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DESIGN AN OPTIMIZED FUZZY CLASSIFIER SYSTEM FOR URBAN TRAFFIC NETWORK

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ABSTRACT

Traffic control in large cities is a difficult and non-trivial optimization problem. This paper presents a optimized classifier system using fuzzy logic for recognize and traffic signal control in a single intersection. Also this paper presents preliminary work into designing an intelligent local controller primarily for distributed traffic control systems by fuzzy logic. The idea is to use a classifier system with a fuzzy rule representation to determine useful control rules within the dynamic environment. Results show that the performance of the proposed traffic controller is best and error is very low.

Keywords: *Fuzzy Classifier; State-Space Equations; Traffic Signal; Fuzzy Controller*

1. INTRODUCTION

Traffic control in large cities is a difficult and non-trivial optimization problem. Most of the automated urban traffic control systems are based on deterministic algorithms and have a multi-level architecture; to achieve global optimality, hierarchical control algorithms are generally employed. However, these algorithms are often slow to react to varying conditions, and it has been recognized that incorporating computational intelligence into the lower levels can remove some burdens of algorithm calculation and decision making from higher levels. An alternative approach is to use a fully distributed architecture in which there is effectively only one (low) level of control. Such systems are aimed at increasing the response time of the controller and, again, these often incorporate computational intelligence techniques[1].

For years many investigators have conducted research into optimal signal control algorithms. Webster gave equations for the optimal cycle length and the green phase time assignment, which are the basis of fixed-time control which has been widely used. Akcelik modified Webster's theory for the over-saturated scenario in a new signal timing algorithm called ARRB. With the development of a variety of inexpensive sensors and computer and communication Technologies, many advanced methods have been developed to adjust signal timings according to real-time traffic data. A number of adaptive traffic control systems have been deployed all over the world, such as SCOOT, SCATS, OPAC, and RHODES. In recent years, artificial intelligence techniques have been introduced into signal control using fuzzy logic controllers and genetic algorithms (GA). These systems have various properties and varying effectiveness in field applications [2]-[11].

Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. The complexity and limitations of previous mechanisms are largely due to the lacking of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases. On the contrary, fuzzy classification[12] assumes the boundary between two neighboring classes as a continuous, overlapping area within which an object has partial membership in each class. This viewpoint not only reflects the reality of many applications in which categories have fuzzy boundaries, but also Provides a simple representation of the potentially complex partition of the feature space. In brief, we use fuzzy if-then rules to describe a Classifier. A typical fuzzy classification rule is like:

If X1 is A and X2 is B then Z is C

where X1 and X2 are features or input variables; A, B are linguistic terms[13] characterized by

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appropriate membership functions [14], which describe the features of an object Z. The firing strength or the degree of appropriateness of this rule with respect to a given object is the degree of belonging of this object to the class C. Fuzzy classifiers are one application of fuzzy theory. A fuzzy classifier system learns rules written in a fuzzy rule language and uses a fuzzy production system[15].

This paper presents a classifier system using fuzzy logic for recognition traffic signal an isolated signalized intersection. The classifier either classifies and controls the traffic light timings (traffic signals) and phase sequence to ensure smooth flow of traffic with minimal Length of Queue(LoQ). Also, this paper presents preliminary work into designing an intelligent local optimized controller primarily for distributed traffic control systems.

This paper is organized as follows. Section II is concentrated for statement pattern recognition in urban traffic. Section III has explained fuzzy classifier. Section IV is focused on simulation results and is stated the classification of signal traffic. Section V presents the conclusion.

2. PATTERN RECOGNITION IN URBAN TRAFFIC

2.1. MODELING OF SINGLE INTERSECTION [11]

The two Phases Signalized Intersection shape that utilizes it for mentioning modeling single intersections in this paper was demonstrating in follows. In this figure, the Leg 1 and Leg 3 are phase 1 and the Leg 2 and Leg 4 are phase 2.

