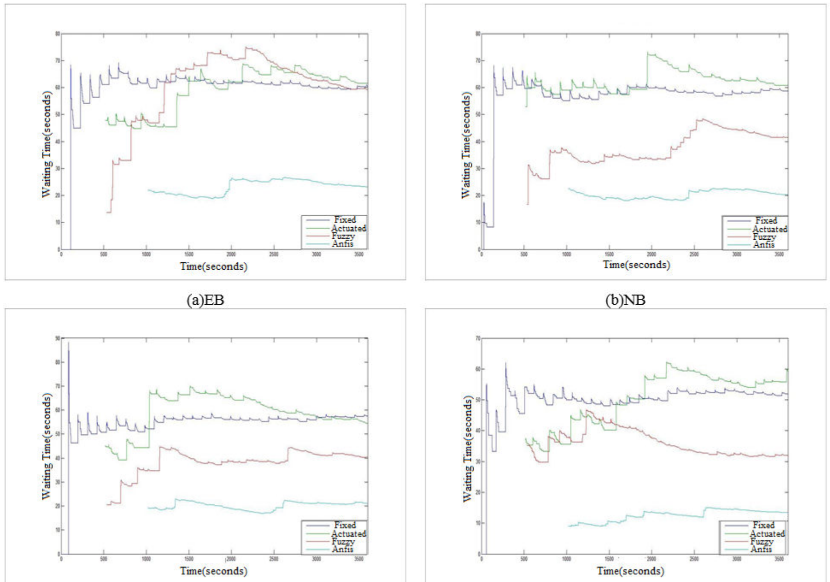


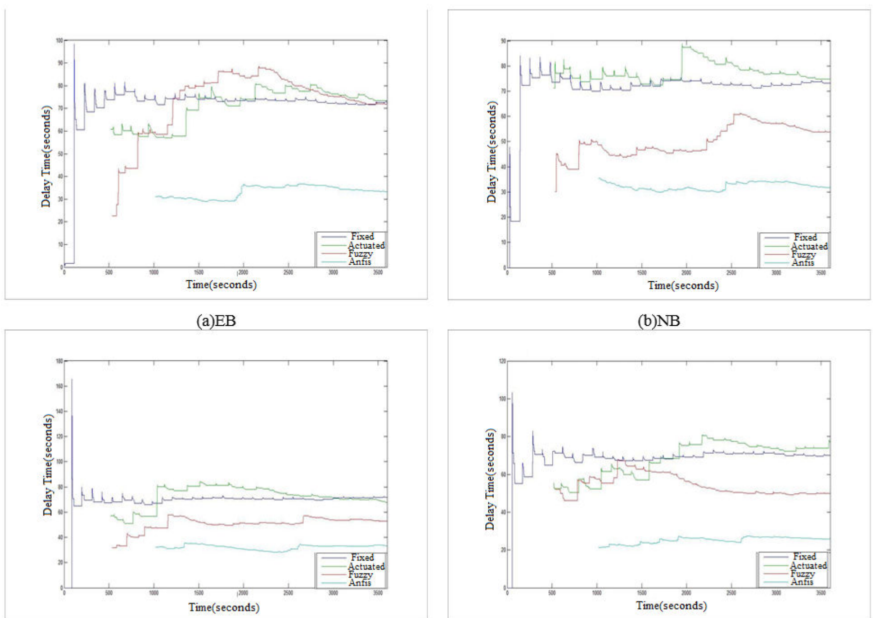
Fig 15. A Comparison of the Results of Average Queue Lengths at Low Traffic Volume.



(a)EB (b)NB

(c)SB (d)WB

Fig 16. A Comparison of the Results of Average Waiting Time at Low Traffic Volume.



(a)EB (b)NB

(c)SB (d)WB

Fig 17. A Comparison of the Results of Average Delay Time at Low Traffic Volume.

