

Signal Control for Oversaturated Intersections Using Fuzzy Logic

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ABSTRACT

The fuzzy logic controller (FLC) presented in this paper simulates the control logic of experienced human traffic controllers such as police officers who supersede signal controls at over-saturated intersections during special events. Given real-time traffic information, the FLC controller decides on whether to extend or terminate the current green phase based on a set of fuzzy rules. A new microscopic simulator, the Intersection Control Simulator (ICS), was developed to facilitate the evaluation of the proposed FLC strategy. The FLC strategy was compared with pretimed and actuated control strategies using a typical intersection with varying traffic volume levels. Based on delay, speed, % stops, time in queue and throughput-to-demand ratio statistics, the FLC strategy produced significant improvements over pretimed and actuated control strategies under heavy traffic volumes. This indicates that FLC has the potential to improve operations at over-saturated intersections. Comparisons with other traffic signal control strategies, evaluation with common simulation software and expansion of the FLC for application to arterials are planned.

INTRODUCTION

Intersections are common bottlenecks in roadway systems. More intelligent traffic signal control would make the current roadway system operate more efficiently without building new roadways or widening existing roadways which is often impossible due to scarce land availability and public opposition to roadway expansion in many locations. It has been recognized that signal improvement is one of the most useful and cost-effective methods to reduce congestion (1).

Most signal controls are implemented with either pretimed controls or actuated controls. A pretimed controller repeats preset signal timings derived from historical traffic patterns. An actuated controller computes phase durations based on real-time traffic demand obtained from the detection of passing and stopped traffic on all lanes leading into an intersection.

Actuated control has an efficiency handicap rooted to its simple operating principle of phase extension until a preset maximum is reached. Thus, a single vehicle arrival prolongs the green and cycle length for the whole intersection without regard for the traffic conditions on all other approaches with a red signal. The performance of actuated control is superior to that of pretimed control at low to medium volumes because of its ability to respond to variable arrivals on each approach. However, its performance deteriorates under heavy traffic conditions as it extends green phases to the maximum green times on all phases when high traffic volumes occur on all approaches (2). Given that maximum greens are set in order to contain delays and cycle lengths within acceptable levels, the “maxed-out” operation at congested intersections defaults the actuated controller into a mediocre pretimed controller. This results in degraded intersection performance when efficiency is required the most (2).

Adaptive control is designed to take account of the traffic conditions for the whole intersection. It has the ability to adjust signal phasing and timing settings in response to real-time traffic demands at all or some approaches. Several methods have been developed for designing adaptive control systems and Li (3,4) categorized them as optimization-based, rule-based, and optimization and rule-based control strategies. The current research focus for intersection control is on the application of artificial intelligence techniques such as expert systems, neural networks, and fuzzy logic.

Current control methods typically cannot accommodate heavy or highly uneven traffic well. Human control logic may be superior to existing signal control logic because of its ability to realize the prevailing traffic demands. For example, police officers often replace signal control when an intersection is unusually over-saturated, e.g., during arrivals to and departures from a sports arena or popular concert, during major Marathon races in U.S cities, during large parades, etc. This paper explores the potential application of fuzzy logic on traffic signal control under over-saturated traffic conditions.

The next section presents a summary of applications of fuzzy logic in traffic control operations. The summary of past research findings leads to the objectives of this study. Then, the principles of fuzzy

sets and fuzzy logic are discussed followed by the methodology of the research presented herein. The simulation tool, Intersection Control Simulator (ICS), and a case study are presented next, followed by our conclusions.

LITERATURE REVIEW

The first known attempt to apply fuzzy logic in traffic control was made by Pappis and Mamdani (5). They simulated an isolated signalized intersection composed of two one-way streets with two lanes in each direction without turning traffic. The fuzzy controller reduced average vehicle delay compared to an actuated controller.

Kelsey and Bisset (6) also simulated a simple two-phase signal control of an isolated intersection with one lane on each approach. The fuzzy logic control performed better than both pretimed and actuated control especially when the traffic flow between different directions was highly uneven.

Niittymaki and Pursula (7) also simulated an isolated intersection. They found that fuzzy logic controller lead to shorter vehicle delay and lower % stops especially when the traffic volume was heavy.

Trabia, Kaseko and Ande (8) designed a fuzzy logic controller for a signalized intersection with left-turning traffic. Traffic volumes and queue lengths counted by detectors were used in a two-stage fuzzy logic algorithm to determine whether to extend or terminate the current signal phase. Fuzzy logic control lead to an average of 9.5% decrease in delay and 1.3% reduction in stops compared to actuated control.

Niittymaki and Kikuchi (9) developed a fuzzy logic algorithm for controlling a pedestrian crossing signal. Through microscopic simulation they found that their fuzzy logic algorithm provided at least equal or better performance than conventional actuated signal control.

Chen, May and Auslander (10) studied a fuzzy logic controller for freeway ramp metering. Their model was applied to the Bay Bridge with simulation. The fuzzy logic controller was able to reduce congestion as well as efficiency losses due to incidents.

Nakatsuyama, Nagahashi, and Nishizuka (11) applied fuzzy logic to control two adjacent intersections on an arterial with one-way movements. Fuzzy control rules were developed to determine whether to extend or terminate the green signal for the downstream intersection based on the upstream traffic.

