ADAPTIVE BUS-PREEMPTION SIGNAL CONTROL SYSTEM -- APPLICATION OF GENETIC FUZZY LOGIC CONTROLLER (GFLC)

Yu-Chiun CHIOU
Assistant Professor
Dept. of Traffic and Transportation
Feng Chia University
100, Wenhwa Rd., Seatwen,
Taichung, Taiwan 40724
Fax: +886-4-2452-0678
E-mail: ycchiou@fcu.edu.tw

Ming-Te WANG
Ph.D. Student
Institute of Traffic and Transportation
National Chiao Tung University
4F, 114 Sec.1, Chung-Hsiao W. Rd.
Taipei, Taiwan 10012
Fax: +886-2-2545-0431
E-mail: mingder@iot.gov.tw

Lawrence W. LAN
Professor
Institute of Traffic and Transportation
National Chiao Tung University
4F, 114 Sec.1, Chung-Hsiao W. Rd.
Taipei, Taiwan 10012
Fax: +886-2-2349-4953
E-mail: lawrencelan@mail.nctu.edu.tw

Abstract: This paper proposes an adaptive genetic fuzzy logic controller (GFLC) bus-preemption strategy to minimize the total person-delays at a signalized intersection. Three hours of low, medium, and high traffic flows are simulated to compare the performance of our proposed adaptive GFLC strategy with that of unconditional bus-preemption strategy and without bus-preemption strategy. Comparing to the without preemption strategy, our adaptive GFLC strategy can curtail the total person-delays by 13.53%~34.41%; while the unconditional strategy can only reduce the total delays by 1.22%~32.30%. Both adaptive GFLC and unconditional preemption strategies have performed much better in light flow conditions than in heavy ones. In addition, we carry out a case study with sixteen hours of daytime traffic flows and the results also show that our GFLC strategy has reduced the total person-delays by 16.21%, which is superior to the unconditional strategy (reducing 12.87%) and the conditional strategy proposed by Su and Lee (reducing 2.89%).

Key Words: bus-preemption, genetic fuzzy logic controller

1. INTRODUCTION

The main purpose of a bus-preemption signal control system is to give a preferential treatment to high occupancy vehicles at the signalized intersections. The underlying logic of the build-in bus-preemption control strategies in the Taipei computerized signal system is to activate the mechanism whenever the bus actuates the detector, without taking into consideration of the traffic flow conditions from different intersection approaches. This unconditional preemption strategy might deteriorate the total person-delays at the intersection, particularly as the traffic flows in the competing approaches get higher. Therefore, it is of practical importance to develop an adaptive bus-preemption signal control system.

Numerous theoretical studies related to bus preemption in the past several decades have been

conducted. For example, Jacobson and Sheffi (1981), Heydecker (1983, 1984) developed an analytical delay model to estimate the total person-delays at the signalized intersection with bus-preemption strategy. Chang, *et al*. (1996) developed an adaptive bus-preemption control logic based on a performance index measuring vehicle delays, bus schedule delays and passenger delays under the environments with and without automatic vehicle location (AVL). Su and Lee (1999) proposed a fully activated bus-preemption control model comprising the strategies of green extension, red truncation, and red interruption by the mechanism of fuzzy logic control. Wu (1999) developed optimal bus-preemption control logic with green extension and red truncation strategies according to the net benefit of delay reduction. Cheng (2000) further extended Wu's work by considering the possibility of bus impeded by the preceding buses.

Fuzzy logic controller (FLC) is commonly used by the above researchers in developing an adaptive bus-preemption system, in which logic rules and membership functions are subjectively preset (for instance, Su and Lee, 1999; Wu, 1999; Cheng, 2000). In order to overcome the subjectively presetting problems, a genetic fuzzy logic controller (GFLC) is developed in this paper to control the bus-preemption signal by an adaptive learning process from real-time traffic flow conditions. The GFLC employs genetic algorithms (GAs) to select optimal logic rules and to tune the membership functions by learning from examples. To enhance the learning efficiency, fluid approximation technique is employed to estimate the person-delays. Three hours of low, medium, and high traffic flows are simulated to compare the performance of our proposed adaptive GFLC strategy with that of unconditional bus-preemption strategy and without bus-preemption strategy. Furthermore, we carry out a case study with sixteen hours of daytime traffic flows to test the applicability and robustness of our proposed GFLC strategy.

2. CONCEPT OF FLC AND GFLC

The FLC, first proposed by Zadeh (1973), uses fuzzy logic rules to form a control mechanism to approximate expert perception and judgment under given conditions. The system is also termed fuzzy control system, or fuzzy inference system, or approximate reasoning, or expert system. Its framework is depicted in Fig. 1.

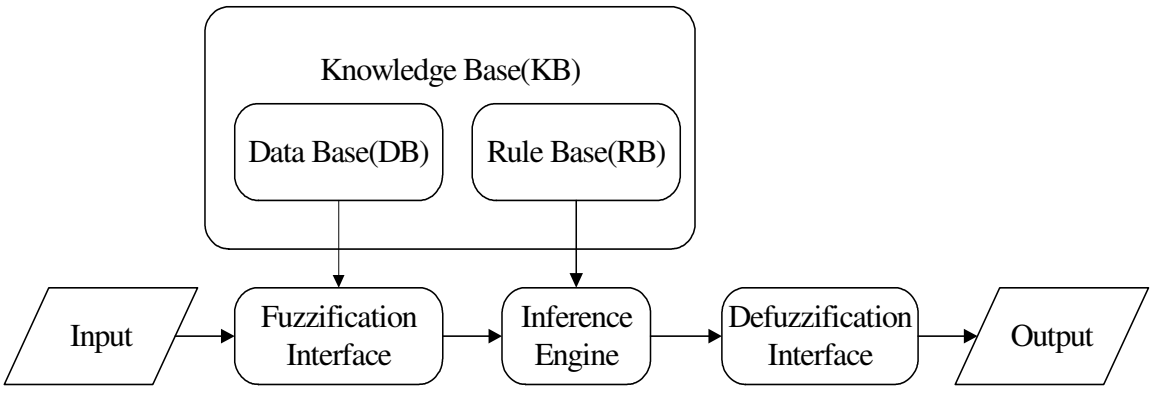

Figure 1. Framework of FLC

The FLC has four basic components as follows:

(1) Rule base (RB), composed of finite if-then rules, from which an inference mechanism is formed. A standard form of RB with m logic rules is represented as:

Rule 1 : IF $x_1 = A_{11}$ AND $x_2 = A_{12}$ AND … AND $x_n = A_{1n}$ THEN $y = B_1$

Rule 2 : IF $x_1 = A_{21}$ AND $x_2 = A_{22}$ AND … AND $x_n = A_{2n}$ THEN $y = B_2$

.
.
.

