INTELLIGENT ISOLATED INTERSECTION

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Abstract:

In this research, an "intelligent" isolated intersection control system is developed. This paper proposes a two-step process that develops the rules of fuzzy control. In the first step, the best sequence of phases is developed for many different patterns of vehicle arrivals. These sequences are developed using a genetic algorithm approach. In the second step, learning from the best strategies, specific rules are defined. The uniqueness of the proposed approach is that the rules are derived from the set of chosen examples assuming that the future traffic arrival patterns are known. This approach also allows a better evaluation of the performance of the fuzzy control because the best solution developed in the first step is used as the reference. The results were found to be very close to the best solution assuming that the future arrival pattern is known.

1. INTRODUCTION

Fuzzy control has been studied for different traffic control problems ([7], [5], [8], [1], [2], [6], [9], [10]). Since the early introduction of the concept of fuzzy control, traffic signal control has been used as an example problem by researchers. To continue and expand the applications of fuzzy control to traffic signal, however, the following two issues are critical. They are (1) how to develop the rules systematically, and (2) how to evaluate the performance. The work presented introduces a novel method that generates the rules from a set of best control strategies that were prepared using a genetic algorithm. The approach is general so that it can be used for developing the rules of other fuzzy control problems also. If the arrival pattern of the vehicles is perfectly predicted, then the set of carefully chosen controls (a decision to terminate or continue the current phase in each small time interval) can be developed. The proposed method develops the best control strategy for different traffic patterns. This task is performed using a genetic algorithm. Then a set of fuzzy rules is constructed. The proposed approach also offers another advantage that was lacking in the past. It provides the reference with which the result of the proposed method can be evaluated. The best strategy obtained by the genetic algorithm provides the solution when the future condition is known, thus, the result from the proposed procedure can be compared with the best strategy.

2. STATEMENT OF THE PROBLEM

The main goal of this paper is to explore new approaches in fuzzy control at isolated intersections, and also at similar facilities or situations (Freeway Entrance-Ramp Control for example). The paper aims to test the proposed concept in a simple model of the isolated intersection, making it a "benchmark model", rather than to attempt to solve traffic control in real situations.

Consider an isolated "T" intersection consisting of two one-way streets as shown in Figure 1.

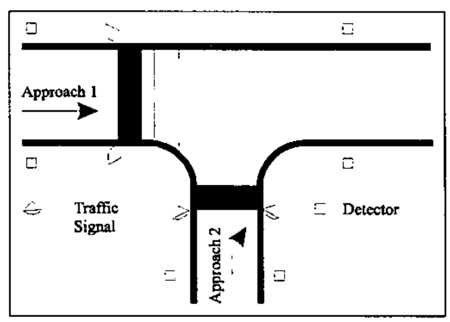

Figure 1 – "T" intersection of two one-way streets

We will assume that our "T" intersection is isolated and relatively "busy" with significant demand variations during certain time periods. In this paper we will not take into consideration the whole set of engineering details like detector placement, calculation of the minimum and maximum green times, yellow and all-red times, and pedestrian requirements. The detectors provide real time information on the numbers of incoming vehicles, stopped vehicles, and the total vehicle waiting time (delay) on each approach. This information is updated in short time intervals. Based on this information, a set of rules is applied to control the signal phase for the next time interval. The decision is either to continue or to terminate the current signal phase. The question is how to build the rules so that they sat the following objectives of signal control: (1) to minimize the total number of stopped vehicles S, and (2) to minimize the total delay D over a given time period (0, T). In other words, our performance index ("cost" or "penalty function") should represent some weighted combination of stops and delays. In certain cases some other factors could be also included in the performance index. For example, the performance function could read as follows:

$$F = w_1 S + w_2 D \quad (1)$$

where: w_1 - the weight (the importance) given to the total number of stopped vehicles; w_2 - the weight (the importance) given to the total delay; $w_1 + w_2 = 1$.

Weights w_1, w_2 are established by the decision maker. Decision-maker (analyst -engineer) can decide for example that $w_1 = 4\ w_2$, with an idea that one stop is equivalent to 4 seconds of delay.

The terms S and D are added with weights of w_1 and w_2. This enables multi-criteria sensitivity analysis and generation of a great number of different control strategies depending on chosen criteria weights (importance). The better the control strategy, the smaller the average delay and the total number of stopped vehicles.

