NEURAL NETWORK AND FUZZY LOGIC FOR DETERMINING BUS PRIORITY AT TRAFFIC SIGNAL

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Abstract: In this paper, we aimed to explore an approach to giving signal priority to the buses at a bottleneck intersection. The idea is to give priority to the buses only when needed and the effect to general traffic is still within acceptable extent. Our proposed approach is to explicitly formulate a model, in which adherence to schedule of the buses is to be maximized subject to some constraints on prevailing traffic condition and signal. Neural networks are used for prediction of traffic condition and bus delay under current signal plan. Based on the predicted delay of an approaching bus obtained from the neural network, reliability of schedule can be calculated. Fuzzy logic is used to determine the appropriate level of signal priority, which should be given to the bus. The results show that the expert system can reduce variation of travel time of the buses compared to currently used system by eliminating unnecessary priorities and reallocating them for necessary ones.

Key Words: Bus priority, neural network, fuzzy logic

1. INTRODUCTION

In the peak period the traffic demand usually exceeds the road capacity, resulting in traffic congestion and loss of time of the commuters. In the case of bus operation in mixed traffic, traffic congestion makes the bus much less attractive than private car. A possible way to increase the efficiency and fairness of road usage is to give priority to the buses due to higher passenger load. However, installation of bus lane into the existing urban road is typically impractical as the recommended minimum number of buses at 60 vehicles per hour, which will justify a reserved bus lane, is too restrictive (Bakker, 1975). In Japan, however, the criterion of at least 50 buses per hour is adopted in general planning practice of bus lane.

Another alternative approach is to give bus priority at traffic signals. Recently in Japan, there have been attempts to encourage people to switch from private vehicle to public transportation by giving buses priority at bottleneck-signalized intersections. It achieves in 20% reduction of bus delay at signals during the morning peak. However drawback of the current practice is that several tests are needed in order to find out the proper strategy in giving priority, causing severe traffic disruption. In addition decisions whether to give priority is not made according to the level of need for priority, but rather constrained by minimum time span between two consecutive priorities.

Field trials of PROMPT in London showed that average bus delay could be slightly reduced by 5 sec/bus/junction, reaching 10 sec (equivalent to 70% saving) at light traffic (Hounsell et al., 1995). However, in the case of medium-high bus traffic, unconditional bus priority at traffic signals may result in excessive increase in delay of the non-priority traffic. Khasnabis et al. (1997), based on their simulation results, pointed out that the 10-min bus headway appears to give the largest reduction in delay without any detrimental effects to the cross street traffic.

In this paper, we therefore aimed to investigate applicability of a scheme for determining level of signal priority needed by approaching buses online so that priority is guaranteed to be given to the right buses at the right time. Existing available data from traffic detectors, if combined with some observed data, would open up the possibility of employing expert system. Based on neural and fuzzy systems, it is expected that the drawbacks of PTPS system can be rectified. First, conditional priority would be made possible by screening out unnecessary calls for priority. Secondly, decisions whether to give priority will be judged based on level of need for priority and prevailing traffic condition rather than constraint on time. Moreover, we can use the scheme for investigation of effectiveness of current practice in giving priority under the PTPS.

2. THEORETICAL BACKGROUND

2.1 Bus Priority at Traffic Signals

Even bus may start moving within a vehicle platoon but due to loading and unloading, bus may fall behind the platoon and become delayed at downstream traffic signal (Taube, 1976). This is a reason why the maximum through band of general traffic may not benefit the buses. Signal priority is given by altering the signal timing plan in a way that benefits buses. Signal priority treatment can be classified into passive priority and active priority.

Passive priority can be used to produce benefits to buses by predetermining timing plan with consideration on the movement of buses. The examples of passive priority are reduction of cycle length, splitting phases and designing of signal offset according to the bus travel time. The advantage of passive priority is that it can help reduce bus delay without any cost of infrastructure. Active priority, on the other hand, is given only when the arrival of bus is detected. Phase extension, early start, special phase and phase suppression are among the most typical example of active priority treatments (Sunkari et al., 1995).