Chiu (12) pioneered fuzzy logic to control multiple intersections in a network of two-way streets with no turning movements. Fuzzy rules were used to adjust cycle time, phase split and offset parameters. Those adjustments to the signal cycle length and splits were made based on the degree of saturation on each intersection approach. The proposed method was tested with simulation and the results showed that fuzzy logic control reduced average delay significantly.

All the aforementioned research concepts were tested with simulation. Few field tests of fuzzy logic control have been conducted to date. In 2001, Niittymaki (13) presented a field test of a simple two-phase fuzzy signal controller. The results showed that the fuzzy logic controller performed better than vehicle-actuated control in terms of delay, % stops and savings in fuel and emissions.

STUDY OBJECTIVE

The research reviewed above generally reported a better performance of fuzzy logic controllers compared to pretimed and actuated controllers. However, most of the reviewed research involved either one-way streets or intersections without turning movements. In addition, fuzzy rules were determined mostly by traffic conditions on the subject approaches without taking into account the traffic conditions on competing approaches. Furthermore, previous research did not develop appropriate fuzzy rules for left-turning vehicles.

Fuzzy logic is suitable for controlling intersections, especially for those with heavy traffic. This is because fuzzy logic is able to emulate the control logic of police officers directing traffic who sometimes replace signal control when the intersection is unusually congested.

This study has two objectives:

1. Design a fuzzy logic algorithm to control over-saturated intersections of two-way streets with left-turning movements.
2. Evaluate the fuzzy logic algorithm and compare it with pretimed control and actuated control using microscopic simulation.

FUZZY SET AND FUZZY LOGIC

Fuzzy set theory is suitable for systems that involve imprecise and vague information. The fuzzy set theory was first introduced by Zadeh in 1965 as a mathematical method for representing vagueness in everyday life (14). It has been recognized as a useful mathematical tool in a variety of research fields, including transportation engineering and planning (15, 16, 17, 18).

Based on basic fuzzy set theory, Zadeh (19) first introduced fuzzy logic in 1973. Fuzzy logic is a mathematical representation of human concept formulation and reasoning. In recent years, fuzzy logic has been applied to practical problems with controls and decisions which involve or are similar to the imprecise human reasoning process. It is a promising mathematical approach for modeling traffic control processes which are characterized by subjectivity, ambiguity and imprecision (20).

Fuzzy Set

In the classic theory of sets, also known as crisp set theory, very precise bounds separate the elements that belong to a certain set from the elements outside the set. In other words, it is easy to determine whether an element belongs to a set or not. The membership of element x in set A is described in the classic theory of sets by the membership function $\mu_A(x)$, as follows:

$$\mu_A(x) = \begin{cases} 1, & \text{if and only if } x \text{ is a member of } A \\ 0, & \text{if and only if } x \text{ is not a member of } A \end{cases}$$

However, many sets encountered in real life do not have precisely defined bounds that separate the elements in the set from those outside the set. For example, if we denote by A the set of “long delay at a signal,” how could we establish which element belongs to this set? Does a delay of 40 sec. belong to this set? What about 30 sec. or 60 sec.? It is obvious that the binary logic of having each single element to either belong to a set (membership = 1) or not belong to a set (membership = 0) is not appropriate for most categories describing real-world situations that do not possess well-defined boundaries. Fundamentally then this initiates the development of fuzzy set theory.

In contrast to the classical set theory, fuzzy sets admit intermediate values of class membership. A fuzzy set is represented by a membership function which expresses the degree that an element of the universal set belongs to the fuzzy set: larger values denote higher degrees of membership, smaller values indicate lower degrees of membership. The most commonly used range of values of membership functions is the unit interval $[0,1]$. Each membership function maps elements of a given universal set X into real numbers in $[0,1]$. In other words, the membership function of a fuzzy set A , $\mu_A(x)$, is defined as

$$\mu_A : X \rightarrow [0,1]$$

Fuzzy Logic

The development of fuzzy logic dates back to 1973 (19). Introducing a concept he called “approximate reasoning”, Zadeh successfully showed that vague logical statements enable the formation of algorithms that can use vague data to derive vague inferences. Fuzzy logic makes it possible to compute with words, which enables complex analysis reflecting the human thinking process. Each fuzzy logic system can be divided into three elements (Figure 1): fuzzification, fuzzy inference and defuzzification (15, 21, 22, 23).

Input data are most often crisp values. Fuzzification maps crisp numbers into fuzzy sets. The fuzzifier decides the corresponding membership grades (or degrees of membership) from the crisp inputs. The resulting fuzzy values are then entered into the fuzzy inference engine. Fuzzy inference is based on a fuzzy rule base which contains a set of If \rightarrow Then fuzzy rules. A typical fuzzy rule would be:

T_{MIN} = minimum green time for each phase, in sec.

T_{MAX_TH} = maximum green time for through lanes which can vary for different approaches, in sec.

T_{MAX_LT} = maximum green time for left-turn lanes which can vary for different approaches, in sec.