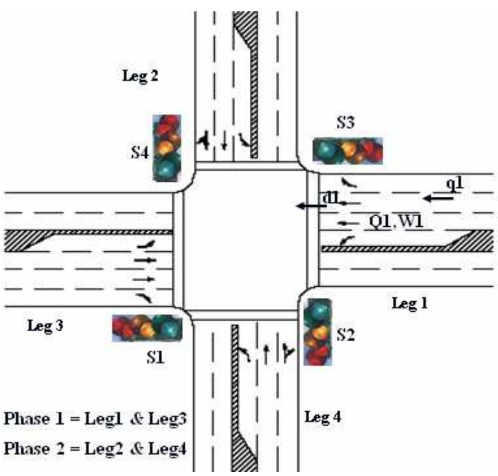

Figure 1. Two Phase Signalized Intersection shape

The length of queue is an important variable that describes the traffic state of an intersection. The queue evolves as

$$Q_i(n+1) = Q_i(n) + q_i(n) - d_i(n)S_i(n) \qquad (1)$$

where $i = 1, 2, \ldots, M$ is the index of the traffic streams; $n = 0, 1, \ldots, N-1$ is the index of the discretized time intervals; $Q_i(n)$, in unit of number of vehicles, is the queue length of the i -th stream at the onset of the n -th time interval; $q_i(n)$ is the number of vehicles that join the i -th queue in the n -th time interval; $d_i(n)$ is the number of vehicles that depart from the i -th queue in the n -th time interval; and $S_i(n)$, which takes 0 (for stop) or 1 (for go), is the signal state of the i -th stream in the n -th time interval. q_i and d_i are normally distributed random signals.

Integrating the length of queue with respect to time yields the average vehicles waiting time of the queue. Let T denote the length of the discretized time interval. If T is short enough, the vehicles arrivals can be treated as being uniform in every time interval. Hence, integrating Eq. (1) yields

$$W_i(n+1) = W_i(n) + TQ_i(n) + \frac{1}{2}Tq_i(n) - \frac{1}{2}Td_i(n)S_i(n) \qquad (2)$$

where $W_i(n)$ is the average vehicle-wise waiting time of the i -th queue from the beginning of the period to the onset of the n -th time interval.

Equations (1) and (2) are the state-space equations describing the dynamic evolution of the traffic state at a single intersection. The waiting time and the number of vehicles are popular performance indices for signal controls. The waiting time is used here as the performance index. Therefore, the optimization objective is

$$\min\left\{W(N) = \sum_{i=1}^{M} W_i(N)\right\} \qquad (3)$$

To facilitate the formulation, the state-space equations and the optimization objective can be rewritten in matrix form as:

$$X(n+1) = AX(n) + B(n)S(n) + C(n) \qquad (4)$$

$$y(n) = CX(n) \qquad (5)$$

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where $X(n)=[Q_1(n)Q_2(n)...Q_M(n)W_1(n)W_2(n)...W_M(n)]^T$ are the state variables and $S(n)=[S_1(n)S_2(n)...S_M(n)]^T$ are the control variables. The state variable X_i is the i-th pattern in signalized intersection for $i=1,2,...,M$ .This Patterns are random variables. The various coefficient matrices and vectors are [16]:

$$A=\begin{bmatrix} I_M & 0 \\ TI_M & I_M \end{bmatrix},$$

$$B(n)=-\begin{pmatrix} d_1(n) & 0 & \cdots & 0 \\ 0 & d_2(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_M(n) \\ \frac{1}{2}Td_1(n) & 0 & \cdots & 0 \\ 0 & \frac{1}{2}Td_2(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{2}Td_M(n) \end{pmatrix} \quad (6)$$

$$C=\begin{bmatrix} I_M & 0 \\ 0 & I_M \end{bmatrix},$$

$$C(n)=[q_1(n)q_2(n)\cdots q_M(n)\frac{1}{2}Tq_1(n)\frac{1}{2}Tq_2(n)\cdots\frac{1}{2}Tq_M(n)]^T$$

2.2. *PATTERN RECOGNITION IN URBAN TRAFFIC PROBLEM*

Pattern Recognition, or decision-making in a broader sense, may be considered as a problem of estimating density functions in a high-dimensional space and dividing the space into the regions of categories or classes[17].

The input to a pattern recognition network is a random vector with n variables as $X=[x_1,x_2,...,x_n]^T$, where T denotes the transpose of the vector. In pattern recognition, we deal with random vectors drawn from different classes. A typical pattern recognition system may consist of various parts as shown in Figure 2.

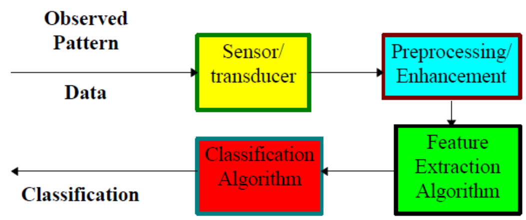

Figure 2. Typical pattern recognition system

In this paper $X(n)=[Q_1(n)Q_2(n)...Q_M(n)]^T$ is a pattern in signalized intersection for $i=1,2,...,M$. Whenever $Q_i(n)$ is i-th sample in pattern. This samples are random variables that were made as two other random variables etc. q_i and d_i as mentioned in equation (1).