Unconditional signal priority means priority is given to the bus whenever its presence is detected. It can excessively increase delay of the cross street traffic. Thus, conditional priority is more preferable because priority is given based on the consideration of various factors, such as schedule adherence, cross-street queue length, current traffic condition, time since last priority (Sunkari et al., 1995).

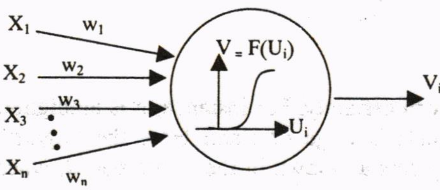
2.2 Neural Network Models

Artificial neuron

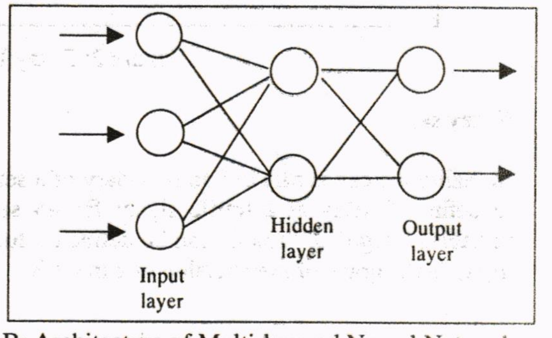
Artificial neuron was proposed to emulate the capability of biological neuron. Its basic function is to add up its inputs and the output is produced by non-linear transformation, here we adopted the sigmoid function, as can be summarized below.

$$U_i = \sum_{j=1}^{N} W_j X_j \tag{1}$$

$$f(U_i) = 1/(1+\exp(-kU_i)) \tag{2}$$



A: Artificial Neuron



B: Architecture of Multi-layered Neural Network

Figure 1: Neural Network

Multi-layered neural network

Multi-layered neural network is created by arranging single neuron into layers, as shown in Fig.1b above, for use in solving more complex problems (Beale et al., 1990). Training of multi-layered neural network is done by adjusting the synaptic weights between the layers so that error between network output and targeted output is minimized (Rumelhart et al., 1986). The most widely known learning rule for multi-layered neural network is the backpropagation rule, in which adjustment of weights is done from the output layer backward to the input layer.

2.3 Simulated Annealing Method

The method is an analogy of thermodynamics namely a crystal is able to find its minimum energy state when it is slowly cooled. Thus, the essence of this process is slow cooling, technically defined as annealing, to ensure that the minimum energy state is achieved (William H. Press, 1996). The four major elements require for the algorithm are the objective function (f), the system state or x, the control parameter (T) with an annealing schedule and a generator of random change of x to $x+\Delta x$. The advantage of this method over other algorithms for searching global minimum is that it is not easily trapped into local minimum. Nevertheless, the success or failure of this algorithm is largely dependent on the choice of annealing schedule, which has to be determined by experiment (William H. Press, 1996). Here we choose the annealing schedule, in which T is reduced to $(1-\varepsilon)T$ after m iterations.

2.4 Fuzzy Logic System

Fuzzy logic system was proposed from the attemp to model human intuition or decision-making. Moreover it also enables us to formulate a model based on imprecise or qualitative data (Teodorovic et al., 1998). The basic elements of a fuzzy logic system are fuzzifier, rules, inference engine and defuzzifier as shown in the following figure.

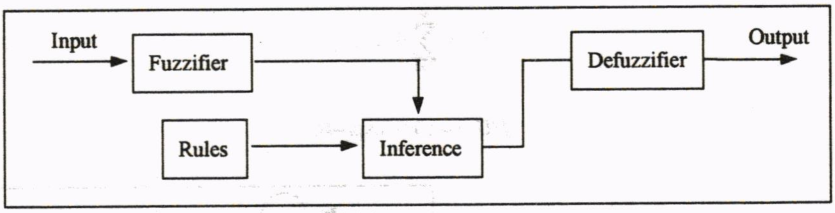


Figure 2: Fuzzy Logic System

Fuzzy set

In reality we can hardly define boundary of a set with certainty. For instance, it is ambiguous to define if delay at a traffic signal for 45 seconds is large or small Here the linguistic variables "large" or "small" can be define by fuzzy sets as shown in the figure below, where $\mu_s(x)$ is the grade of membership of x in set **S**.