The fuzzy logic controller determines whether to extend or terminate the current green phase after a minimum green time of T_{MIN} has been displayed. If the green time is extended, then the fuzzy logic controller will determine whether to extend the green after a time interval Δt . The interval Δt may vary from 0.1 to 10 sec. depending on the controller processor speed. $\Delta t = 5$ sec. in this study. If the fuzzy logic controller determines to terminate the current phase, then the signal will go to the next phase. If not, the current phase will be extended and the fuzzy logic controller will make the next decision after Δt and so forth until the maximum green time is reached.

The decision making process is based on a set of fuzzy rules which takes into account the traffic conditions with the current and next phases. The general format of the fuzzy rules is as follows:

If {QC is X_1 } and {AR is X_2 } and {QN is X_3 } Then {E or T}.

where,

X_1, X_2, X_3 = natural language expressions of traffic conditions of respective variables

E = Extension of green phase

T = Termination of green phase

QC and QN are divided into four fuzzy sets: “short,” “medium,” “long” and “very long.” AR is divided into three fuzzy sets: “low,” “medium” and “high.” The number of fuzzy rules is dependent on the combinations of fuzzy sets for $X_1, X_2,$ and X_3 . A total of $4 \times 3 \times 4 = 48$ fuzzy rules are listed in Table 1.

The parameters QC, QN, and AR are characterized by fuzzy numbers as shown in Figure 2. Trapezoidal fuzzy numbers are used in this study. Q_1 to Q_6 are threshold values to define fuzzy sets for QC and QN; AR_1 to AR_4 are threshold values to define fuzzy sets for AR.

The input data (traffic conditions) are first fuzzified using the proposed fuzzy sets for QC, QN, and AR. Then the fuzzified input data are entered into the fuzzy inference system which is composed of a set of fuzzy rules as described above. The max-min composition method (15,17, 23) is applied for making inferences. The membership grades (or degrees of membership, between 0 and 1) for E (Extend) and T (Terminate) are compared. The one with the highest membership grade is chosen as the control action.

The initial threshold values for fuzzy sets for QC, QN, and AR are shown in Figure 3.

The entire fuzzy logic control process can be represented with a simple example as follows. Suppose that after a time interval $\Delta t = 5$ sec. (within the maximum green time), the fuzzy logic controller

needs to make a decision whether to extend or terminate the current green phase based on the following traffic conditions:

$$QC = 7.5 \text{ veh/lane}$$

$$AR = 0.18 \text{ veh/sec/lane}$$

$$QN = 10.5 \text{ veh/lane}$$

Based on Figure 3, the input data QC, AR, and QN are fuzzified as shown in Table 2. Based on the fuzzified input data, it is found that fuzzy rules 19, 20, 23, 24, 31, 32, 35, and 36 in Table 1 are involved in this fuzzy inference. The fuzzy inference procedure using max-min composition method is shown in Table 3. Based on the fuzzy logic inference procedure, the fuzzy logic controller will decide to extend the green time for the current phase.

SIMULATION TOOL

A new intersection simulation software, Intersection Control Simulator (ICS), was developed based on the intersection simulator NIT (3, 24). NIT was originally developed to evaluate a new adaptive control strategy TACOS (3, 4). ICS is a microscopic, stochastic, interval-oriented traffic simulator programmed in C++. ICS emulates NETSIM and Integration and was designed to be able to simulate the intersection operation under pretimed, actuated, and FLC control.

ICS scans the traffic system and summarizes measures of effectiveness (MOE) at each time interval. MOE for each lane are necessary to evaluate the performance of different signal control strategies. Link-based, approach-based and intersection-wide MOE can be derived from lane-based MOE using weighted aggregation. The lane-based MOE estimators of ICS include a throughput estimator, a speed estimator, a delay estimator and a queue estimator. A comprehensive test showed that ICS is a valid tool for testing various intersection control strategies (3, 4, 24).

CASE STUDY

FLC was evaluated against pretimed and actuated control strategies. The MOE used in the evaluation were (1) network delay, (2) network speed, (3) % stops, (4) network time in queue, and (5) network throughput-to-demand ratio. The best control strategy is the one that provides the lowest delay, highest speed, lowest % stops, lowest time in queue, and highest throughput-to-demand ratio.

The geometry of the intersection is illustrated in Figure 4(a). Left-turn lanes were made long enough to accommodate left-turning traffic queues. Traffic volumes varying from 20% to 100% of the highest volume are shown in Figure 4(b). The 100% traffic volume level represents a condition where two conflicting movements have a volume-to-capacity ratio greater than 1.0, thus, the intersection is substantially over-saturated

Two simplifications were applied: no right turn on red and no pedestrian demand. The pretimed signal timings shown in Figure 4(c) were optimized with TRANSYT-7F using “delay and stops” as the objective function. Figure 4(d) displays the actuated control phases and phase timing. Vehicle extension intervals of 2, 3 and 4 sec. were tried and the value that produced the best performance in terms of speed and delay was used to compare actuated control with FLC. The phase flags for the actuated signal timing were set as: Vehicle Recall = ON, Double Entry = ON, Simultaneous Gapout = ON, Lag = ON, all the rest = OFF. In addition to presence detectors at the stop line, all lanes have passage detectors 15 m (50 ft.) upstream the stop line. These detectors place calls when the phase is active.