Rule i : IF $x_1 = A_{i1}$ AND $x_2 = A_{i2}$ AND … AND $x_n = A_{in}$ THEN $y = B_i$

.
.
.

Rule m : IF $x_1 = A_{m1}$ AND $x_2 = A_{m2}$ AND … AND $x_n = A_{mn}$ THEN $y = B_m$

where $x_1,\ldots, x_n$ are state variables, y is control variable. A_{i1} ,…, A_{in} and B_i ($i=1,\ldots,m$) are respectively the linguistic variables of $x_1,\ldots, x_n$ and y in the universal of discourse of $U_1,\ldots,U_n$ and V.

(2) Data base (DB), formed by the specific membership functions of linguistic variables: A_{i1} ,…, A_{in} and B_i, in order to transform crisp inputs into fuzzy ones.

(3) Inference engine, formed by the operators within the logic rules. Generally, logic rules use AND or OR as connecting operators between state variables, taking minimum and maximum values, respectively.

(4) Defuzzification, the synthesis of inference results of all activated logic rules into crisp outputs for making a decision.

Of these four components, inference engine and defuzzification are consistently used in many studies. However, the methods for formulating the RB and DB are somewhat subjective and complex. Due to the excellent performance of genetic algorithms (GAs) in solving combinatory and parameter optimization problems, numerous studies have been found by applying GAs to the construction of FLCs in the past decade. Its framework is depicted in Fig. 2.

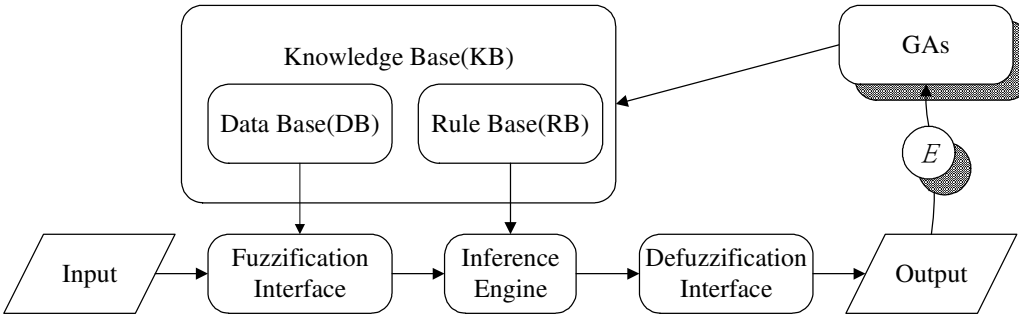

Figure 2. Framework of GFLC

Literature related to GFLC can be divided into four categories. (1) Use of GAs to tune membership functions under a given set of logic rules (e.g. Herrera, *et al*., 1995, 1998; Karr, 1991). (2) Use of GAs to select logic rules with known membership functions (e.g. Lekova, *et al.,* 1998; Chin and Qi, 1998; Thrift, 1991). (3) Use of GAs to learn both logic rules and membership functions simultaneously (e.g. Tarng, *et al.*, 1996; Herrera, *et al.*, 1998; Wang and Yen, 1999). (4) Use of GAs to learn both logic rules and membership functions in

sequence (e.g. Karr, 1991; Kinzel, *et al.*, 1994; Chiou and Lan, 2002). Logic rules and membership functions are two essential components of a FLC. If only one component is learned in constructing a FLC, the other one must be set subjectively and the applicability of that FLC would be greatly reduced. Consequently, this paper uses the GFLC model with both components learned. A very long chromosome would be needed if both components are learned simultaneously, thus we use a sequential solving procedure and propose a new encoding method.

3. UNCONDITIONAL BUS-PREEMPTION CONTROL LOGIC

Two bus preemption strategies, green extension and red truncation, are built in the Taipei computerized signal control system, as depicted in Fig. 3. The basic control logic rules are briefly described as follows:

Rule 1: In the green phase, **IF** H > GR > L, **THEN** implement green extension strategy.
Where GR represents the remaining green time at the moment when a bus actuates the detector; H represents the time needed for a bus traveling from the detector to the far-side of intersection; L represents the time needed for a bus traveling from the detector to the near-side of intersection (stop line).

Rule 2: In the red phase, **IF** (RR + AR) > L, **THEN** implement red truncation strategy.
Where RR represents the remaining red time when a bus actuates the detector and AR represents all-red.