We can classify a sample without a class label to a normal or abnormal machine, depending on $g(x_1,x_2)<0$ or $g(x_1,x_2)>0$. We call $g(x_1,x_2)$ a discriminant function, and a network which detects the sign of $g(x_1,x_2)$ is called a pattern recognition network, a categorizer, or a classifier.

This paper design a fuzzy discriminant function or a fuzzy classifier for classify a pattern to one of the two classes.

Therefore, there are two classes at signalized intersection in above. One class is equivalent phase 1 and second class is equivalent phase 2. In Fixed-time control and Fuzzy intelligent control model , the control variables are equivalent of this classes. For Example the control variables in class 1 of intersection are $(S_1,S_2,S_3,S_4)=(0,1,0,1)$ that means traffic light is green in lane 2 and 4 and it is red in lane 1 and 3, Therefore, the vehicles can GO in lane 2 and 4 and they should STOP in lane 1 and 3. On the other hand, the control variables in class 1 of intersection are $(S_1,S_2,S_3,S_4)=(1,0,1,0)$ that means traffic light is green in lane 1 and 3 and it is red in lane 2 and 4. Therefore, the vehicles can GO in lane 1 and 3 and they should STOP in lane 2 and 4.

3. FUZZY CLASSIFIER

A classifier system is a machine learning system which learns rules to guide its performance in an arbitrary environment. Its main components are a production system, an apportionment of credit function and a genetic algorithm[17].

In order to design a classifier, we must study the characteristics of the distribution of X for each

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category and find a proper discriminant function. This process is called learning or training, and samples used to design a classifier are called learning or training samples. Obviously, as the number of inputs to a classifier becomes smaller, the design of the classifier becomes simpler. In order to enjoy this advantage, we have to find some way to select or extract important features from the observed samples. It is commonly considered that a pattern recognition system consists of two parts; a feature extractor and a classifier, when the classifier part is examined more closely, it is found to consist of a discriminant function selector, which chooses a posteriori probability functions for the Bayes classifier, and a maximum value selector, which decides the class assignment of the test sample. Figure 3 shows a block diagram of a classifier in a general n-dimensional space[17].

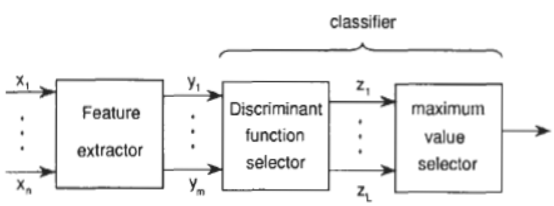

Figure 3. Block diagram of a traditional classifier

Fuzzy classifiers are one application of fuzzy theory. A fuzzy classifier system learns rules written in a fuzzy rule language and uses a fuzzy production system. Although there is a wide range of fuzzy production systems differing in their syntax and semantics, we concentrate in the following on fuzzy production systems with a very simple syntactic structure. The reasons for this are twofold. First, these production systems have been successfully applied to various control problems in robotics and industrial automation. Secondly, the simple syntactic structure of the rule language and the small number of rules for a rule-base are characteristics common to fuzzy control applications which make these problems amenable to genetic machine learning[18].

In fuzzy classification, a sample can have membership in many different classes to different degrees. Typically, the membership values are constrained so that all of the membership values for a particular sample sum to 1. Linguistic rules describing the control system consist of two parts; an antecedent block (between the IF and THEN) and a consequent block (following THEN). A Classifier Model is Following:

R1: If x is A1 and y is B1 then class is $\omega 1$

R2: If x is A2 and y is B2 then class is $\omega 2$

Depending on the system, it may not be necessary to evaluate every possible input combination, since some may rarely or never occur. Optimum evaluation is usually done by experienced operators. The inputs are combined logically using the AND operator to produce output response values for all expected inputs. The active conclusions are then combined to logical sum for each membership function. Finally, all that remains is combined in defuzzification process to produce the crisp output. Figure 4 shows a block diagram of a pattern classification system with fuzzy classifier.