Five different combinations of control parameters (Q_1 - Q_6 , AR_1 - AR_4 , T_{MAX_TH} , T_{MAX_LT} , and T_{MIN}) were tried for FLC control and the best one in terms of delay, speed, % stops, and time in queue was chosen for the comparison among FLC, pretimed and actuated control strategies. Because of the stochastic nature of simulation models, each simulation run may produce different results. For this study, 20 simulation runs were performed for each scenario, resulting in a total of $(5+2) \times 5 \times 20 = 700$ simulation runs. The average values of delay, speed, % stops, time in queue, and throughput-to demand ratio from the 20 simulation runs were averaged to obtain the final MOE for each scenario. Each simulation run was based on a 30-minute simulation time.

The simulation results for FLC are listed in the lower half of Table 4. The columns with shaded background are the best FLC control for each volume level. As expected, FLC control parameters increase with increasing traffic volumes.

FLC is compared with pretimed and actuated control as summarized in Figure 5. The summary table in Figure 5(a) shows average proportional differences of FLC’s MOE over pretimed and actuated control for the test intersection. FLC produced the best performance for all MOE examined.

Further inspection of the delay, speed, % stops, time in queue, and throughput-to-demand ratio (Figure 5) show that:

- Delay: FLC produced the lowest delay at the 60%, 80%, and 100% volume levels. The improvements are more significant with increasing traffic volume. FLC produced a lower delay than pretimed control but a higher delay than actuated control at the 40% volume level. Both pretimed and actuated controls produced lower delay than FLC at the 20% volume level.
- Speed: FLC produced the highest speed at the 60%, 80% and 100% volume levels. FLC produced a higher speed than pretimed control but a lower speed than actuated control at the 40% volume level. Both pretimed and actuated controls produced a higher speed than FLC at the 20% volume level.

- % stops: FLC produced a lower % stops than pretimed control at all levels of traffic volume. FLC also produced a lower % stops than actuated control at the 20%, 40%, and 60% volume levels. However, actuated control performed better than FLC at the 80% and 100% volume levels.
- Time in Queue: FLC produced the lowest time in queue at the 60%, 80% and 100% volume levels. FLC produced a shorter time in queue than pretimed control but a longer time in queue than actuated control at the 40% volume level. Both pretimed and actuated controls produced shorter times in queue than FLC at the 20% volume level.
- Throughput-to-demand ratio: FLC consistently produced higher throughput-to-demand ratios than pretimed and actuated control at all volume levels. The improvement is more pronounced at higher levels of traffic volume.

Overall, the FLC strategy produced substantial improvements over the pretimed and actuated control strategies under heavy traffic conditions in terms of delay, speed, time in queue and throughput.

The FLC parameters in all five trials for heavily loaded volume levels (80% and 100%) produced superior delay, speed, time in queue and throughput estimates compared with pretimed and actuated control estimates (Table 4). This indicates that parameters for running the FLC can be selected with ease for intersections with heavy traffic volumes.

CONCLUSION

A basic fuzzy logic control (FLC) algorithm for full intersections with two-way streets and left-turn lanes was developed. The FLC strategy simulates the control logic of experienced humans such as police officers directing traffic who often replace signal controls when intersections experience unusually heavy traffic volumes (e.g., during special events.) The FLC controller makes the decision whether to extend or terminate the current green phase based on a set of fuzzy rules and real-time traffic information.

The microscopic intersection control simulator (ICS) facilitated the evaluation of the proposed FLC strategy. FLC was compared with pretimed and actuated control strategies using a typical intersection with varying traffic volume levels. Measures of effectiveness including delay, speed, % stops, time in queue, and throughput-to-demand ratio were examined. FLC showed substantial improvements over pretimed and actuated control strategies for all MOE except % stops under heavy traffic volumes. Overall, the simulation results indicated that FLC has the potential to improve operations at over-saturated intersections. The parameters required for running FLC can be set easily for intersections with heavy traffic.

The application of this control strategy depends on queue length estimation. This can be accomplished by algorithms using upstream arrivals and stopline departures, or by using midblock loops, or by using unintrusive sensors including image based sensors.

A large number of improvements are planned for the future; they include the following:

- ◆ Additional simulation tests on intersections with different levels of geometric complexity, phasing and demand.
- ◆ One of the reviewers noted that similar to common traffic-actuate control the proposed FLC also uses a maximum green, therefore the FLC may also default to a suboptimal pretimed operation at over-saturated conditions. So far, simulations indicate that the maximum green time has a limited role in the control. However, enrichment of the fuzzy rules is planned so that maximum green times could be eventually avoided.
- ◆ The time interval Δt may be tested with shorter steps to further increase signal efficiency considering the fast processing speed of current controllers.
- ◆ Laboratory comparisons with other adaptive control strategies such as OPAC, RHODES and RTACL are important. These control strategies along with the FLC described herein are planned to be evaluated using VISSIM's VAP module (25) that allows for the development of user-defined signal logic. The use of well-known software such as VISSIM will facilitate independent comparisons among different control strategies.
- ◆ Expansion of the FLC strategy to arterial and network applications.

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List of Tables

TABLE 1. Fuzzy Rules

TABLE 2. Fuzzification of Input Traffic Data

TABLE 3. Fuzzy Inference using Max-Min Composition Method

TABLE 4. Parameters for Fuzzy Logic Controller

List of Figures

FIGURE 1. Fuzzy logic system.

FIGURE 2. Fuzzy sets for QC, QN and AR.

