FUZZY TRAFFIC SIGNAL CONTROL AND A NEW INFERENCE METHOD – MAXIMAL FUZZY SIMILARITY

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Abstract

New methods, like fuzzy logic, are coming into the field of adaptive traffic signal control. Development of the fuzzy control can roughly be divided into two research approaches: development of fuzzy control functions, and development of fuzzy inference methods. Both approaches are discussed in this paper. First, a lately developed fuzzy inference method, called maximal fuzzy similarity, is introduced. Second, two fuzzy traffic signal control functions, phase selector and green extender, are presented and their performance is evaluated by simulations. Third, the applicability of the maximal fuzzy similarity inference method in traffic control systems is compared to the traditional Mamdani inference method. The comparison is made using them separately in the above mentioned control functions. In the simulations, the phase selector function improved significantly the control performance, while the fuzzy green extender worked better than the non-fuzzy control only with high volumes. The fuzzy sets and inference seem to have meaning only when the input values (volumes) are high enough. The main difference between the tested inference methods was the fact, that the defuzzification method of Mamdani inference, center of area, leads to more compromising control decisions than the similarity method. Instead of combining the outputs of all the control rules, the similarity inference launches the action of the rule with highest similarity to the input values and ignores the output values of other rules. Thus, the Mamdani method is slightly more appropriate to conditions, where compromises are needed, while the similarity method with more extreme control actions has better performance with conditions requiring more radical adjustments to the control.

1 INTRODUCTION

New methods, like fuzzy logic, are coming into the field of adaptive traffic signal control. The aim of using fuzzy methods is the attempt to model expert's thinking in the situations where development of an exact mathematical model of the phenomenon is very difficult or even impossible. Human decision-making and reasoning in general, and in traffic and transportation in particular, are characterized by a generally good performance. Even if the decision-makers have incomplete information, and key decision attributes are imprecisely or ambiguously specified, or not specified at all, and the decision-making objectives are unclear, the efficiency of human decision-making is unprecedented (*1*).

The main goals of fuzzy logic in the traffic signal control, and as a matter of fact, also in traffic signal control in general, are

1. improving of traffic safety in the intersection
2. maximizing the capacity of the intersection
3. minimizing the delays
4. clarifying the traffic environment
5. influencing the route choices.

Because the aims of traffic signal control, and the use of fuzzy logic to improve the control system, are various, the development of fuzzy controller is divided into smaller stages. The development of fuzzy controller has two main aspects: to invent and test new functions and rules to improve the control performance in practice, and to define the most suitable theoretical systems, like fuzzy inference methods and optimization of the fuzzy sets and rule bases, for traffic signal control applications.

In this paper, both the performance of practical fuzzy control applications and the suitability of two theoretical fuzzy inference method to the control functions are discussed. First, a lately developed fuzzy inference method, called maximal fuzzy similarity, is introduced. Second, two fuzzy traffic signal control functions, phase selector and green extender, are presented and their performance is evaluated by simulations. The usability of the concrete control functions are measured in two simulation study, in which a control with fuzzy phase selector function is compared to a fixed phase sequence control, and the fuzzy green extender based control is compared to traditional non-fuzzy vehicle actuated signal control. To test the applicability of the maximal fuzzy similarity inference to the traffic control applications, the performance of the above mentioned fuzzy control functions is first measured using the similarity inference method, and then the more traditional Mamdani inference method (*2*).

2 MAXIMAL FUZZY SIMILARITY

The fuzzy inference method called maximal fuzzy similarity is based on well-defined Lukasiewicz-multi-valued logic and it is a true generalization of the equivalence relation. The main idea in this new method is to base fuzzy reasoning only on expert's knowledge. The other defuzzification techniques of the fuzzy output, like center of mass, which do not have as strong mathematical background as the fuzzy similarity, are replaced with well-defined many-valued logic.

The emphasis of this study is on the empirical testing of two fuzzy inference systems, the maximal fuzzy similarity and classical Mamdani type inference, and on comparing the similarity based system to the better known Mamdani system. The lately developed similarity based system is presented below. Information of the Mamdani's control system can be found, for example, in (*2*).

2.1 Constructing a system based maximal fuzzy similarity algorithm

A fuzzy inference system S is composed of an input universe of discourse X (IF-parts of the rules), and an output universe of discourse Y (THEN-parts of the rules). We assume there are n input variables and one output variable. The dynamics of S are characterized by a finite collection of IF-THEN-rules; e.g.