The results from the evaluation controller in medium and high volume show the same trend as the result from the evaluation controller based on the low volume data for each intersection. The ANFIS traffic controller is the best control method followed by the fuzzy traffic controller. The vehicle-actuated controller has better performance than fixed-cycle controller and the worst performance controller is fixed-cycle controller. It shows that it is feasible to use ANFIS and fuzzy based traffic controllers in real intersection traffic control problems with more than two phases, and ANFIS and fuzzy methods can be used to decide when to make phase switch as well as how to choose phase sequence. The ANFIS and fuzzy controller have the ability to adjust green signal length according to real-time traffic flow conditions. The simulation graphs of performance measure for both scenario are shown in Figs.18 to 23.

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.

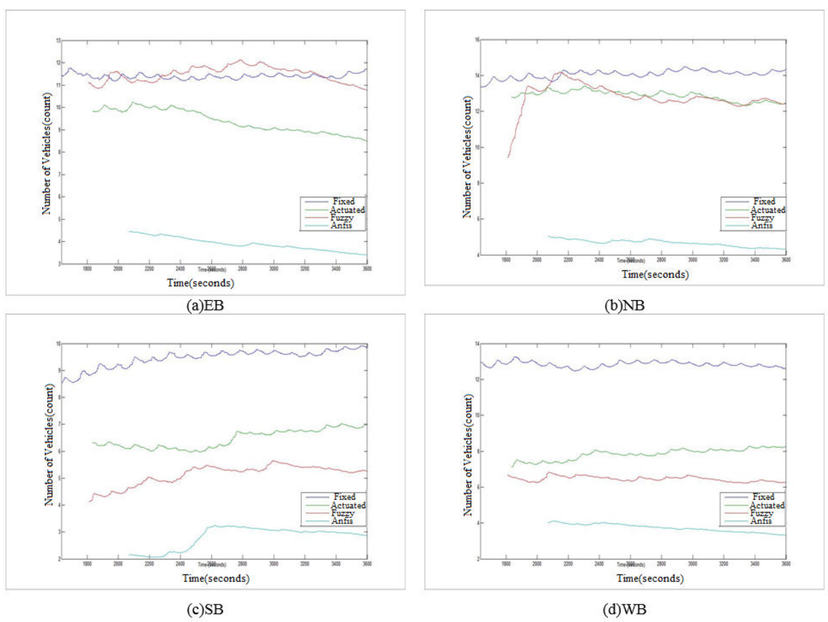
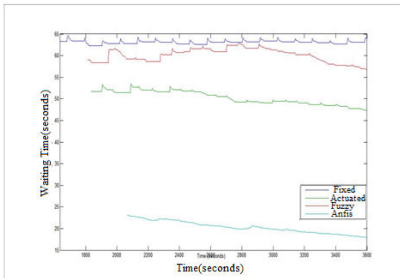
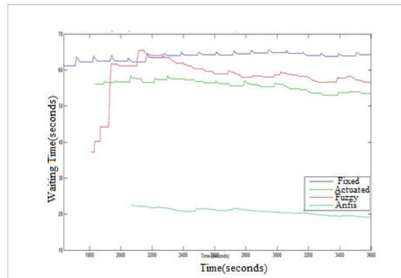


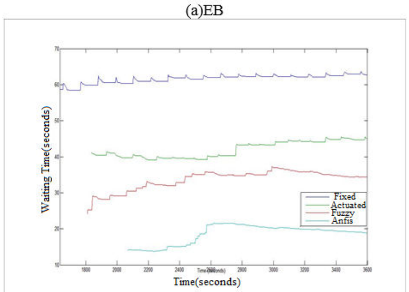
Fig 18. A Comparison of the Results of Average Queue Lengths at Medium Traffic Volume.