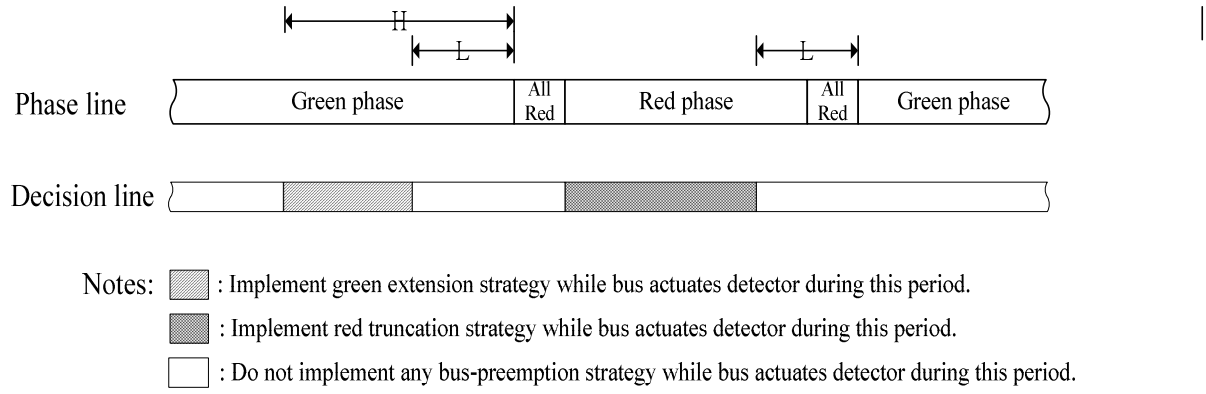

Figure 3. Unconditional Bus-preemption Control Logic

The above control logic rules can be implemented only in the following conditions:
(1) If the phase comes to a transition period, such as all-red phase, it will not activate any strategy.
(2) The total green extension time should not exceed the maximal green time (G_{max}).
(3) The red time after truncated should not be less than the minimal green time (G_{min}).
(4) No compensation mechanism is provided.
(5) All parameters, such as H, L, G_{max} and G_{min} are given.

4. ADAPTIVE GFLC BUS-PREEMPTION CONTROL STRATEGY

In this paper, we employ GFLC to control the dissemination of a bus arrival message in order to minimize the total person-delays of the intersection with four approaches. The system structure is depicted in Fig. 4. The fitness function, logic rule encoding method, membership function encoding method, genetic operators, and iterative evolution algorithm for the GFLC model are described as follows.

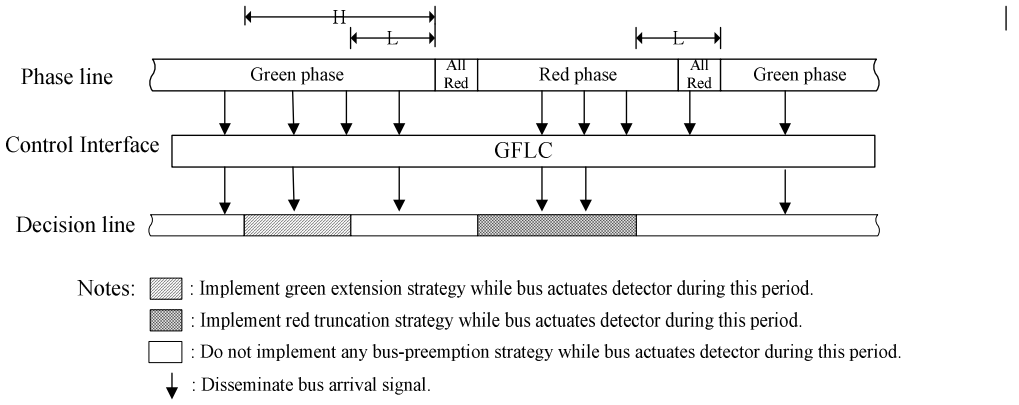

Figure 4. Adaptive GFLC Bus-preemption Control Strategy

4.1 Fitness Function

Our GFLC adaptive bus-preemption strategy aims to minimize the total person-delays (*TPD*) at intersection. The fitness function of GAs is defined as:

$$f = \frac{1}{TPD} \tag{1}$$

A fluid approximation technique is employed to estimate the delays. The estimation of vehicle-delays for each cycle under different bus-preemption strategies is depicted in Fig. 5. The person-delays can be calculated by multiplying the vehicle-delays by the average occupancy of cars. The delays of bus are evaluated one-by-one depending on whether it is stopped at the intersection or not. The bus-delays for a stopped bus are measured by the remaining red time when it arrives at the stop line. The average bus loading factor is then used to transform the bus-delays into person-delays.

4.2 Encoding Method for Logic Rules

We adopt the encoding method, proposed by Thrift (1991), which can effectively curtail the length of chromosome so as to save the computer memory and searching space. Taking two state variables and one control variable as an example, if each linguistic variable has five linguistic degrees (NL: negative large, NS: negative small, ZE: zero, PS: positive small, PL: positive large), the chromosome length is 25. Genes take integers from 0 to 5, where 0 represents the exclusion of the rule and other numbers indicate the inclusion of rule as well as the linguistic degree of control variable. This encoding method is shown in Fig. 6. A chromosome with a gene sequence of 00020400100000001000030000, for example, represents five logic rules, which are:

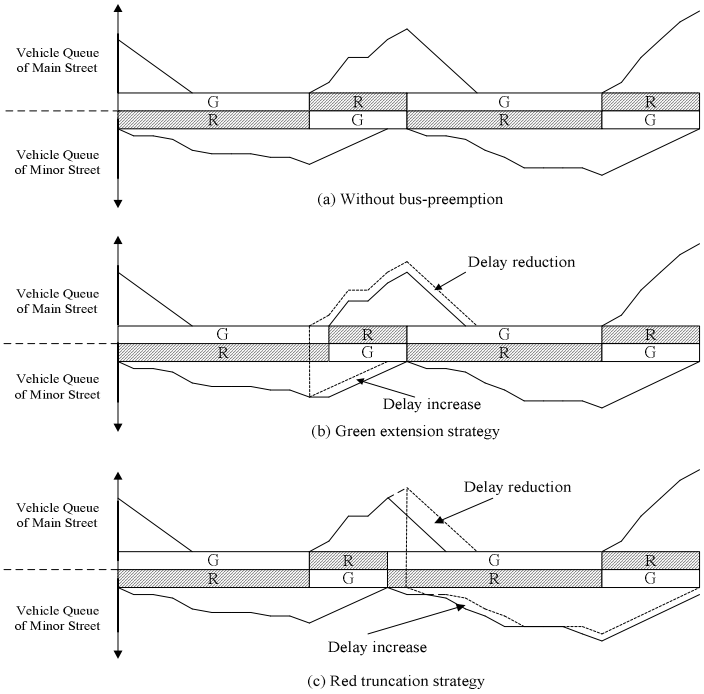

Figure 5. An Estimation of Vehicle-delays

Rule 1: **IF** $x_1 = NL$ AND $x_2 = PS$ **THEN** $y = NS$
Rule 2: **IF** $x_1 = NS$ AND $x_2 = NL$ **THEN** $y = PS$
Rule 3: **IF** $x_1 = NS$ AND $x_2 = PS$ **THEN** $y = NL$
Rule 4: **IF** $x_1 = PS$ AND $x_2 = NL$ **THEN** $y = NL$
Rule 5: **IF** $x_1 = PL$ AND $x_2 = NL$ **THEN** $y = ZE$