Rule 1. IF x is A_1 and y is B_1 and z is C_1 THEN w is D_1
Rule 2. IF x is A_2 and y is B_2 and z is C_2 THEN w is D_2
.
.
.
Rule k. IF x is A_k and y is B_k and z is C_k THEN w is D_k

where A_1 ,…, D_k are fuzzy sets. Generally, the output fuzzy sets D_1 ,…, D_k should obtain all the same values $\in$[0,1] the input fuzzy sets A_1 ,…, C_k do, however, the outputs can be crisp actions, too. All these fuzzy sets are to be specified by the fuzzy control engineer.

We avoid disjunction between the rules by allowing some of the output fuzzy sets D_i and D_j , $i \neq j$, be possibly equal . Thus, a fixed THEN-part can be followed by various IF-parts. Some of the input fuzzy sets may be equal, too (e.g. B_i=B_j for some, $i\neq j$). However, the rule base should be consistent; a fixed IF-part precedes a fixed THEN-part. Moreover, the rule base can be incomplete; if an expert is not able to define the THEN-part of some combination, i.e., 'IF x is A_i and y is B_i and z is C_i THEN w is ?' then this rule should simply be skipped.

In (*3*), a general algorithm to construct fuzzy IF-THEN inference systems was introduced. It was shown that the algorithm relays on Zadeh's (*4*) fuzzy similarity, a binary [0,1]-valued relation Sim(,) such that for all elements x,y,z

$Sim(x,x) = 1$,
$Sim(x,y) = Sim(y,x)$ and
$Sim(x,y) \otimes Sim(y,z) \leq Sim(x,z)$,

where $\otimes$ is a continuous t-norm. Obviously, Sim(,) is a generalization of equivalence relation.

In particular, it was shown that if $\otimes$ is the Lukasiewicz t-norms and Sim_1 ,…, Sim_n are fuzzy similarities (called partial fuzzy similarities), then their weighted mean is a fuzzy similarity, too, and call total fuzzy similarity. It was also shown that the induced fuzzy inference system can be viewed as a fuzzy theory in the framework of Pavelka's many-valued logic (*5*).

A total fuzzy similarity based inference system S is to be constructed as follows.

Step 1. Create the dynamics of S, i.e., define the IF-THEN rules, give the shapes of the input fuzzy sets (e.g. A_1,…, C_k) and the shapes of the output fuzzy sets (e.g. D_1 ,…, D_k).

Step 2. Give weights to various parts of the input fuzzy sets (e.g. to A_i:s, B_i:s and C_i:s) to emphasize the mutual importance of the corresponding input variables.

Step 3. Put the IF-THEN-rules in a linear order with respect to their mutual importance, or give some criteria on how this can be done when necessary, i.e., give a criteria on how to distinguish inputs causing equal degree of total fuzzy similarity in different IF-parts.

Step 4. For each THEN-part i, give a criteria on how to distinguish outputs with equal degree on membership (e.g. w_o and v_o such that $\mu(D_i)(w_o) = \mu(D_i)(v_o)$, $w_o \neq v_o$).

A general framework for the inference system is now ready. Assume then that we have actual input values, e.g. x_o, y_o and z_o .The corresponding output value w_o is to be found in the following way.

Step 5. Consider each IF-part of the rule base as a crisp case (membership degree 1 for each term), and compare the actual input values separately with each IF-part, i.e. count total fuzzy similarities between the actual inputs and each IF-part of the rule base; this is equivalent to counting weighted means, e.g.

$m_1*\mu(A_1)(x_o) + m_2*\mu(B_1)(y_o) + m_3*\mu(C_1)(x_o) = Sim(input(x_o, y_o, x_o) ,Rule\ 1)$,
$m_1*\mu(A_2)(x_o) + m_2*\mu(B_2)(y_o) + m_3*\mu(C_2)(x_o) = Sim(input(x_o, y_o, x_o) ,Rule\ 2)$,
.
.
.
$m_1*\mu(A_k)(x_o) + m_2*\mu(B_k)(y_o) + m_3*\mu(C_k)(x_o) = Sim(input(x_o, y_o, x_o) ,Rule\ k)$,

where m1, m2, m3 are the weights given in Step 2.