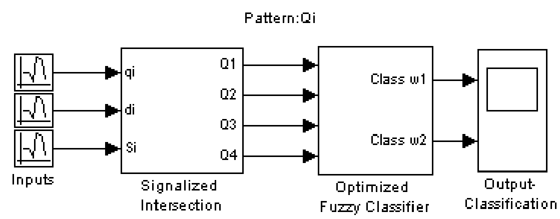

Figure 4. Block diagram of a pattern classification system

The pattern classification system classifies a feature vector $X(n)$ that is in R^n according to the decision rules: X is in the i- th class if and only if $g_i(X)$ is greater than $g_j(X)$ for all j not equal to i, where g_i is a discriminant function mapping R^n to R. In this paper, g_i is not mathematical function, but it was designed by fuzzy logic as follows.

The first stage of designing of fuzzy classifier, g_i, is the selection of performance variables. Here the input and output variables of the fuzzy classifier in single intersection are selected . The input variables are $Q_i(n)$. The output variables are $S_i(n)$ for $i = 1, 2, \ldots, 4$, that were explained in before section. $Q_i(n)$ are samples that were classified to one of two classes of $\omega 1$ or $\omega 2$.

The second stage of designing of fuzzy classifier is the determination of variables surface i.e., fuzzy sets (fuzzification). The fuzzy sets or the linguistic variables for the inputs and outputs given above are designed. $S_i(n)$ are divided into two fuzzy sets: “Go” and “STOP”. $Q_i(n)$ are divided into three fuzzy sets that denote by Y_i: “Small(S)”, “Medium(M)” and “Large(L)”. The next stage of designing of fuzzy classifier is to form the fuzzy

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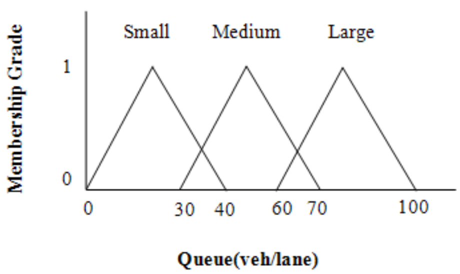
relationship between the inputs and outputs i.e., rules. The rules are formed from the available inputs-outputs data sequences of the urban traffic network, based on if-then statement. A rule base of 80 rules is set for the various fuzzy conditions in classifier that can occur. The Number of rules are enlisted in the form of a matrix in TABLE I [11].

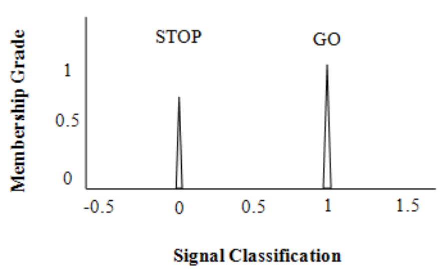
Table 1. The Number of Fuzzy Rules

Rules Number	Fuzzy Inputs				Fuzzy Outputs			
	Q١	Q٢	Q٣	Q٤	S١, S٢ Class١		S٣, S٤ Class٢	
١	S	S	S	L	STOP	STOP	GO	GO
٢	S	S	M	S	GO	GO	STOP	STOP
٣	S	S	M	M	STOP	STOP	GO	GO
٤	S	S	M	L	STOP	STOP	GO	GO
٥	S	S	L	S	GO	GO	STOP	STOP
٦	S	S	L	M	GO	GO	STOP	STOP

The adopted membership functions for the fuzzy sets associated to the input Q_i and to the output S_i were triangles, as shown in Figures 5.



(a)



(b)

Figure 5. Inputs and Outputs Fuzzy Classifier: (a) input fuzzy sets Q_1, Q_2, Q_3, Q_4 (b) output fuzzy sets S_1, S_2, S_3, S_4: the output of classifier for class1(STOP) and class2(GO)

The exact numerical crisp value of the output number of vehicles that join the i -th queue in the n -th time interval for the given inputs is calculated using the defuzzification techniques, which is the last stage of fuzzy modeling. There are several methods of defuzzification available. The exact value of output is calculated from the centre of gravity defuzzification technique, which is mostly used in the fuzzy logic system.