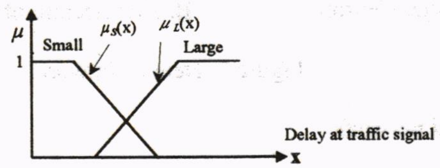


Figure 3: Membership Function of Fuzzy Set "Large" and "Small"

Fuzzy rule

Fuzzy rules can be formulated to represent decisions of expert, which are usually based on experiences or intuitions. A rule used by expert for control can be expressed by fuzzy rule as:

If x is **A** and y is **B** then z is **C**

The consequence of the rule, fuzzy set **C**, is obtained by the concept of max-min composition as illustrated in Fig. 4 and the following expression.

$$\mu_{R_1 \circ R_2}(x,z) = \max_{y \in Y}\{\min[\mu_{R_1}(x,y), \mu_{R_2}(y,z)]\} \tag{3}$$

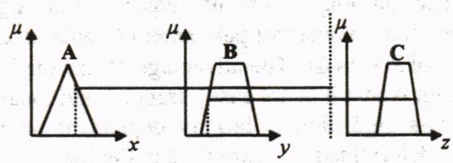


Figure 4: Single Fuzzy Rule

Fuzzy Reasoning

Combining a set of fuzzy rules by the union of fuzzy relations is called "*fuzzy reasoning*". The last step of fuzzy reasoning is defuzzification, in which the output numerical value is obtained. The criteria for choosing one numerical value from resulting fuzzy set are the smallest maximal value, the largest maximal value, mean of the range of maximal values, center of gravity and so on (Teodorovic et al., 1998).

3. DATA AND METHODOLOGY

3.1 PTPS Project

Public transportation priority system, known as PTPS, is a project aimed to encourage people to shift from private cars to public transportation by securing smooth passage of the buses at bottleneck intersections. The study site in this paper is the Hatori intersection, where the National Route 1 intersects with our targeted street, in Fujisawa city. It is the most congested intersection of the targeted corridor for public transportation priority. The targeted corridor is serving the buses carrying commuters to the JR Tsujido station during morning peak.

Due to limited space of the roadway, installation of bus lane is considered ineffective. As a result, priority is given to public transportation only in the form of priority at signals. A couple of signal plans have been set up namely as priority signal plan and non-priority signal plan. Infrared beacons are used for detecting an approaching bus and send the bus ID to the traffic control center. In the case that green time of priority signal plan is still insufficient, additional priority is then provided so that the bus can smoothly pass through the intersection either by extension of bus phase or shortening of non-bus phase. Additional signal priority will be given only if there was no priority given in the last 8 minutes. The system is in operation during morning peak, from 7.00-9.00, of weekdays.

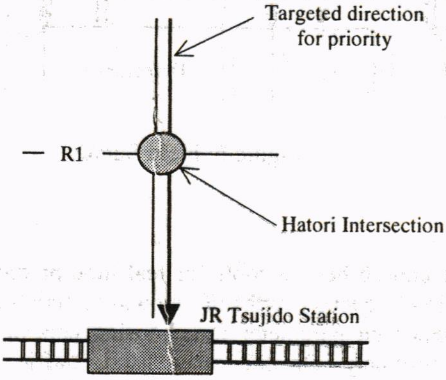


Figure 5: Study Site

3.2 Data

In order to train neural networks, data on prevailing traffic condition, bus delay, and signal parameters are needed. Some of the data is routinely collected at database of the Kanagawa police's traffic control center but some have to be collected by field surveys as summarized in table1.