Step 6. Fire an output value w_o such that $\mu(D_i)(x_o) = Sim(input(x_o, y_o, x_o),Rule\ i)$ corresponding to the maximal (largest) total fuzzy similarity, if such a Rule i is not unique, use the mutual order given in Step 3, and if there are several such output values w_o utilize the criteria given in Step 4.

In case the outputs are concrete actions that can either be taken or not we define 'take the action only in case (total maximal) Similarity(input(x_o, y_o, x_o) ,Rule i) $\in[c,1]$ where c is a suitable value'. Of course, we can specify our algorithm by putting extra demands. For example, in some cases the degree of total fuzzy similarity of the best alternative should be greater than some fixed value $\alpha\in[0,1]$, sometimes all the alternatives possessing the highest fuzzy similarity should be indicated, or the difference between the best candidate and second one should be larger than a fixed value $\beta\in[0,1]$. All this depends on an expert's choice.

3 DESCRIPTION OF THE SIMULATED FUZZY CONTROL FUNCTIONS

The studied fuzzy control functions, phase selector and green phase extender, can be located in different levels of the multi-level signal control strategy presented in Fig. 1. The phase selector is working on the phasing and sequence level, while the green extender belongs to the green extension level of the multi-level signal control system.

Both studied functions have already proved their performance in simulations. The green extender function has been found competitive also in field experiments, and at this moment, there are some green extension -based fuzzy controllers (including also bus priorities) installed in Finnish intersections. More information can be found for example from (*7*). During summer 2001, the first fuzzy controller including the phase selector -function was installed in a test intersection. The results of the field measurements will be available later.

The traffic situation -level is not discussed in this study. However, the fuzzy control is quite flexible and should adapt satisfactorily to the prevailing traffic conditions. The significance of the evaluation of overall traffic situation is likely to increase, when the fuzzy control method is expanded to control systems for wider areas and networks.

3.1 Fuzzy Phase Selector

In the first simulation case, the performance of fuzzy phase selector was tested. The phase selector determines the most suitable phase order for the prevailing traffic conditions. This is accomplished by selecting the next green phase. The traffic situation is monitored continuously, and the decision of the next phase is updated, when the green phase is terminated.

Fig. 2 presents the phases and the basic phase order of the intersection model, in which the control function was tested. The normal cycle A-B-C-A can be changed for example to A-C-A-B-C, depending on traffic situation. If the current green phase A is to be terminated, the phase selector decides whether to launch next the phase B (next phase in order) or the phase C (last phase in order).

The fuzzy inference is based on weights $W(p_i)$ of each phase p_i = A, B, C. The weights can, for example, be defined by the number of queuing vehicles, or as in our application, by the total waiting time of the vehicles waiting for the green signal in each red phase. The rules are formed to give priority to the phase with highest demand for green time. If the phase A is just terminated the phase selection rules are as following

IF *W(B)* is high	AND *W(C)* is any	THEN next phase is phase *B*
IF *W(B)* is medium	AND *W(C)* is over saturated	THEN next phase is phase *C*
IF *W(B)* is low	AND *W(C)* is more than medium	THEN next phase is phase *C*
IF *W(B)* is less than low	AND *W(C)* is more than medium	THEN next phase is phase *C*

When the phase selector is using the fuzzy similarity based inference method, it is possible that the value of maximal similarity is not unique. In this case, the phase with highest total waiting time is selected to appear next. In other words, fuzzy rule base is neglected and the decision making process is purely crisp.

3.2 Fuzzy Green Extender

In the other simulation case, the fuzzy green extender was studied. The main goal of the green extender is to maximize the capacity of an intersection by minimizing the inter-green times of the signal groups. The extender tries to find the right timing for the green phase by tuning the duration of the current green phase with green extensions of different lengths, or by terminating the current phase. The basic principle is that each signal group has a minimum green time (5 seconds in this case) at first. After the obligatory minimum green time, extensions are granted to the current green phase, if the demand on the green approach is sufficient in relation to the demand of green in the approaches facing the red light.