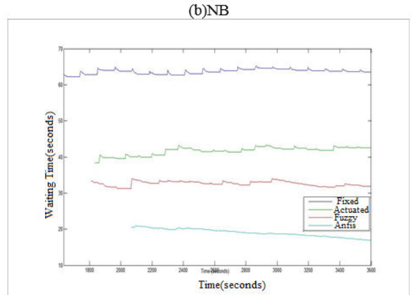
(a)EB



(b)NB

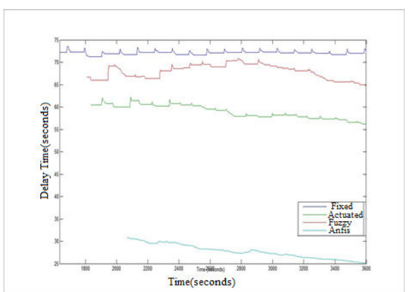


(c)SB

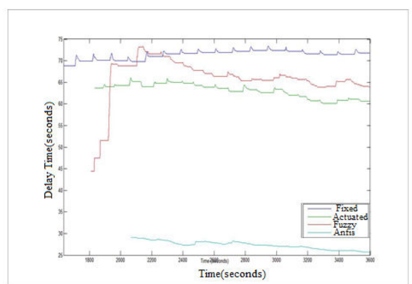


(d)WB

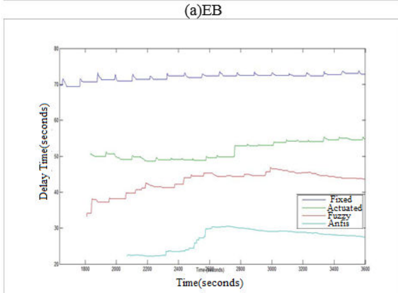
Fig 19. A Comparison of the Results of Average Waiting Time at Medium Traffic Volume.



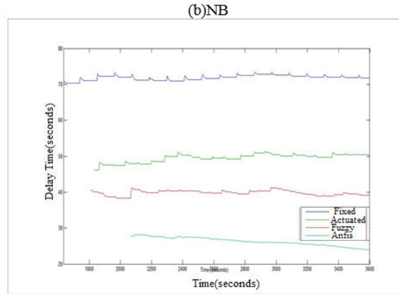
(a)EB



(b)NB



(c)SB



(d)WB

Fig 20. A Comparison of the Results of Average Delay Time at Medium Traffic Volume.

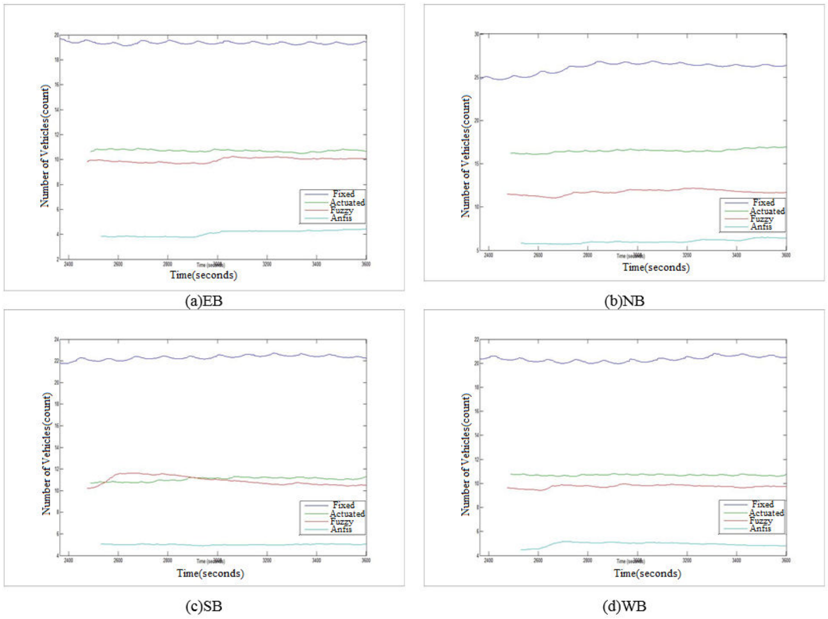


Fig 21. A Comparison of the Results of Average Queue Lengths at High Traffic Volume.