Table1. Data collection

Data	Survey	Database
Traffic Volume		●
Occupancy		●
Signal parameters		●
Arrival&Departure timing of buses	▲	
Maximum queue lengths	▲	

Signal parameters of the signal A and 5-minute traffic volume and occupancy collected by the detectors number 1 through 4 as shown in Fig. 6, were obtained from the traffic database. Field surveys were conducted mainly for observing maximum queue lengths of inbound direction of the both streets and arrival time at the bus stop B and departure time from the stop line at the signal A of the buses during 7.00-9.00. The surveys were conducted in 5 weekdays from November to January. Arrival and departure of the buses were recorded by using video cameras and the maximum queue lengths have to be observed by surveyors. Physical characteristics of the study site are shown in the figure below.

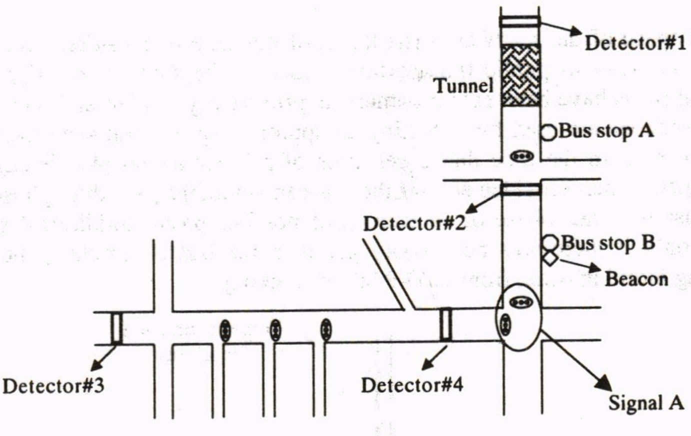


Figure 6: Field Survey

3.3 Neural Networks

Neural networks were chosen here as tools for real time prediction of delay of buses at the traffic signal and maximum queue lengths of inbound direction of the both streets. Maximum queue length is an important parameter for choosing control strategy but, at the present, cannot be collected routinely. On the other hand, traffic volume and occupancy are automatically collected by the detectors, which are installed at specific points along the study site. Data on signal parameters such as green phase of the routes and cycle length are also available. We expect that neural networks can be trained for prediction of maximum queue lengths based on the relationship of the data, which can be derived from the observed phenomena. We have chosen the multi-layered neural network as it is reported by other researchers about its advantages over other types of neural networks (Saito et al., 1999). Simulated annealing method is chosen as learning rule of the network in order to avoid entrapment into a local minimum as suggested by Nakatsuji et al., 1990.

3.4 Fuzzy Logic for Determining Bus Priorities

Due to imprecision associated with estimates from the neural networks, fuzzy logic is used for determining appropriate level of priority that should be given to the bus online. Input variables are classified into two categories. Ones associated with uncertainty, including bus schedule adherence and maximum queue length of the both streets, are fuzzy inputs. On the contrary, volume-capacity ratio (v/c) of the both streets are given and thus treated as crisp numbers. The input variables and the level of priority are represented by fuzzy sets as follow.

Maximum queue length: Very long, long, medium and short
Volume/capacity: Large, medium and small
Adherence to schedule of bus: Early, punctual, and late
Level of Priority: Maximum, large, medium, small, do nothing

The boundaries of the fuzzy sets are set according to distribution of the observed data. Fuzzy reasoning is used for determining appropriate level of priority with consideration on both adherence to schedule of the buses and traffic condition. The boundaries of resulting fuzzy set from the fuzzy reasoning are set at the values, which maximize punctuality of the buses.