There are two inputs for the fuzzy inference system, A (the number of vehicles approaching the green signal group) and Q (the number of queuing vehicles in the red phases), based on which the green extensions (output) are decided. The extensions are fuzzy numbers between 0 and 12 seconds. The decision of the green extension (or termination) is done when the previous extension is over. The current green phase is terminated, if no more extension is granted (output of the extension inference is 0 seconds), or when the maximum number of extensions is reached. In the simulated applications, the number of consecutive rule sets was 5, and thus, the maximum number of extensions was five. One of these five rule sets is presented below as an example.

4th RULE SET:
After 3rd extension (minimum green + 1st ext .+ 2nd ext.+ 3rd ext.):

IF *A* is zero	AND *Q* is any	THEN *EXTENSION* is zero (terminate current phase)
IF *A* is more than few	AND *Q* is less than medium	THEN *EXTENSION* is short
IF *A* is medium	AND *Q* is less than medium	THEN *EXTENSION* is medium
IF *A* is many	AND *Q* is less than few	THEN *EXTENSION* is long

IF *A* is any AND *Q* is too long THEN *EXTENSION* is none (terminate current phase)

In the case of similarity extender, if the inference gave the same maximal similarity value for more than one rule, the rule with smallest output (shortest extension) was chosen.

4 TEST SIMULATIONS

The performance of the phase selector and green extender functions was tested by HUTSIM-simulations (*7*). In the simulation study the functions were separated and tested in their own simulation runs, in order to gather more specific information of the performance effects of the control functions separately. In a real signal control system, both the phase selector and the green extender -functions are used at the same time, as in the phase selector –simulations. The fuzzy phase selector monitors continuously the traffic situation in the intersection, and chooses the right phase when the green extender decides to terminate the current green phase. After the phase selection is made and the new phase is launched, the fuzzy green extender determines the exact timing and length of this phase.

4.1 Simulation setup

The phase selector –simulations were carried out with two different fuzzy inference methods. First, the fuzzy phase selector used Mamdani type inference. Second, the maximal fuzzy similarity inference was used. For comparison, the simulation was also run without using a phase selecting function at all. Phase selector's effect on control performance can be evaluated by comparing the results of the phase selector simulations to the performance of the control working without phase selecting function. In phase selector simulations, the length of the green phase were defined by the same Mamdani type green extender in all cases.

The green extender simulations were accomplished with three types of green extender: fuzzy extender using Mamdani inference with COA-defuzzification (Center Of Area), fuzzy extender using maximal similarity inference and traditional vehicle actuated (VA) control, which is based on non-fuzzy green extensions. The VA control is widely used in the real intersections, and it is obvious point of comparison when evaluating the applicability of fuzzy systems in real traffic environment.

All the simulations were carried out in the same model of a real intersection in Helsinki, Finland. As the simulation model, also the traffic volumes and combinations were the same for the simulations of both control functions, and for all the versions with different inference methods. The intersection model used in the simulation study was a T-intersection with three phases, which were presented in Fig.2. The layout of the intersection area is presented in Fig. 3. In Fig. 3 X represents the total traffic volume of the major flow. The minor flow volumes used in the simulations are formed from the major flow volume with multipliers of 0.1, 0.2 and 0.5. Numbered items in Fig. 3 are traffic detectors of each approaching lane. Detectors' connections to the traffic signal groups and the distance of each detector from the stopping line are listed in Table 1.

4.2 Simulation Results of Fuzzy Phase Selector

The results of fuzzy similarity based selector were compared to Mamdani-type fuzzy phase controller and to a non-fuzzy control algorithm. According to the simulation results, presented in Fig. 4–6, the performance of the maximal fuzzy similarity based control method was very good compared to the others. In the figures, the Minor-Major flow ratio represents the relative difference between major and minor flow traffic volumes.

4.3 Simulation Results of Fuzzy Green Extender

The average delays per vehicle of each control mode are shown in Figures 7, 8 and 9. The non-fuzzy vehicle actuated control method has the lowest delays with low volumes, while the fuzzy extenders seem to be more effective with high volumes. One reason for this is the importance (or the lack of it) of the fuzzy inference in low traffic demand conditions: traditional logic is able to handle situations with one or two approaching vehicles well, and fuzzy inference is not needed. However, when the volume increase, the fuzzy variables like “many”, “medium” and “a few” begin to have a real meaning.