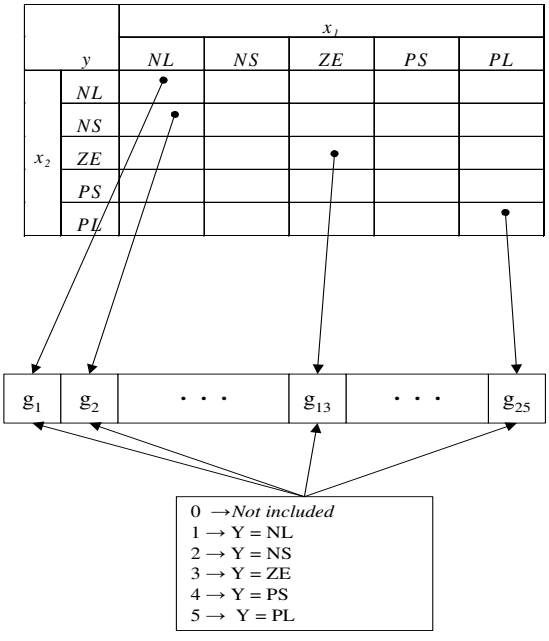

Figure 6. Encoding Method for Logic Rules

4.3 Encoding Method for Membership Functions

Considering a triangle fuzzy number, let three parameters c_k^r, c_k^c and c_k^l represent the coordinates of right anchor, cortex, and left anchor of k^{th} linguistic degree, respectively. A total of 15 parameters should be calibrated for a variable with five linguistic degrees. Several constraints must be imposed, such as $c_k^r \geqq c_k^c \geqq c_k^l$ for any fuzzy number with the same degree, and $c_k^r \geqq c_{k-1}^r$, $c_k^c \geqq c_{k-1}^c$, $c_k^l \geqq c_{k-1}^l$ for fuzzy numbers with different degrees. If we employ GAs to tune the aforementioned parameters directly, the search performance will deteriorate dramatically as a result of imposing all the constraints. Thus, this paper proposes a new encoding method to overcome this problem.

Assume that the first and last degrees of fuzzy numbers are left and right skewed triangles, respectively, and the others are isosceles triangles, as shown in Fig. 7. For a variable with five linguistic degrees, eight parameters must be calibrated and the orders among them are:

$$c_{\max} = c_5^c = c_5^r \geq c_4^r \geq \begin{matrix} c_5^l \\ c_3^r \end{matrix} \geq \begin{matrix} c_4^l \\ c_2^r \end{matrix} \geq \begin{matrix} c_3^l \\ c_1^r \end{matrix} \geq c_2^l \geq c_1^c = c_1^l = c_{\min} \tag{2}$$

$$c_k^c = \frac{(c_k^r + c_k^l)}{2}, \quad k=2,\ 3,\ 4 \tag{3}$$

where c_{max} and c_{min} are the maximum and minimum values of the variable, respectively. The order between c_5^l and c_3^r, c_4^l and c_2^r, c_3^l and c_1^r are indeterminate.

In order to tune these eight parameters, another nine position variables $r_1 \sim r_9$ are designed. It is assumed that:

$$c_2^l = c_{\min} + r_1 \times sf \tag{4}$$

$$c_1^r = c_2^l + r_2 \times sf \tag{5}$$

$$c_3^l = c_2^l + r_3 \times sf \tag{6}$$

$$c_2^r = \max\{c_1^r, c_3^l\} + r_4 \times sf \tag{7}$$

$$c_4^l = \max\{c_1^r, c_3^l\} + r_5 \times sf \tag{8}$$

$$c_3^r = \max\{c_2^r, c_4^l\} + r_6 \times sf \tag{9}$$

$$c_5^l = \max\{c_2^r, c_4^l\} + r_7 \times sf \tag{10}$$

$$c_4^r = \max\{c_3^r, c_5^l\} + r_8 \times sf \tag{11}$$

where

$$sf = \frac{(c_{\max} - c_{\min})}{\sum_{i=1}^{9} r_i}$$

In achieving two significant digits, each position variable is represented by four real-coding genes, as depicted in Fig. 7. The maximum value of the position variable is 99.99 and the minimum value is 0. Thus, in the case of two state variables and one control variable, each with five linguistic degrees, the chromosome is composed of 108 genes.