4. RESULTS

4.1 Validation of Neural Networks

4.1.1 Prediction of bus delay

Here we use neural networks for estimating required green time for the bus to travel from the bus stop B until it passes through the intersection. This value is meaningful for judging if signal extension should be given to the bus and can be used for estimating delay at traffic signal as well. Out of 232 patterns of data, 164 patterns were used for training and the remaining is used for validation. After trials of different input variables and structures, the optimum one is obtained as illustrated in table 2. It is noteworthy that data on traffic volume and occupancy is obtained from the detector no. 2.

Outputs from the optimum neural network are summarized in table 2. Classification power of the neural network, which is sorting of cases that a bus can pass through the intersection within one cycle of green time or otherwise, is about 90% correct. Most of errors in classification are caused by just few seconds of discrepancy between the estimated and actual required green time. In terms of accuracy of the estimates, the neural network gives the results with the accuracy of 85-90% correct depending on desired interval of confidence. We arbitrarily set minimum allowable error at ± 2 seconds. Outputs with error less than this are considered as error-free. It was found that the neural network tends to give slightly more under-estimated results as shown in table 3.

Table 2: Structure of the neural network for estimating bus delay

Variables	Structure
Green time (last 3 cycles) Cycle length (last 3 cycles) Arrival phase of bus Traffic volume (last 5 minutes) Occupancy (last 5 minutes)	Input nodes = 9 Hidden nodes = 4 Output nodes = 1

Table 3: Accuracy of the neural network for estimating bus delay

RMSE		Classification (Percent)		Type of Error (% of total)				Accuracy of Estimation			
				Over		Under		±7s		± 25%	
Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0.23	0.25	89.5	94.7	36	32	45	47	90.1	90.7	85.0	85.3

4.1.2 Prediction of maximum queue length

Two neural networks are tuned for estimation of maximum queue lengths on the both streets. 170 patterns and 53 patterns of data are used for training and validation for the case of the bus route. Neural network for route 1 requires 157 and 68 patterns of data for calibration and validation respectively. Data on traffic volume and occupancy is taken from the detector no. 1 and 2 for the case of bus route, and from no. 3 and 4 for the case of route 1. The optimum structure of the neural networks is identical as summarized in table 4.

Table 4: Structure of the neural networks for estimating maximum queue length of the both streets

Variables	Structure
Green time (last 3 cycles)	Input nodes = 8
Cycle length (last 3 cycles)	Hidden nodes = 4
Elapsed time (from 7.00)	Output nodes = 1
Traffic volume (last 10 minutes)	
Occupancy (last 10 minutes)	

The results obtained from the optimum neural networks are summarized, separately for the case of bus route and route 1, as shown in table 5 and 6. Classification power, as expressed by percent that the neural networks correctly classify the maximum queue lengths into 4 categories as defined earlier, is about 80-85% correct. In terms of accuracy of estimates, approximately 85% of estimates with 25% interval of confidence cover the desired outputs. Here the minimum allowable error is set at ±20 meters. The estimates for the case of route 1 are inclined to be under-estimated. The results for the case of bus route are mixed, as estimates of training data are more or less unbiased but those of test data are over-estimated.

Table 5: Accuracy of the neural network for estimating maximum queue length of the bus route

RMSE		Classification (Percent)		Type of Error (% of total)				Accuracy of Estimation			
				Over		Under		±25%		± 20%	
Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0.20	0.22	83.2	84.8	28	50	35	26	88.6	82.6	83.2	80.4

Table 6: Accuracy of the neural network for estimating maximum queue length of route 1

RMSE		Classification (Percent)		Type of Error (% of total)				Accuracy of Estimation			
				Over		Under		±25%		± 20%	
Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
0.18	0.21	82.4	82.1	30	27	48	59	85.2	82.1	81.0	78.6

4.2 Fuzzy logic system

Fuzzy rules, in which maximum queue lengths, v/c and adherence to schedule of the bus are taken into account, are proposed. Maximum queue length and v/c are chosen here as variables for representing prevailing traffic condition of the both streets. Adherence to schedule of the bus can reflect the level of need for priority. Based on distribution of the observed data, we define boundaries of the fuzzy sets of the input variables as illustrated in Fig. 7.