The differences between Mamdani and similarity based extenders are small, but the Mamdani inference seems to fit better to low volumes, and the similarity inference seems to have better capacity. In fact, the mutual order of advantage between fuzzy extenders and VA-extender, and between Mamdani and similarity extender seem to vary in the same way, although the differences are much smaller between the fuzzy extenders. The COA defuzzication of Mamdani balances the extension decisions leading to somewhat “softer” control with fewer maximum and minimum extensions than the maximal similarity based decision making, which selects the rule with maximal similarity to the situation described by the input parameters. This may improve Mamdani extender performance with low volumes, because small numerical changes in the input have greater weight and lengthen the extensions. On the other hand, in high volume conditions the COA-method may prevent the maximum extensions by “softening” the decision with the weight of lower extension rules. This leads to lower capacity than the similarity extender has: the similarity extender launches easier the rule with maximum extension, because the output values of the other rules are not considered.

5 CONCLUSIONS

The performance improvement achieved using fuzzy phase selector was at good level good in all traffic volumes. On the other hand, one may argue that some phase selecting method will always be better than no selecting function at all. Still, the delay decrease gained was quite significant. Relatively high improvement was found especially with high volumes, when the fuzzy phase selector with maximal fuzzy similarity inference was used. However, if the volumes were still increased, the advantage gained with the selector would vanish, because when traffic volumes are very high and homogeneous there are no meaning to use phase selector at all. This was seen in the simulation with highest main and minor flow volumes.

The performance of Mamdani type selector and similarity selector were similar with small and medium traffic volumes, but with high traffic volumes, the method based on maximal fuzzy similarity gave clearly better results. This is probably due to the compromising characteristic of Mamdani's center of area –defuzzication, the crisp output value and the formulation of phase selecting rule base. The first rule 'if weight of next phase in order is high and the weight of last phase in order is any, then launch next phase in order' have in every decision making moment during high demand at least some weight in COA-defuzzification. There is always vehicles queuing in the red phase next to be green (according to the basic phase sequence), and the weight of next phase is quite often 'high'. So, the next phase is skipped seldom in Mamdani inference, because the 'high' weight of the next phase in order drags the COA further from the decision to skip the next phase. Instead, the similarity based inference selects the most similar rule to the input values and ignores the other rules. The first rule, launching the next phase in order, is neglected if one of the rules telling to skip the next phase has even slightly bigger similarity to the traffic situation. This feature makes the similarity inference's suitability better than Mamdani's for this kind of rule sets with crisp control action and a few choices: the 'right' decision is made more often, when the 'wrong' rules can not affect the system.

In the case of fuzzy green extender both fuzzy controlling methods gave quite good results compared to the vehicle actuated signal control, when the traffic volumes were relatively high. Between the inference methods, no significant differences were found. With low traffic volumes traditional VA-signal controller, based on non-fuzzy extensions, gave better results than the fuzzy extenders. In the situations with one or two approaching vehicles and small queues on the red phases, traditional logic is able to handle situations well, and the few queuing vehicles do not effect the average delays of the intersection. One reason for the poor performance of fuzzy logic in low volumes is the fact that low volumes lead to low number of approaching vehicles, and the advantages of the fuzzy inference in evaluating linguistic variables, like "many", "medium" and "a few" are not utilized. However, when the volume increase, the queue gathering in the red phase has to be taken into account when deciding the control actions, in order to improve the control performance. This fact, as well as the increasing need of evaluation of linguistic variables, improves the fuzzy extenders' performance in high demand conditions.

As in the case of phase selecting function, the COA defuzzication of Mamdani balances the extension decisions leading to somewhat "softer" control than similarity inference. This leads to fewer maximum and minimum extensions even when they are needed. Due to this fact, the similarity extender had better performance in high volumes. The Mamdani inference worked slightly better with low and medium volumes. The COA-defuzzication gives easier extensions for few approaching cars, because the center of area takes all the rules into account and the decision slides towards the rules with longer extensions, while the similarity inference sees only the rule of zero extension. This diminishes the intergreen times for Mamdani inference, because the phase is not changed so often than with similarity extender. In all, the differences caused by inference method were not very significant in the case of fuzzy green extender.