4. SIMULATION RESULTS

The simulation is carried out using MATLAB 7.4 and the Fuzzy Logic Toolbox. The Fuzzy logic toolbox is useful to build quickly the required rules and changes are easily made. This significantly reduces the development time of the simulation model. The novel fuzzy classifier and new fuzzy traffic controller that can optimally control traffic flows under both normal and exceptional traffic conditions. The Criterion of optimization is the decrement length of queues vehicles in intersection. The results of simulation was stated in the both of open and close loop models. In simulation, $T = 5$ is sampling time and the cycle time of traffic light is 100 seconds. In this paper the inputs to signalized intersection, q_i and d_i, are random variables that have normal distribution with mean between 3 and 5 and variance of 1. The simulator is run 1000 seconds with the following assumptions[19]:

1. A four arm intersection and each arm has three lanes.

2. The arrival of vehicles is independent on each lane.

The inter-arrival of vehicles is also independent and normal distribution is used to generate arrivals. This results in inter-arrival of vehicles is 5 seconds.

3. Pedestrian crossing is considered.

4. Sensors are placed at a certain distant from the intersection, the maximum vehicle that can be detected queuing is 30 vehicles.

5. Maximum green time is 40 seconds and the minimum green time is 5 seconds.

The number of vehicles that depart from the i -th queue in the n -th time interval is adapted by equation:

$$d_i(n) = \min(Q_i(n) + q_i(n), d_{si}(n)) \quad (7)$$

such that saturation flow rate is

$$d_{si}(n) = d_{cons.}(n) + \beta q_i(n) \quad (8)$$

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for $i = 1, 2, 3, 4$. The $d_{cons.}$ parameter is greater equal fifty, ($d_{cons.} \geq 50$). The β parameter is between 0 and 1, such that its variations are related in following:

Table 2. Position of traffic by variations of beta

The Position of Traffic	β
Non Saturation	$\beta \geq 0.7$
Saturation	$0.4 \leq \beta \leq 0.6$
Super Saturation	$0.1 \leq \beta \leq 0.3$
Instable	$\beta = 0$

The traffic information was recorded every 5 seconds and was used in the simulations. The traffic lights of Leg1 and Leg3 in Fig.1 were considered green in one forty seconds and red in after sixty seconds. On the other hand, The traffic lights of Leg2 and Leg4 in Fig.1 were considered red in one forty seconds and green in after sixty seconds. The goal of simulation is the decrement of the length of queue vehicles. The summation of number vehicles in Queues on intersection were demonstrated in every 5 seconds in Figure 6.

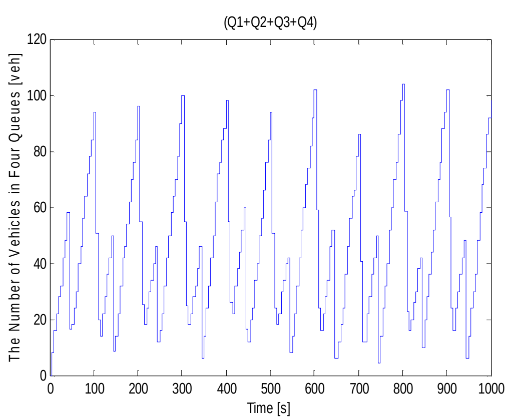

Figure 6. The Number of vehicles in Four Queues of Intersection without controller

The random variables of q_i that have normal distribution are demonstrated in Figure 7.

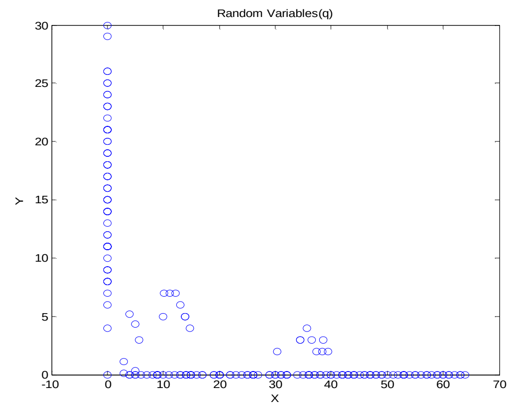

Figure 7. Generation of q_i Samples

The output of controller is the control of variables (S_i). This control of variables for the Leg1 and Leg3 of intersection were demonstrated in Figure 8. Also, the summation of number vehicles in Queues on intersection were demonstrated in every 5 seconds in Figure 9.