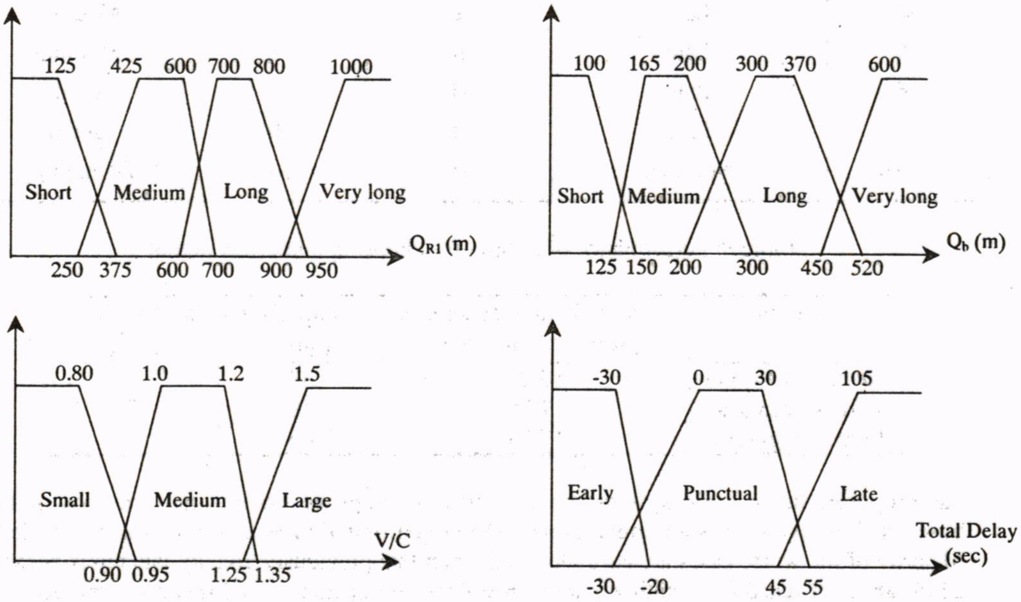


Figure 7: Membership Function of Fuzzy Sets of Input Variables

Fuzzy reasoning, which is composed of 8 fuzzy rules, is proposed. Appropriate level of priority, ranging from do nothing to maximum priority, can be obtained grade of membership of the rules. Here we formulate the rules based upon punctuality of the bus and difference between prevailing traffic condition and degree of saturation of the both streets as summarized in the table 7. Positive values of difference between maximum queue lengths and v/c mean condition on the bus route is worse than that of route 1 and vice versa for negative values. For instance rule 1 can be expressed as; if the bus is late and maximum queue length on the bus route is longer than that on route 1 by 2 steps and v/c for the bus phase is larger than that of route 1 by 2 steps then maximum priority should be given.

At the next step, boundaries of the resulting fuzzy set from the above rules are set at the values, which optimize adherence to schedule of the buses under the assumption that the PTPS system is not in operation. It is assumed that green time available to the bus phase is equivalent to that of non-priority signal plan. The fuzzy reasoning is then employed to judge if signal priority should be given.

Several criteria for choosing single numerical output from the resulting fuzzy set are tested. it was found that criterion based on mean of the range of maximal values is marginally superior to the other criteria as it can give largest increase of membership function of fuzzy set "punctual" of the buses. Nevertheless, it can be stated that regardless of choice of criteria

Table 7: Fuzzy rules for determining level of priority

Rule	Adherence to schedule	$Q_b - Q_{R1}$	$(v/c)_b - (v/c)_{R1}$	Level of priority
1	Late	2	2	Max
2	Late	1	1	Large
3	Late	0	2	Large
4	Late	1	0	Medium
5	Late	0	1	Medium
6	Late	-1	1	Small
7	Late	-1	0	Small
8	Not Late	-1	-1	Do nothing

Table 8: Performance of criteria for choosing numerical output

Criteria	Increase in membership of fuzzy set "punctual"	Comparison with do nothing	
		Better	Worse
Mean of maximal	18.24	48	7
Largest maximal	17.76	48	7
Center of gravity	17.25	46	6

our proposed fuzzy logic system can significantly improve on-time performance of the buses, as improved cases are much greater than deteriorated ones as summarized in table 8. Majority of the worse cases are attributed to the fact that previously trivially late buses became a little ahead of schedule, resulting in lower membership function of the fuzzy set "punctual".