FIGURE 3. Initial threshold values for fuzzy sets for QC, QN and AR.

FIGURE 4. Basics of signalized intersection used in case study.

FIGURE 5. Results of case study.

TABLE 1. Fuzzy Rules

No.	Fuzzy Rules
1	If {QC is short} and {AR is low} and {QN is short}, Then {E}.
2	If {QC is short} and {AR is low} and {QN is medium}, Then {T}.
3	If {QC is short} and {AR is low} and {QN is long}, Then {T}.
4	If {QC is short} and {AR is low} and {QN is very long}, Then {T}.
5	If {QC is short} and {AR is medium} and {QN is short}, Then {E}.
6	If {QC is short} and {AR is medium} and {QN is medium}, Then {T}.
7	If {QC is short} and {AR is medium} and {QN is long}, Then {T}.
8	If {QC is short} and {AR is medium} and {QN is very long}, Then {T}.
9	If {QC is short} and {AR is high} and {QN is short}, Then {E}.
10	If {QC is short} and {AR is high} and {QN is medium}, Then {E}.
11	If {QC is short} and {AR is high} and {QN is long}, Then {T}.
12	If {QC is short} and {AR is high} and {QN is very long}, Then {T}.
13	If {QC is medium} and {AR is low} and {QN is short}, Then {E}.
14	If {QC is medium} and {AR is low} and {QN is medium}, Then {E}.
15	If {QC is medium} and {AR is low} and {QN is long}, Then {T}.
16	If {QC is medium} and {AR is low} and {QN is very long}, Then {T}.
17	If {QC is medium} and {AR is medium} and {QN is short}, Then {E}.
18	If {QC is medium} and {AR is medium} and {QN is medium}, Then {E}.
19	If {QC is medium} and {AR is medium} and {QN is long}, Then {T}.
20	If {QC is medium} and {AR is medium} and {QN is very long}, Then {T}.
21	If {QC is medium} and {AR is high} and {QN is short}, Then {E}.
22	If {QC is medium} and {AR is high} and {QN is medium}, Then {E}.
23	If {QC is medium} and {AR is high} and {QN is long}, Then {E}.
24	If {QC is medium} and {AR is high} and {QN is very long}, Then {T}.
25	If {QC is long} and {AR is low} and {QN is short}, Then {E}.
26	If {QC is long} and {AR is low} and {QN is medium}, Then {E}.
27	If {QC is long} and {AR is low} and {QN is long}, Then {E}.
28	If {QC is long} and {AR is low} and {QN is very long}, Then {T}.
29	If {QC is long} and {AR is medium} and {QN is short}, Then {E}.
30	If {QC is long} and {AR is medium} and {QN is medium}, Then {E}.
31	If {QC is long} and {AR is medium} and {QN is long}, Then {E}.
32	If {QC is long} and {AR is medium} and {QN is very long}, Then {T}.
33	If {QC is long} and {AR is high} and {QN is short}, Then {E}.
34	If {QC is long} and {AR is high} and {QN is medium}, Then {E}.
35	If {QC is long} and {AR is high} and {QN is long}, Then {E}.
36	If {QC is long} and {AR is high} and {QN is very long}, Then {E}.
37	If {QC is very long} and {AR is low} and {QN is short}, Then {E}.
38	If {QC is very long} and {AR is low} and {QN is medium}, Then {E}.
39	If {QC is very long} and {AR is low} and {QN is long}, Then {E}.
40	If {QC is very long} and {AR is low} and {QN is very long}, Then {E}.
41	If {QC is very long} and {AR is medium} and {QN is short}, Then {E}.
42	If {QC is very long} and {AR is medium} and {QN is medium}, Then {E}.
43	If {QC is very long} and {AR is medium} and {QN is long}, Then {E}.
44	If {QC is very long} and {AR is medium} and {QN is very long}, Then {E}.
45	If {QC is very long} and {AR is high} and {QN is short}, Then {E}.
46	If {QC is very long} and {AR is high} and {QN is medium}, Then {E}.
47	If {QC is very long} and {AR is high} and {QN is long}, Then {E}.
48	If {QC is very long} and {AR is high} and {QN is very long}, Then {E}.

E: Extend; T: Terminate

TABLE 2. Fuzzification of Input Traffic Data

Input	Traffic Data	Fuzzified Category	Membership Grade
QC	7.5 veh/lane	Medium	0.25
		Long	0.75
AR	0.18 veh/sec/lane	Medium	0.70
		High	0.30
QN	10.5 veh/lane	Long	0.75
		Very long	0.25

TABLE 3. Fuzzy Inference using Max-Min Composition Method

Traffic Information			Control Action	Max-Min Composition
QC	AR	QN		
Medium (0.25)	Medium (0.70)	Long (0.75)	T	Min (0.25, 0.70, 0.75) = 0.25
Medium (0.25)	Medium (0.70)	Very long (0.25)	T	Min (0.25, 0.70, 0.25) = 0.25
Medium (0.25)	High (0.30)	Long (0.75)	E	Min (0.25, 0.30, 0.75) = 0.25
Medium (0.25)	High (0.30)	Very long (0.25)	T	Min (0.25, 0.30, 0.25) = 0.25
Long (0.75)	Medium (0.70)	Long (0.75)	E	Min (0.75, 0.70, 0.75) = 0.70
Long (0.75)	Medium (0.70)	Very long (0.25)	T	Min (0.75, 0.70, 0.25) = 0.25
Long (0.75)	High (0.30)	Long (0.75)	E	Min (0.75, 0.30, 0.75) = 0.30
Long (0.75)	High (0.30)	Very long (0.25)	E	Min (0.75, 0.30, 0.25) = 0.25
			T: Max (0.25, 0.25, 0.25, 0.25) = 0.25 E: Max (0.25, 0.70, 0.30, 0.25) = 0.70 0.70 > 0.25 → Final decision: <u>EXTENSION</u>	

E: Extend; T: Terminate

The number in parenthesis “()” is the corresponding membership grade.