Compared to the Mamdani method, the maximal fuzzy similarity inference seems to fit especially well in the phase selector, which has a crisp output, several rules and only two choices for the control action. In this kind of situation, the maximal fuzzy similarity works better than Mamdani inference, because the better choice (more similar to the prevailing conditions) is chosen. In a control system with more continuous output, like the green extender's decision of the length of extension, performance of Mamdani inference is quite equal to the similarity method. Still, the Mamdani method and COA-defuzzification has its disadvantages especially in the limit of the system operating range. The facts, that the maximal fuzzy similarity has well-defined mathematical background, it is easy to use and it was in all slightly better than Mamdani in these two fuzzy control systems with different characteristics, indicate at least as good usability as the Mamdani type inference has. However, the choice of fuzzy inference method and the planning of the rule base should be done at the same time taking also the system restrictions into account, in order to form a well working system.

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Table 1 Detector locations.

Detector No.	**Controlled Signal Grp.**	**Distance (meters)**
1	I	100
2	I	40
3	II	40
4	III	40
5	IV	40
6	V	100
7	V	100

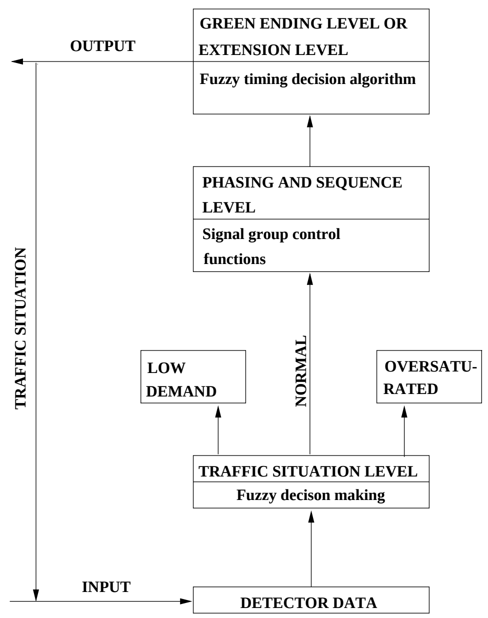

Fig. 1 - Fuzzy traffic signal control in different levels (6).

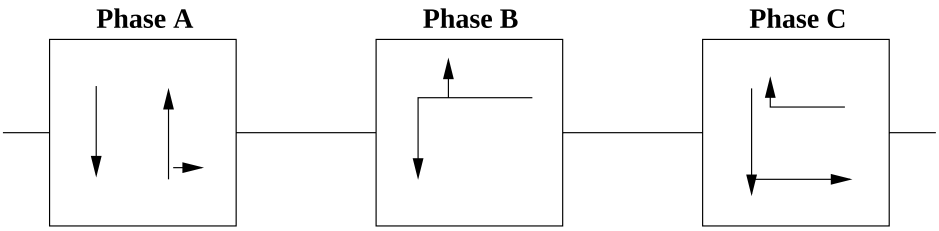

Fig. 2 - Basic phase sequence of the signal control at the test intersection.

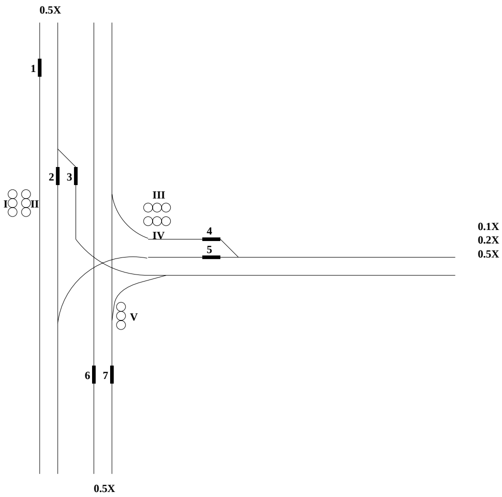

Fig. 3 - Layout of the simulated intersection area in Helsinki, Finland.

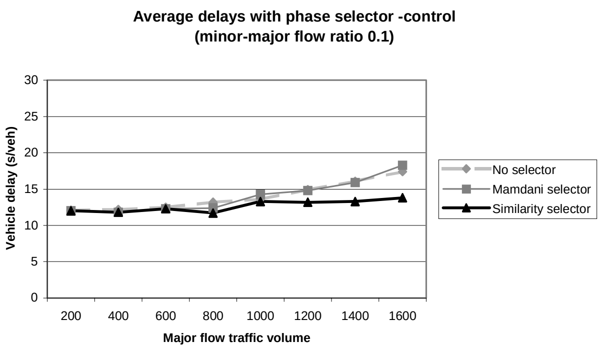

Fig. 4 - Average vehicle delays in phase selector -control simulations, major-minor flow volume ratio 0.1.