3. REPRESENTATION OF SIGNAL PHASE SEQUENCE IF THE FUTURE CONDITIONS ARE KNOWN

Let us assume, for the moment, that the future conditions on each approach of the intersection in Figure 1 are predicted. In other words, the exact time of the arrival of each vehicle is predicted on each approach during time T. If such a prediction is possible, then we should be able to develop the optimal signal phase sequence for the future. In this section, we will show how to develop the optimum sequence of signal phases assuming that the future conditions at the intersection are known.

Let us introduce the following notation:

Z_{min} - minimum allowed duration of green time for any approach,

Z_{max} - maximum allowed duration of green time for any approach.

Let Z_{max} be an integer multiple of Z_{min}, and k be the ratio between Z_{max} and Z_{min}.

$$Z_{max} = k\ Z_{min} \quad (2)$$

Let us divide time period T into m small time periods (stages), each having width Z_{min}.

$$m\ Z_{min} = T \quad (3)$$

We will assume that the signal phase can change only at any multiple of Z_{min}. Consider just one of the approaches of Figure 1. Let 1 denote the situation when the signal phase on the approach in question is green, and, 0 the situation when the approach in question is red. Then over the period (T), each small time interval may be designated either 0 or 1, and the chain of the numbers such as the following indicates the pattern of signal phase change over T:

101011100001111100...110001010110001111

|←——— a string of m elements ———→|

This sequence represents how the signal phase changed during time T. When developing the 1-0 sequence, more than k consecutive 1's or k consecutive 0's should not be allowed because of the limit of the maximum length of green time for the approach. The length of stage intervals equals to minimum green signal interval time length. It is well known that minimum green time intervals are different for different signal phases. More complex intersections are characterized by the existence of few different signal phases. In cases when developing the 1-0 sequence, different constraints must be taken into account with each of them reflecting minimum and maximum signal phase green times. At the same time, one should think about the development of a different alphabet in future that would appropriately represent the chain of the numbers indicating the pattern of signal phase change over T. Because the vehicle arrival pattern is known, the total number of vehicles that have passed the intersection, the total vehicle delays and the total number of vehicles stopped during time period T can be calculated for the given arrival pattern. In other words, the sequence of 0's and 1's above is associated with this set of performance parameters. We are interested in the sequence that minimizes the value of the objective function.

4. USE OF GENETIC ALGORITHM TO SEARCH FOR THE BEST SEQUENCE OF SIGNAL PHASES

To find the best phase sequence that minimizes the objective function, a technique of genetic algorithm (GA) is introduced ([3], [4]). The best sequence is searched for among a set of possible solutions. In the first step, possible solutions to the problem are generated. Second, these solutions are evaluated with respect to the objective function (in our case Relation (1)); N solutions are randomly chosen from the set of solutions. The probability of choosing particular solution depends on the objective function value of that solution. Third, the selected solutions undergo the phases of *reproduction*, *crossover* and *mutation*. In the end, a set of solutions is identified. This set is now used to repeat another search sequence. The set of solutions after each iteration is expected to be "better" than the previous one. The iterations stop when a prespecified stopping condition is satisfied. The final solution is considered as the approximate best solution. Many different hypothetical traffic scenarios are generated, and for each scenario, the best solution consisting of a string of 1's and 0's, is developed using Genetic Algorithm. This set of solutions constitutes the knowledge base on which the fuzzy rules can be developed. For any best solution a summary of the number of vehicles wishing to proceed on the approach 1 at the beginning of small time interval, the number of vehicle wishing to proceed on the approach 2 at the beginning of small time interval, number of time intervals elapsed since the last signal phase change (+ for continuous green, - for continuous red for approach 1), and number time intervals until the next phase change (+ for continuous green, - for continuous red for approach 1) can be organized for each small time period as shown in Table I. The first "best solution" that corresponds to the first hypothetical traffic scenario will occupy first m rows of the Table I. The second "best solution" that corresponds to the second traffic scenario will be placed in (m+1)-st, (m+2)-nd, ..., and (2m)-th row, etc. At this moment Table I is very large. Since we will develop fuzzy rules from the data contained in Table I, one can conclude that the number of fuzzy rules will be also very large. Later, we will explain why the number of generated fuzzy rules will be much smaller than the number or rows in Table I. In the first time interval the right to pass is given to the approach with a greater number of detected vehicles.