TABLE 4. Parameters for Fuzzy Logic Controller

		Volume Level																								
		20%					40%					60%					80%					100%				
		Trials	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4
Parameters	Q ₁	1	1	1	0.5	0.5	2	2	1	1	1	2	2	2	1	1	2	3	2	2	2	2	3	3	3	3
	Q ₂	2	2	2	1	1	4	4	2	2	2	4	4	4	2	2	4	6	4	4	4	4	6	6	6	6
	Q ₃	3	3	3	1.5	1.5	6	6	3	3	3	6	6	6	4	4	6	9	6	6	6	6	9	9	9	9
	Q ₄	5	4	4	2	2	8	8	5	5	4	8	8	8	6	6	8	12	8	8	8	8	12	12	12	12
	Q ₅	7	5	5	2.5	2.5	10	10	7	7	5	10	10	10	8	8	10	15	10	10	10	10	15	15	15	15
	Q ₆	9	6	6	3	3	12	12	9	9	6	12	12	12	10	10	12	18	12	12	12	12	18	18	18	18
	AR ₁	0.05	0.04	0.04	0.04	0.03	0.05	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
	AR ₂	0.10	0.08	0.08	0.08	0.06	0.10	0.10	0.10	0.08	0.08	0.10	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
	AR ₃	0.15	0.12	0.12	0.12	0.09	0.15	0.15	0.15	0.12	0.12	0.15	0.15	0.15	0.13	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.20
	AR ₄	0.20	0.16	0.16	0.16	0.12	0.20	0.20	0.20	0.16	0.16	0.25	0.20	0.20	0.17	0.20	0.25	0.25	0.25	0.25	0.20	0.25	0.25	0.25	0.20	0.30
T _{MAX TH}	30	30	20	20	20	60	40	40	40	30	60	60	40	40	40	60	60	40	40	40	60	60	90	60	60	
T _{MAX LT}	15	15	15	15	15	30	20	20	20	15	30	30	20	20	20	30	30	30	20	20	30	30	30	30	30	
T _{MIN}	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	
MOE	Delay (sec/veh)	26.9	27.2	24.8	19.8	19.5	45.5	36.5	27.4	26.8	25.1	42.8	41.8	37.7	27.3	26.4	50.2	57.1	45.1	44.5	43.6	103.9	91.5	101.6	100.8	87.0
	Speed (mph)	18.9	18.8	19.4	20.6	21.0	15.1	16.7	18.8	18.9	19.3	15.6	15.7	16.5	18.8	19.0	14.4	13.4	15.2	15.3	15.4	9.3	10.1	9.5	9.5	10.5
	% Stops	64.5%	65.5%	67.1%	63.2%	61.6%	68.6%	67.7%	64.7%	64.2%	65.1%	71.8%	71.2%	71.2%	68.8%	68.1%	78.5%	79.0%	78.8%	77.8%	77.9%	85.1%	84.7%	84.6%	84.9%	84.2%
	Queue Time (veh-min)	157	158	137	102	99	580	437	305	301	275	765	755	651	423	408	1191	1384	1029	1012	1000	3593	2930	3425	3288	2782
	Throughput/Demand	99.5%	99.4%	99.7%	99.7%	100.0%	99.9%	99.6%	99.6%	99.8%	99.6%	99.5%	99.1%	99.6%	99.8%	99.5%	99.5%	99.5%	99.8%	99.7%	99.2%	94.6%	97.2%	95.3%	95.7%	96.7%