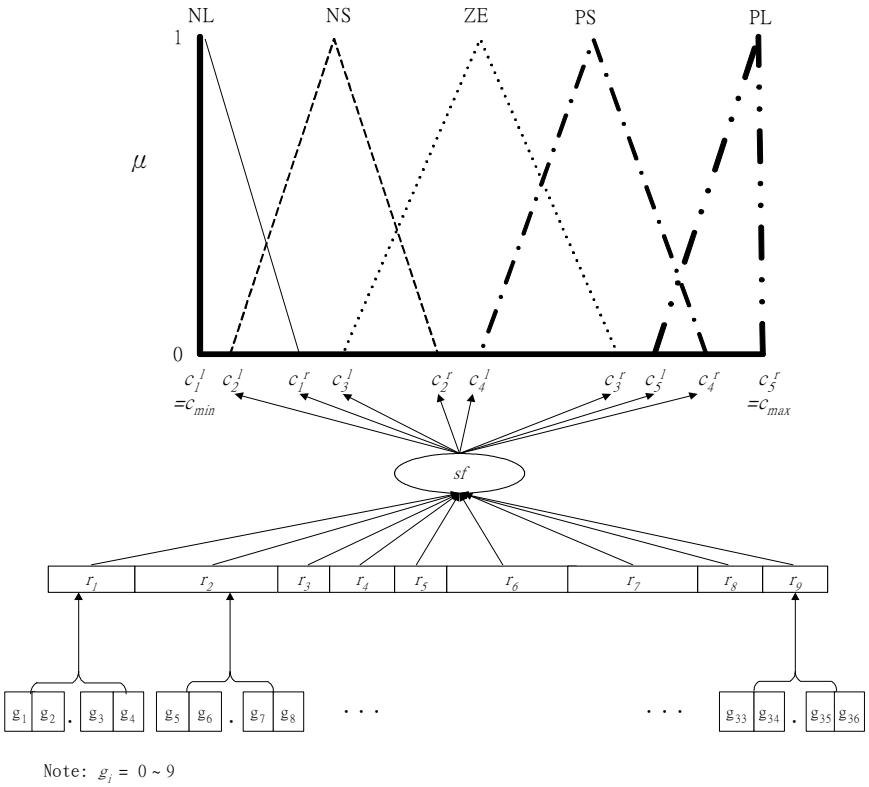

Figure 7. Encoding Method for Membership Functions

4.4 Genetic Operators

Because the genes in our GFLC strategy are not encoded binary, simple genetic algorithms (Goldberg, 1989) cannot be used. Thus, we employ the max-min-arithmetical crossover, proposed by Herrera, *et al.* (1995) and the non-uniform mutation, proposed by Michalewicz (1992). A brief description is given below.

(1) Max-min-arithmetical crossover

Let $G_w^t = \{ g_{w1}^t, \ldots, g_{wk}^t, \ldots, g_{wK}^t \}$ and $G_v^t = \{ g_{v1}^t, \ldots, g_{vk}^t, \ldots, g_{vK}^t \}$ be two chromosomes selected for crossover, the following four offsprings will be generated:

$$G_1^{t+1} = aG_w^t + (1-a)G_v^t \quad (12)$$

$$G_2^{t+1} = aG_v^t + (1-a)G_w^t \quad (13)$$

$$G_3^{t+1} \text{ with } g_{3k}^{t+1} = min\{g_{wk}^t, g_{vk}^t\} \quad (14)$$

$$G_4^{t+1} \text{ with } g_{4k}^{t+1} = max\{g_{wk}^t, g_{vk}^t\} \quad (15)$$

where a is a parameter ($0 < a < 1$) and t is the number of generations.

(2) Non-uniform mutation

Let $G^t = \{ g_1^t, \ldots, g_k^t, \ldots, g_K^t \}$ be a chromosome and the gene g_k^t be selected for mutation (the domain of g_k^t is $[g_k^l, g_k^u]$), the value of g_k^{t+1} after mutation can be computed as follows:

$$g_k^{t+1} = \begin{cases} g_k^t + \Delta(t, g_k^u - g_k^t) & if \quad b = 0 \\ g_k^t - \Delta(t, g_k^t - g_k^l) & if \quad b = 1 \end{cases} \tag{16}$$

where b randomly takes a binary value of 0 or 1. The function $\Delta(t,z)$ returns a value in the range of [*0, z*] such that the probability of $\Delta(t,z)$ approaches to 0 as t increases:

$$\Delta(t,z) = z(1 - r^{(1-t/T)^h}) \tag{17}$$

where r is a random number in the interval [*0,1*], T is the maximum number of generations and h is a given constant. As shown in Eq.(16), the value returned by $\Delta(t,z)$ will gradually decrease as the evolution progresses.

4.5 Iterative Evolution Algorithm

We develop an iterative evolution algorithm to select the logic rules and tune the membership functions. The basic concept is similar to a bi-level mathematical programming. The upper level uses the membership functions tuned by the lower level to solve the composition of logic rules. The lower level uses the given logic rules learned from the upper level to determine the shapes of membership functions. Considering a FLC with n state variables x_1, x_2 ,…, x_n and one control variable y, each with d_1, d_2.,…, d_n and d_{n+1} linguistic degrees, respectively; and assuming the membership functions of all linguistic degrees to be triangle-shaped, our proposed iterative evolution algorithm is structured as follows:

Step 0: Initialization: *s=1*.

Step 1: Selecting logic rules.

Step 1-1: Generating an initial population with p chromosomes. Each chromosome has $\prod_{i=1}^{n} d_i$ genes, and each gene randomly takes one integer from [*0,* d_{n+1}].

Step 1-2: Calculating the fitness values of all chromosomes based on incumbent membership functions.

Step 1-3: Selection.

Step 1-4: Crossover.

Step 1-5: Mutation.

Step 1-6: Testing the stop condition. The stop condition is set based on whether the mature rate (the proportion of same chromosome in a population) has reached a given constant η. If so, proceed to Step 2, otherwise go to Step 1-3.

Step 2: Tuning membership functions.

Step 2-1: Generating an initial population with p chromosomes. Each chromosome has 36*(n+1)* genes and each gene randomly takes one integer from [*0, 9*].

Step 2-2: Calculating the fitness values of all chromosomes based on the incumbent logic rules.

Step 2-3: Selection.

Step 2-4: Crossover.

Step 2-5: Mutation.

Step 2-6: Testing the stop condition. Let f_s be the largest fitness among the population for the s^{th} evolution epoch. The stop condition is set based on whether the mature rate has reached a given constant η. If so, proceed to Step 3 and let *s=s+1*, otherwise go to Step 2-3.

Step 3: Testing the stop condition. If $(f_{s+1} - f_s) \leqq \varepsilon$, where ε is an arbitrary small number, then stop. Incumbent logic rules and membership functions are the optimal learning results. Otherwise, go to Step 1.

5. COMPUTATIONAL EXPERIMENT

5.1 Data and Parameters

For investigating the applicability and robustness of the proposed GFLC bus-preemption strategy, a computational experiment is conducted at an intersection with configuration shown in Fig. 8. There are a total of 4 lanes, containing 2 bus-exclusive lanes on the major street and 2 lanes on the minor street. The signal phase of this intersection is pre-timed as 140 seconds green time and 60 seconds red time in the major approaches.