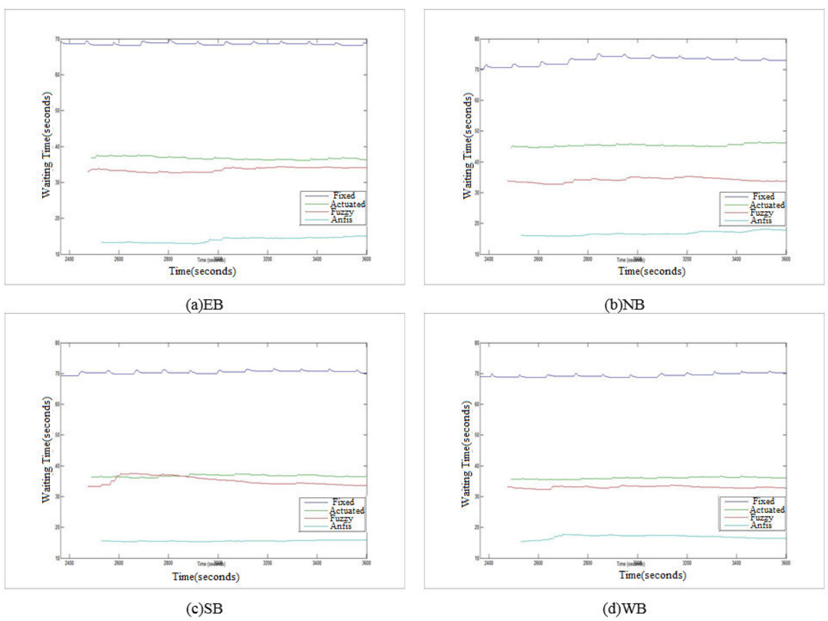
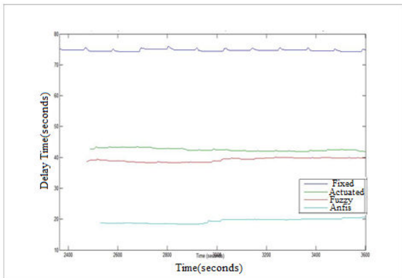
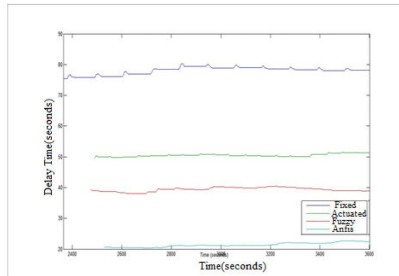


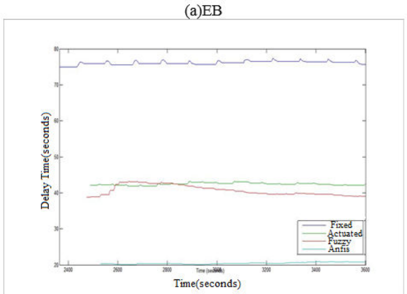
Fig 22. A Comparison of the Results of Average Waiting Time at High Traffic Volume.



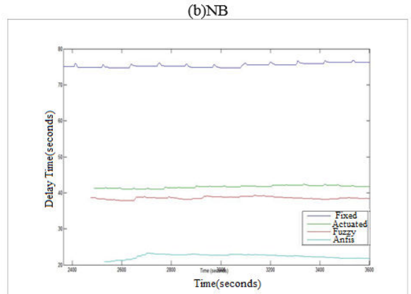
(a)EB



(b)NB



(c)SB



(d)WB

Fig 23. A Comparison of the Results of Average Delay Time at High Traffic Volume.

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-cycle controller and cannot be tuned in accordance with the real time traffic condition data.

7. 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 fuzzy controller and traditional controller.

ANFIS controller can be trained by a set of input values and modeled output values to learn the rule consequent parameters and also to tune the membership functions. If the sample data provided to train the ANFIS controller reflects the real-time traffic flow conditions at a particular intersection, ANFIS controller will have optimized performance over fuzzy, vehicle-actuated, fixed-cycle controllers in controlling traffic signal at the intersection.

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 multilane- 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, vehicle-actuated, and fixed-cycle controller in different traffic volumes.

The effectiveness of ANFIS controller is superior to the traditional controllers, such as fixed-cycle and vehicle-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. Vehicle-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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