Table I
Vehicle arrival and waiting status and the best control for each time interval

Ordinal number of small time period	Number of vehicles in the first approach	Number of vehicles in the second approach	Number time intervals that has elapsed since the last signal phase change	Number time intervals until the signal phase change
1	2	3	-1	-2
2	4	3	-2	-1
3	5	1	-3	0
.	.	.	.	.
.	0	7	2	0

5. DEVELOPING THE FUZZY RULES

Each row in Table I shows the specific condition in a small interval and the best action to be taken for the next interval. Thus, one can develop a set of rules by reviewing different rows in the table, with the antecedent being the values in columns 2, 3, and 4 and the consequent being the value in column 5. The table thus provides the basis for the best control for a given traffic pattern. Corresponding to each row in Table I, one fuzzy control rule, such as below, can be developed:

If the total number of approaching vehicles is SMALL, and if the total number of vehicles waiting in the other approach is LARGE, and if time elapsed since the last phase change is VERY LONG

Then the time length until the next phase change is VERY SHORT

Each fuzzy rule is constructed from the set of input-output data pairs shown in Table I, which is a summary of best control for each time period obtained using genetic algorithm. Let us use the following notation to represent the values of the variables in each column in Table I except column 1. $(x_1^1,x_2^1,x_3^1;y^1)$, $(x_1^2,x_2^2,x_3^2;y^2)$,..., where x_1^i, x_2^i, x_3^i are the input and y^i is the conclusion of *i th* row with subscripts 1, 2, and 3 corresponding to columns 2, 3, and 4 of Table I, respectively. One fuzzy rule is developed using one input -output pair, $(x_1^i, x_2^i, x_3^i, y^i)$.

For example, the rule corresponding to the situation shown in Figure 2 is the following one:

If x_1 is A_1 and x_2 is A_2 and x_3 is B_5,

Then y_1 is C_3

where A_1, A_2, B_5, C_3,... are corresponding fuzzy sets.

The number of fuzzy rules generated this way will be much smaller than the number of rows in Table I. The reason behind it is rather simple; rows that contain "similar" data will very often generate the same rule. It is possible that 10, 15, or 30 rows always generate the same rule. Most frequently, minor differences in data will not cause the creation of the new rule. The existence of the so-called "conflicting rules" can further decrease the fuzzy rule base size. Some rules may be conflict; in other words, rules with the same antecedents but different consequents may be produced. In such a case, the Wang and Mendel [11] method suggests measuring the validity of each rule by the following test, and selecting the rule that has the maximum value in the expression below:

$$D(Rule\ i) = \mu_{A_1}(x_1^i)\cdot \mu_{A_2}(x_2^i)\cdot \mu_{B_5}(x_3^i)\cdot \mu_{C_3}(y^i) \qquad (4)$$

This operation indicates that the rule selected has the highest logical strength.

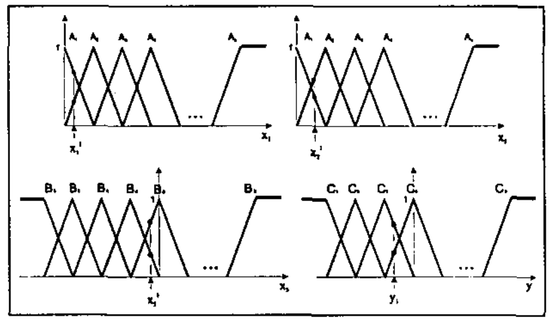

Figure 2 – The generation of one fuzzy rule

The proposed "intelligent" isolated intersection control algorithm consists of the following steps:

- Step 1 Construct the basic structure of the fuzzy rule for the given objective by defining the variables used in the antecedent and consequent.
- Step 2 Construct all possible membership functions for each variable in the rule.
- Step 3 Generate a large number of vehicle arrival patterns at the intersection.
- Step 4 For each pattern, using genetic algorithm, find the best signal phase sequence that results in the minimum value of the objective function expressed in relation (1)
- Step 5 Collect a set of best solutions, each corresponding to a vehicle arrival pattern.
- Step 6 Develop a rule corresponding to each row of Table I using the Wang and Mendel's method (Figure 2).