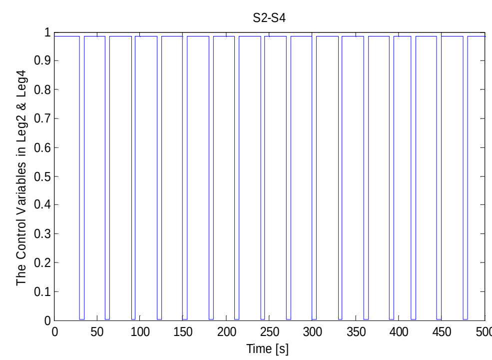

Figure 8. The Control of Variables of Leg1 and Leg3

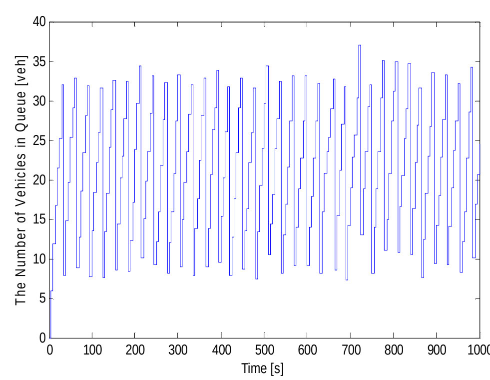

Figure 9. The Number of vehicles in Four Queues of Intersection with Fuzzy controller

Fuzzy classifier system in Figure 3 receive the samples of signalized intersection

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$X(n)=[Q_1(n)Q_2(n)...Q_M(n)]^T$ and classify any pattern to class1 or class2 the adaptation of TABLE I. The result of classification and the output of fuzzy classifier system for 20 sample times is represented in TABLE III.

Table 3. A Prototype of the output fuzzy Classifier system

Class ۱		Class ۲	
Signal S۱, S۳		Signal S۲, S۴	
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۱	GO	۰	STOP
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۱	GO	۰	STOP
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۰	STOP	۱	GO
۱	GO	۰	STOP
۰	STOP	۱	GO

The total classification of the output fuzzy classifier system is demonstrated in Figure 10.

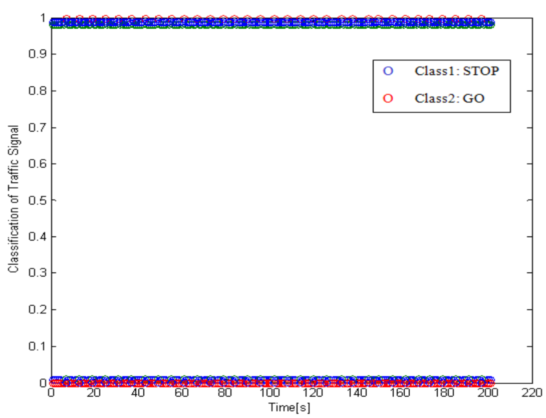

Figure 10. The output of fuzzy Classifier

The output of signalized intersection in Figure 4 with fuzzy classifier system is demonstrated in Figure 11.

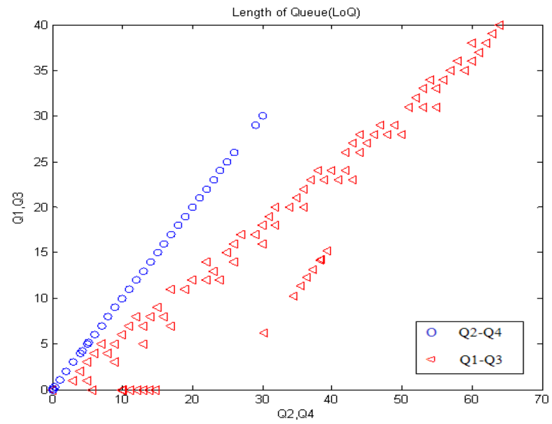

Figure 11. The output of signalized intersection

5. CONCLUSION

In this paper was presented preliminary work into designing an intelligent local controller primarily for distributed traffic control systems using classifier system with fuzzy logic. The optimized controller was tested using simulink program on Matlab 7.4. Simulation results show that the fuzzy controller increments the percentage of improvement and reduces the average length of queue vehicles in any lane of intersection compared to fixed-time control(TABLE IV). Also, the output of signalized intersection in Figure 11 shows that designed fuzzy classifier is the best classifier that discriminate samples with lower error. The other methods for optimizing and designing of fuzzy classifiers and control in complicated intersections and nonisolated intersections in urban traffic network and investigation into heuristic methods of solving the developed optimal control problem should be done in the future.

Table 4. the compare of results Length of Queue Vehicles in any lane of Intersection

LoQ	Queue1	Queue2	Queue3	Queue4	Total Queues
Fixed Time Control	1515	240	375	300	600
Fuzzy Control	955	100	255	150	450
Improvement Percentage (%)	**36.96**	**58.33**	**32.00**	**50.00**	**25.00**

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