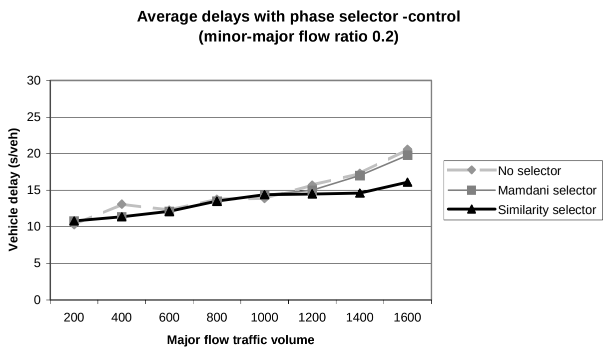

Fig 5 - Average vehicle delays in phase selector -control simulations, major-minor flow volume ratio 0.2.

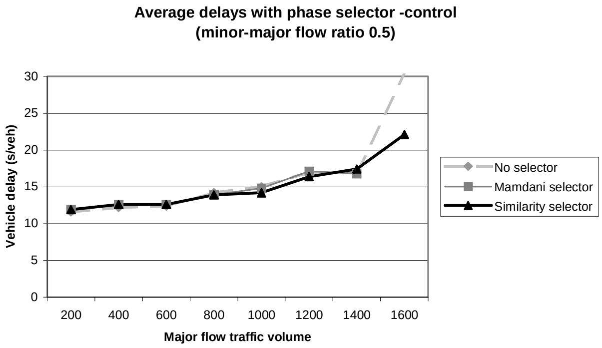

Fig. 6 - Average vehicle delays in phase selector -control simulations, major-minor flow volume ratio 0.5.

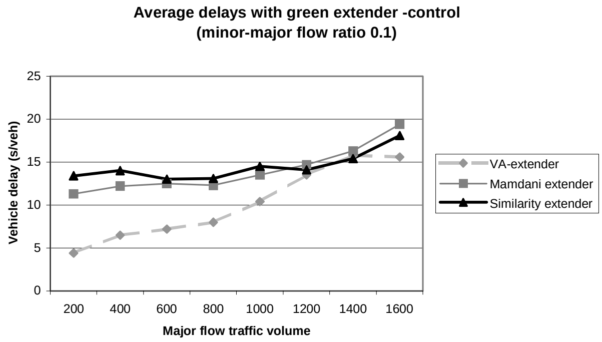

Fig.7 - Average vehicle delays of green extender -control simulations, major-minor flow volume ratio 0.1.

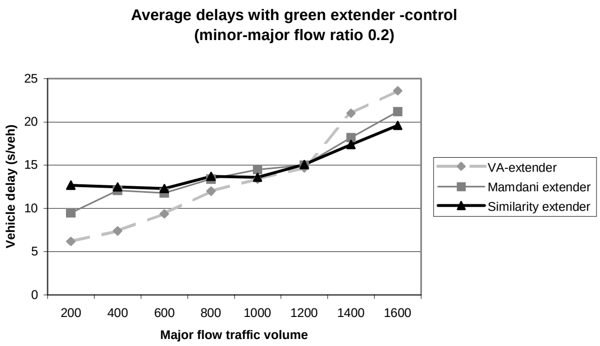

Fig. 8 - Average vehicle delays of green extender -control simulations, major-minor flow volume ratio 0.2.

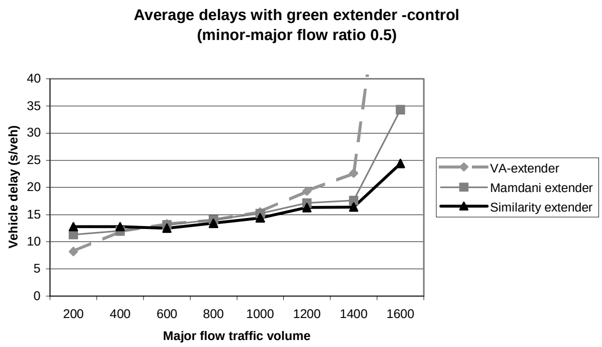

Fig. 9 - Average vehicle delays of green extender -control simulations, major-minor flow volume ratio 0.5.