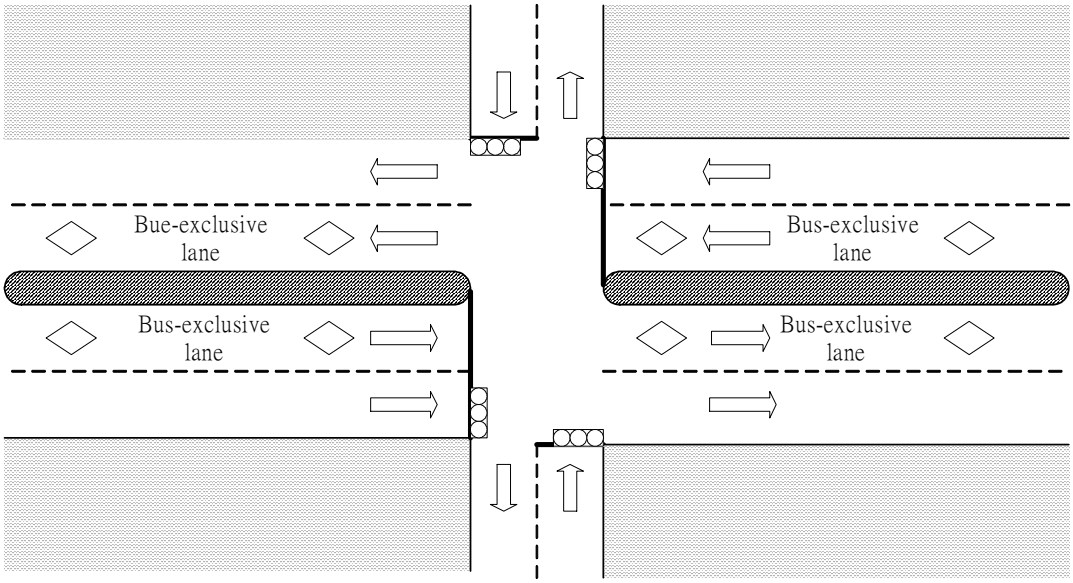

Figure 8. The Configuration of Experimental Intersection

The proposed GFLC bus-preemption strategy has three state variables: flow rates (buses are excluded) of the major street, flow rates of the minor street (assume no buses), and number of stopped buses and one control variable: dissemination of bus arrival message. These four variables are all assumed with five linguistic degrees represented by triangle membership functions. Thus a total of 625 potential logic rules have to be considered. With one gene for each rule, there are 125 genes in a chromosome. As for tuning the membership functions, a total of 36 position parameters have to be calibrated. With four genes for each parameter, there are 144 genes in a chromosome.

The parameters of the GFLC are set as: population size=100, crossover rate=0.9, mutation rate=0.1, a=*0.3*, h=0.5, η =80%, ε =0.001. The center of gravity method is employed for defuzzification. Assume that the average loading factors of bus and car are 40 persons and 2.5 persons, respectively. The maximal green time (G_{max}) is 170 seconds and minimal green time (G_{min}) is 30 seconds.

5.2 Scenario Analysis

In order to examine the control performance of GFLC bus-preemption under different traffic demands, three scenarios are analyzed with low, medium and high traffic flows which represent saturation degrees of 0.3~0.5, 0.5~0.7, and 0.7~0.9, respectively. Fluid

approximation technique is used to estimate the person-delays. The control performance are compared in Table 1 and summarized in Table 2.

As anticipated, the unconditional strategy curtails 77.75%~86.98% of the bus passenger-delays in favor of buses; while only 65.47%~88.50% of the bus passenger-delays are cut-off for the adaptive GFLC strategy. In terms of the total person-delays for all vehicles of the four approaches, however, the adaptive GFLC strategy can reduce 13.53%~34.41%, which is superior to the unconditional strategy with a reduction of 1.22%~32.30%. Also note that both adaptive GFLC and unconditional strategies have performed much better in light flows than in heavy ones and that the adaptive GFLC strategy performs even better than the unconditional strategy as the traffic grows.

Table 1. Person-delays for Different Control Strategies under Various Traffic Demands

Scenarios	Types of vehicles	Adaptive GFLC bus-preemption strategy		Unconditional bus-preemption strategy		Without bus-preemption (base) strategy
High demand	Buses	200.80	(65.47%)	129.36	(77.75%)	581.52
	Other vehicles	4,259.57	(6.93%)	4,965.90	(-8.51%)	4,576.63
	All vehicles	4,460.37	(13.53%)	5,095.26	(1.22%)	5,158.15
Medium demand	Buses	116.16	(74.68%)	93.88	(79.53%)	458.68
	Other vehicles	1,466.45	(7.02%)	1,644.27	(-4.25%)	1,577.22
	All vehicles	1,582.61	(22.26%)	1,738.15	(14.62%)	2,035.90
Low demand	Buses	43.60	(88.50%)	49.36	(86.98%)	379.12
	Other vehicles	632.40	(2.94%)	648.39	(0.48%)	651.55
	All vehicles	676.00	(34.41%)	697.75	(32.30%)	1,030.67

Note: The unit of person-delays is 1,000 person-seconds. Figures in parenthesis represent the percentages of person-delays reduction in comparison with the base strategy--without bus preemption.

Table 2. Performance Comparison between Adaptive GFLC and Unconditional Strategies

Percentage of reduction	High demand			Medium demand			Low demand		
	Adaptive GFLC	Unconditional		Adaptive GFLC	Unconditional		Adaptive GFLC	Unconditional	
Buses	65.47%	77.75%	(-12.29%)	74.68%	79.53%	(-4.86%)	88.50%	86.98%	(1.52%)
Other vehicles	6.93%	-8.51%	(15.43%)	7.02%	-4.25%	(11.27%)	2.94%	0.48%	(2.45%)
All vehicles	13.53%	1.22%	(12.31%)	22.26%	14.62%	(7.64%)	34.41%	32.30%	(2.11%)

Note: The figures represent the reduction percentages of person-delays in comparison with the base strategy (without bus preemption). Figures in parenthesis represent the difference of reduction of person-delays between adaptive GFLC and unconditional strategies.