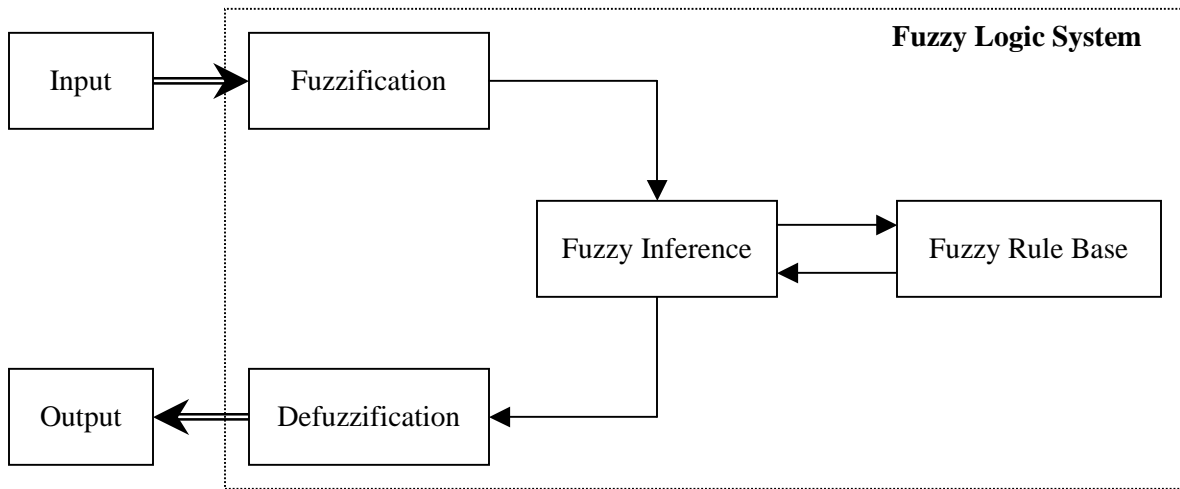


FIGURE 1. Fuzzy logic system.

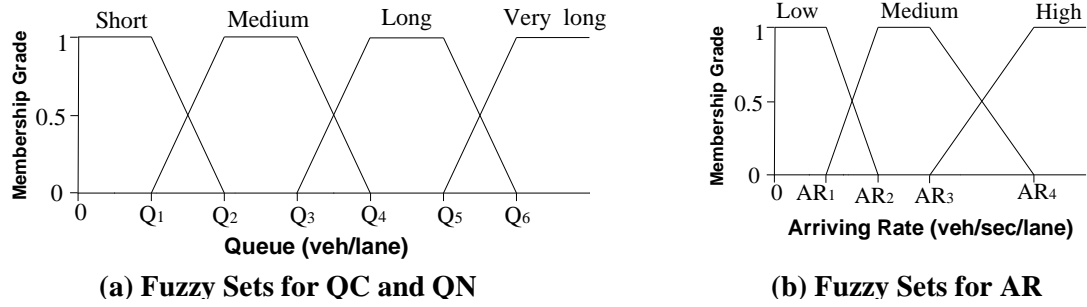


FIGURE 2. Fuzzy sets for QC, QN and AR.

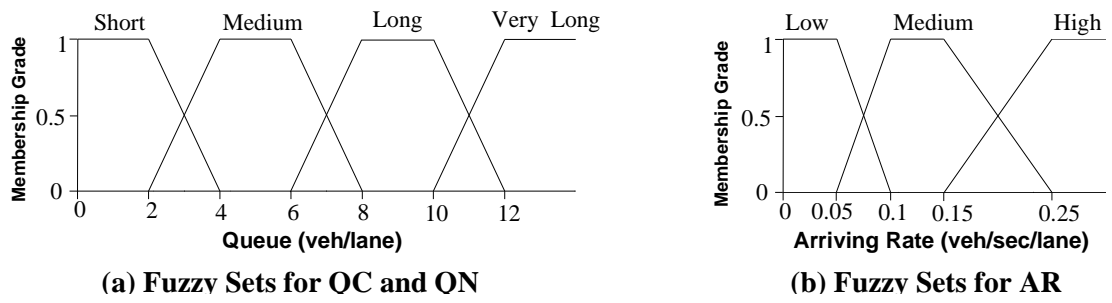
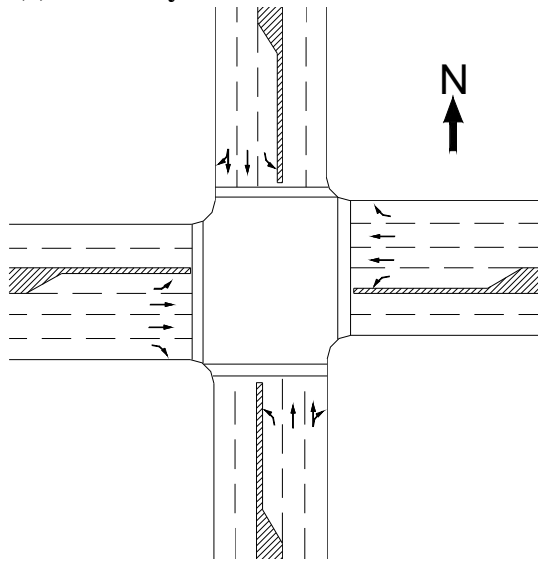


FIGURE 3. Initial threshold values for fuzzy sets for QC, QN and AR.

(a) Geometry



(b) Traffic Volume (veh/hr)

		20%	40%	60%	80%	100%
EB	LT	80	160	240	320	400
	TH	160	320	480	640	800
	RT	80	160	240	320	400
WB	LT	60	120	180	240	300
	TH	120	240	360	480	600
	RT	60	120	180	240	300
NB	LT	40	80	120	160	200
	TH	100	200	300	400	500
	RT	40	80	120	160	200
SB	LT	40	80	120	160	200
	TH	100	200	300	400	500
	RT	40	80	120	160	200

(c) Pretimed Signal

Phase	G for 20% volume	G for 40% volume	G for 60% volume	G for 80% volume	G for 100% volume	Y	AR
A	6 sec	6 sec	12 sec	19 sec	28 sec	4 sec	1 sec
B	5 sec	5 sec	5 sec	5 sec	5 sec	4 sec	1 sec
C	5 sec	5 sec	12 sec	18 sec	27 sec	4 sec	1 sec
D	5 sec	5 sec	8 sec	14 sec	19 sec	4 sec	1 sec
E	9 sec	9 sec	18 sec	29 sec	41 sec	4 sec	1 sec
Cycle length =		55 sec	80 sec	110 sec	145 sec		