4.3 Comparison of effectiveness with the PTPS

Here we investigate effectiveness of the proposed expert system by comparing its performance with the PTPS, in terms of maximizing adherence to schedule of the buses. Out of 247 cases, the proposed system is superior in 65 cases and inferior in only 17 cases. Fig. 8

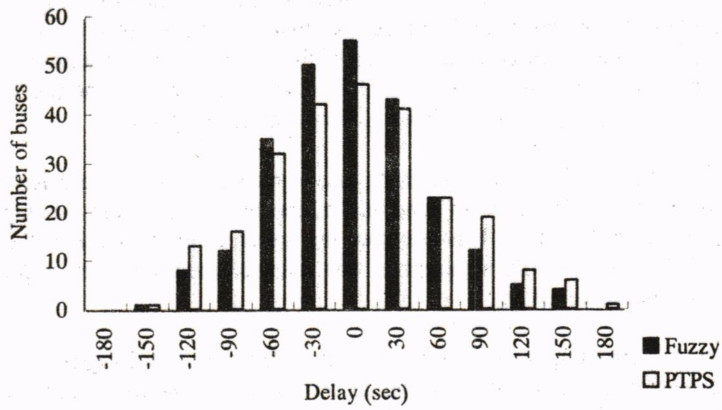


Figure 8: Distribution of Delay of Buses under PTPS and Fuzzy Logic Control

shows the distribution of delay of the buses. Positive values of delay mean the bus is late and negative values are vice versa. It is clear that the proposed expert system can reduce variation of travel time of the buses by reducing the number of buses, which are either ahead or behind the schedule over 60 seconds. Rather than attempting to minimize travel time of the buses as in the PTPS, the proposed system is aimed to increase reliability in travel time of the buses. In addition, it is expected that the system will also improve traffic flow of the cross street traffic as the number of unnecessary signal extensions given to the buses, which could be screened out by the system, is found to be 20% out of the total.

5. DISCUSSIONS AND CONCLUSIONS

This study is aimed to show potential of employing expert system for determining priority for buses at traffic signal. Available traffic detectors and database make it possible to use neural networks for on-line prediction of delay of the buses and prevailing traffic condition. However, outputs from the neural networks are inevitably associated with imprecision. Fuzzy logic system is thus adopted due to its capability in processing uncertain information.

The results show that estimates from the neural networks can be used to represent the observed data, if some interval of confidence is allowed. The physical characteristics as well as random nature of the variables impose difficulties in obtaining extremely precise estimates. Anyway, it is expected that if physical characteristics of the site is simpler, accuracy of the estimates should be even higher.

Fuzzy reasoning based on adherence to schedule of the bus and differences between traffic condition of the both streets was proved powerful enough for determining appropriate level of priority for the bus. A criterion, by which numerical output is the mean of maximal values of the resulting fuzzy set, was found to be marginally superior to the other criteria. Comparing to the current system used in the PTPS, our proposed system can reallocate green time of unnecessary priorities and detect necessary ones, which would be otherwise slipped up by the PTPS. As a result, travel time of the buses becomes more consistent as shown by lower variation of the travel time. The system can be expected for use to enhance effectiveness of the PTPS project.

In this study, formulation of fuzzy rules and calibration of membership function of fuzzy sets were done separately. Use of neuro-fuzzy systems, in which these processes are combined and optimized, might produce better results. Field trails of the proposed system are also needed so that more precise investigation its effectiveness can be carried out.

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