5.3 Case study

In order to investigate the applicability and robustness of our proposed adaptive GFLC bus-preemption strategy, a case study is further performed by using a generated sixteen-hour daytime traffic flow pattern as shown in Fig. 9.

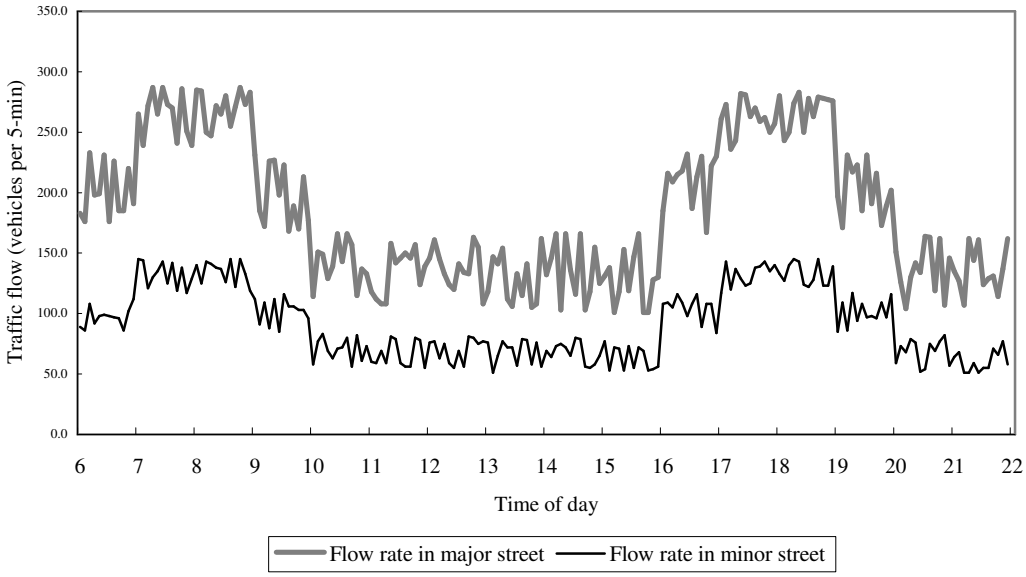

Figure 9. Sixteen Hours of Daytime Traffic Pattern for Case Study

To train the GFLC, three-hour traffic data covering peak and off-peak flows are drawn from the sixteen hours of daytime traffic pattern. The learning process of GFLC is converged after one iterative evolution with 54 generations progressed. A total of 104 logic rules are selected. The tuned membership functions are depicted in Fig. 10. The trained GFLC is then used to control the bus-preemption signal with the generated sixteen hours of traffic flows in which a total of 319 cycles have been progressed. Of the total arriving buses, 965 buses have activated the control mechanism of GFLC and 620 of them are given preemption.

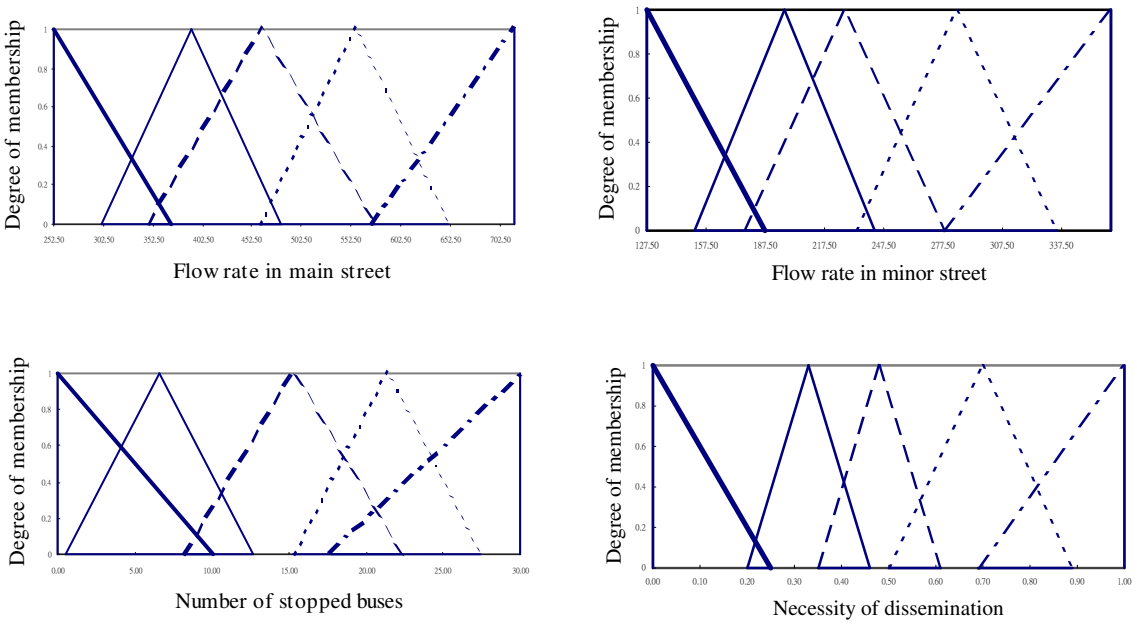

Figure 10. Tuned Membership Functions

Table 3 compares the control performance among different bus-preemption strategies based on the sixteen-hour traffic flows pattern. An adaptive FLC strategy proposed by Su and Lee (1999) is also compared in Table 3. Note that the results of this case study are consistent with those of the scenario analysis. The unconditional strategy can reduce the bus passenger-delays by 83.99%, while only 63.58% and 7.48% reduction of bus passenger-delays are found in our GFLC and Su and Lee's FLC. In terms of the total person-delays for all vehicles, however, our adaptive GFLC strategy can reduce 16.21%, which is superior to the unconditional strategy (12.87%) and Su and Lee's FLC (2.89%).