(d) Actuated Signal

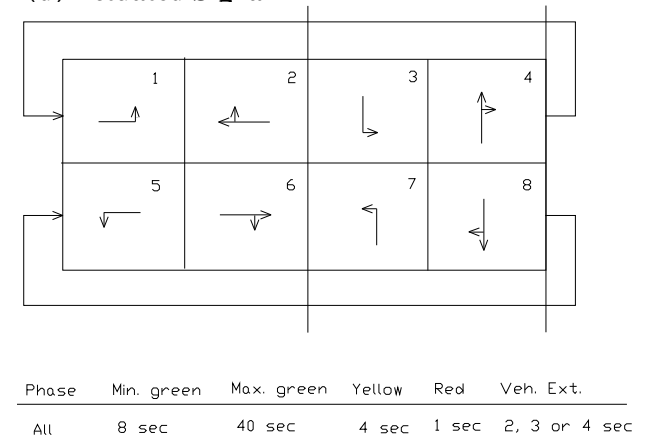


FIGURE 4. Basics of signalized intersection used in case study.

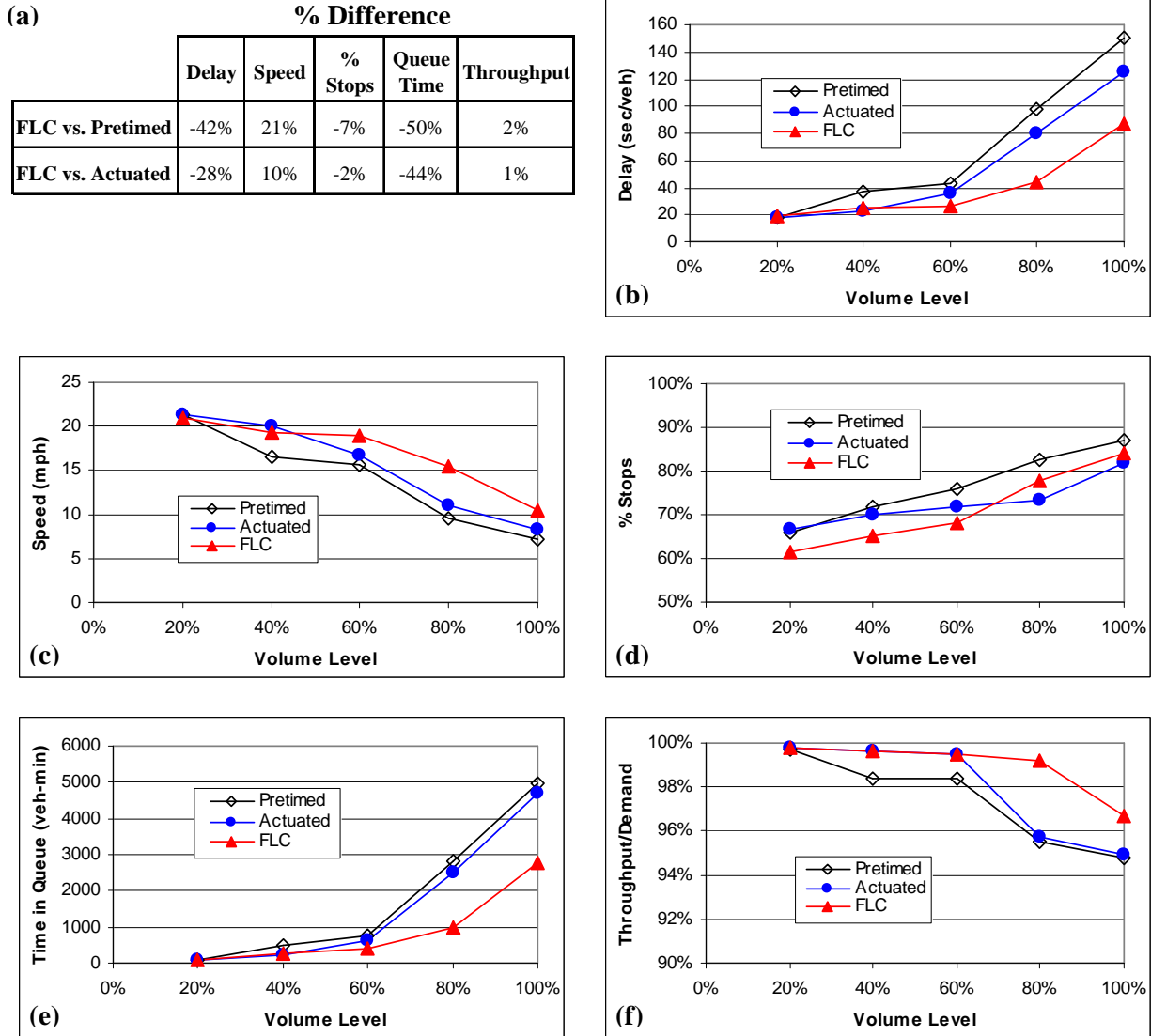


FIGURE 5. Results of case study.