6. TESTING RESULTS OF THE PROPOSED METHOD

In this section, we compare the results obtained by the proposed process above with the "best" solution obtained by the genetic algorithm. For the sake of brevity, we denote the results from the proposed process "our results" and the best result obtained by genetic algorithm "GA result". Because the GA result was the retrospectively derived best solution for a given traffic pattern, the performance associated with it is considered as the target or reference for evaluation. The criterion used to compare the two cases (our result vs. GA result) is the performance index defined in relation (1) (weighted combination of two objectives: the minimum number of stopped vehicles and the minimum total delay). First, a set of fuzzy control rules is developed using the proposed process for a given set of traffic pattern. Second, our results and the GA results are compared with respect to Eq(1) for the same set of traffic patterns that were used to develop the rules. Third, for a different set of traffic pattern (for the traffic arrival patterns that are not previously used), the best control strategy is developed by the GA method and the performance is measured by Eq(1). This performance is then compared with the one that is obtained using the previously developed fuzzy rules. This last step makes sure that the comparison *is not biased.* A simulation model that generates different traffic patterns for the two approaches in Figure 1 is constructed. The vehicle arrivals are assumed to follow the Poisson process. Thirty-two patterns are generated with each pattern lasting for 10 minutes (600 seconds). The headway between two successive vehicles is not less than 1.5 seconds. The size of the small time interval at which control decisions are made is 6 seconds. The best decision at each small time interval is developed using the genetic algorithm. The specific values of weights between the minimum total delay (w_1) and minimum total number of stopped vehicles (w_2) are as follows: ($w_1 = 0$; $w_2 = 1$), ($w_1 = 0.4$; $w_2 = 0.6$), ($w_1 = 0.6$; $w_2 = 0.4$), ($w_1 = 1$; $w_2 = 0$). Thus, for a given traffic pattern, six best solutions, corresponding to each weight combination, are developed. Figure 3 show the number of stopped vehicles for the traffic arrival patterns that *are not previously used.* In this figure (as in the case of the total delay), most points line up along the 45-degree line. This indicates that our result and GA results are very similar and that the rules from the proposed method can yield solutions close to the best solution.

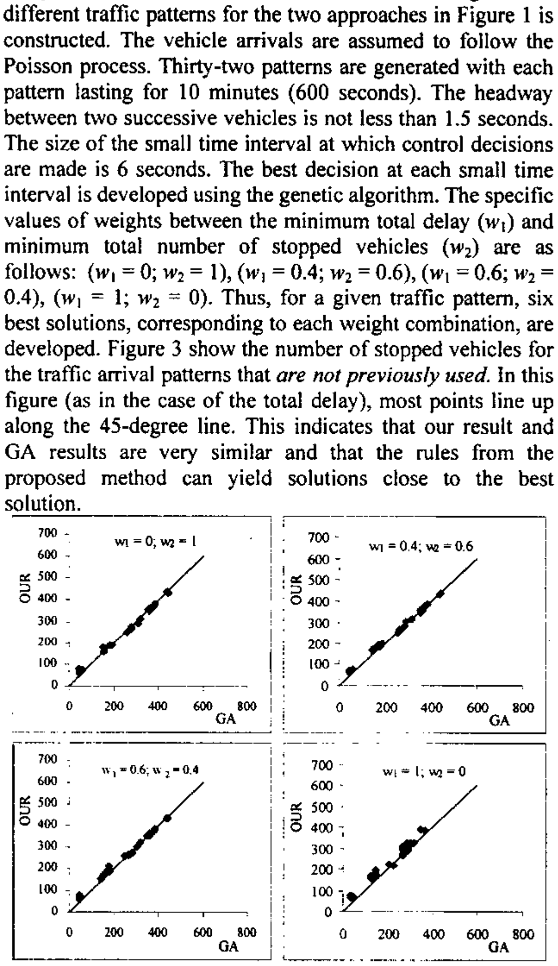

Figure 3 – Total Number of Stopped Vehicles for the GA Results and "OUR" results

7. CONCLUSIONS

The proposed approach has two steps. First, given the objective of the control, many possible traffic arrival patterns are generated. For each pattern, the best timing sequence is then developed. This is achieved by the genetic algorithm (GA) method. Second, based on the best timing sequence, the rules are built one at a time using the Wang and Mendel's method. In short, the proposed process learns from the solutions obtained assuming that the future situations are known. Combining many solutions, a set of rules is developed. All pairs ("traffic scenario- appropriate control strategy") were used to produce a fuzzy rule base. Evaluating the performance of the rules developed by this process is also noble. Because the best solution is known for a particular arrival pattern (the solution from the genetic algorithm method), the performance of the proposed rules can easily be checked against the result of the best solution. Many tests show that the outcome (the total delay and the total number of stopped vehicles) of the proposed rules is nearly equal to the best solution.

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