Table 3. Person-delays for Different Control Strategies for Case Study

Types of vehicles	Adaptive strategy		Unconditional strategy	Without bus-preemption (base) strategy
	GFLC	FLC by Su and Lee		
Buses	854.60 (63.58%)	2,170.96 (7.48%)	375.68 (83.99%)	2,346.44
Other vehicles	9,211.69 (4.72%)	9,496.40 (1.77%)	10,092.19 (-4.39%)	9,667.54
All vehicles	10,066.29 (16.21%)	11,667.36 (2.89%)	10,467.87 (12.87%)	12,013.98

Note: The unit of person-delays is 1,000 person-seconds. Figures in parenthesis represent the percentages of person-delays reduction in comparison with the base strategy--without bus preemption.

6. CONCLUDING REMARKS

Based on the build-in bus-preemption control logic of Taipei computerized signal control system, we propose an adaptive GFLC bus-preemption strategy which can take into account the traffic flow conditions at the moment when a bus actuates the detector. The scenario analysis reveals that the adaptive GFLC and unconditional strategies can curtail the total person-delays at the signalized intersection by 13.53%~34.41% and 1.22%~32.30%, respectively, comparing to the without bus-preemption strategy. It implies that the proposed adaptive GFLC strategy performs better than the unconditional bus-preemption strategy. We also find both the adaptive GFLC and unconditional bus-preemption strategies perform much better in light flows than that in heavy ones. The adaptive GFLC strategy performs even better than the unconditional strategy as the traffic grows. The case study further shows that our adaptive GFLC strategy can reduce the total person-delays by 16.21%, which is superior to the unconditional strategy (12.87%) and Su and Lee's FLC (2.89%).

The experiments of this paper only cover a three-hour scenario analysis and sixteen-hour case study. Application of our proposed adaptive GFLC to real traffic patterns and tactics other than green extension and red truncation are worthy of exploring. The comparison of our adaptive GFLC and other bus-preemption strategies is based on the given signal timing plan that may not be optimal. In order to precisely estimate the net improvement of any bus-preemption strategy, optimal timing plans need to be determined in advance.

ACKNOWLEDGEMENTS

The authors would like to thank the National Science Council of the Republic of China for sponsoring this research under Contract No. NSC-91- 2211-E–035 –031.

REFERENCES

Chang, G. L. Vasudevan, M. and Su, C. C. (1996) Modelling and evaluation adaptive bus-preemption control with and without automatic vehicle location systems, **Transportation Research, Vol. 30A**, 251-268.

Cheng, S. F. (2000) A simulation study on bus priority signal of bus platoon, Master Thesis, Department of Civil Engineering, National Taiwan University. (in Chinese)

Chiou, Y. C. and Lan, W. L. (2002) Genetic fuzzy logic controllers, **The Fifth International IEEE Conference on Intelligent Transportation Systems**, Singapore, 200-208.

Chin, T. C. and Qi, X. M. (1998) Genetic algorithms for learning the rule base of fuzzy logic controller, **Fuzzy Sets and Systems, Vol. 97**, 1-7.

Goldberg, D. E. (1989) **Genetic Algorithms in Search, Optimization, and Machine Learning**, Addison-Wesley.

Herrera, F., Lozano, M. and Verdegay, J. L. (1995) Tuning fuzzy logic controllers by genetic algorithms, **International Journal of Approximate Reasoning, Vol. 12**, 299-315.

Herrera, F., Lozano, M. and Verdegay, J. L. (1998) A learning process for fuzzy control rules using genetic algorithms, **Fuzzy Sets and Systems, Vol. 100**, 143-158.

Heydecker, B. G. (1984) Delay at a junction where there is priority for buses, **Ninth International Symposium on Transportation and Traffic Theory**, 113-132.

Heydecker, B. G. (1983) Capacity at a signal-controlled junction where there is priority for buses, **Transportation Research, Vol. 17B, No. 5**, 341-357.

Jacobson, J. and Sheffi, Y. (1981) Analytical model of traffic delays under bus signal preemption: theory and application, **Transportation Research, Vol. 15B, No. 2**, 127-138.

Karr, C. L. (1991) Design of an adaptive fuzzy logic controller using a genetic algorithm, **Proceeding of the Fourth International Conference on Genetic Algorithms,** Morgan Kaufmann, 450-457.

Kinzel, J., Klawonn, F. and Kruse, R. (1994) Modifications of genetic algorithms for designing and optimising fuzzy controllers, **Proceedings of First International Conference on Evolutionary Computation**, IEEE Piscataway, N. J., 28-33.

Lekova, A., Mikhailov, L., Boyadjiev, D. and Nabout, A. (1998) Redundant fuzzy rules exclusion by genetic algorithms, **Fuzzy Sets and Systems, Vol. 100**, 235-243.

Michalewicz, Z. (1992) **Genetic Algorithms + Data Structures = Evolution Programs**, Springer, Berlin.

Su, C. C. and Lee, S. Y. (1999) A fully-actuated signal model for bus preemption control, **Journal of Transportation Planning, Vol. 28, No. 2**, 167-202. (in Chinese)

Tarng, Y. S., Yeh, Z. M. and Nian, C. Y. (1996) Genetic synthesis of fuzzy logic controllers in turning, **Fuzzy Sets and Systems, Vol. 83**, 301-310.

Thrift, P. (1991) Fuzzy logic synthesis with genetic algorithms, **Proceeding of the Fourth International Conference on Genetic Algorithms,** Morgan Kaufmann, 509-513.

Wang, L. and Yen, J. (1991) Extracting fuzzy rules for system modeling using a hybrid of genetic algorithms and Kalman filter, **Fuzzy Sets and Systems, Vol. 101**, 353-362.

Wu, Y. T. (1999) A simulation study on bus priority signal control strategies on bus exclusive lane, Master Thesis, Department of Civil Engineering, National Taiwan University. (in Chinese)

Zadeh, L. (1973) Outline of a new approach to the analysis of complex systems and decision processes, **IEEE Transactions on Systems, Man and Cybernetics,** SMC-3, 28-44.