# THE MULTI-OBJECTIVE OPTIMISATION OF A TRAFFIC CONTROL SYSTEM

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## INTRODUCTION

The practice of optimising signal timings to maximise vehicle throughput or minimise vehicle delay is well-established, and can be carried out off-line, for static vehicle flows, or on-line, responding to changes in flow at given intervals. The methods used for the optimisation process vary, from hill-climbing, as in TRANSYT (Vincent *et al*, 1980), to Genetic Algorithms (GAs), as in the Cabal system, described in (Clement and Anderson, 1997). The output of all these methods is a series of fixed time signal plans. The drawback of this approach is its inability to respond quickly to unexpected fluctuations in demand, which are all too frequent in today's congested urban environment. The popularity in the UK of systems such as SCOOT (Hunt *et al*, 1981) for urban networks, and MOVA (Pierce and Webb, 1990) for isolated intersections, shows that there is a significant demand for vehicle-responsive traffic signal control. When originally developed, these systems were concerned solely with reducing delay to road vehicle users. However, a changing climate of concern for the welfare of a wider range of road users, and a desire to be able to implement more sophisticated techniques of traffic management, such as gating and bus priority, means that these systems have had to be enhanced, in order to achieve the new requirements of their users (Bretherton *et al*, 1998).

It is now more important than ever to incorporate a wide range of policy objectives into urban traffic signal control systems. In the UK, the Government recently published its White Paper on the Future of Transport, "A New Deal for Transport: Better for Everyone" (DETR, 1998). It covers a wide range of proposed policy initiatives, including the promotion of walking and cycling as part of a sustainable transport environment. Although traffic signal control cannot provide the complete solution, it has an important part to play in the realisation of these

objectives, for example by "reducing waiting times for pedestrians at traffic signals and giving them priority in the allocation of time at junctions where this supports more walking."

The Transport Operations Research Group (TORG) carried out a Delphi study amongst the UK transport community with the aim of ascertaining the range of objectives that could pertain to various scenarios, such as an isolated intersection, or an urban network. Detailed results from the two rounds are given in Anderson *et al* (1998a), the general outcome being that it was unrealistic to try to reach consensus on the objectives of traffic signal control and their relative priorities, since every installation will be faced by different constraints and requirements, and these may vary over time. The study served to highlight the fact that one of the most important features of a traffic signal control strategy is flexibility.

The controller described in this paper was designed from the outset to incorporate a broad spectrum of policy objectives. This was to be achieved by optimising the parameters governing the behaviour of the experimental road-user-responsive signal controller. This optimisation process operates at a different level from the optimisation of the signal timings themselves, as the optimised controller is still free to set the signals in response to the second-by-second demands. Different parameters will alter the way in which the controller responds to the demands for greentime from the various road user groups.

## OVERVIEW OF PAPER

Previous experience in TORG of developing a fuzzy logic traffic signal control system for an isolated intersection (Sayers *et al*, 1996) demonstrated its potential to provide the required flexibility of performance. In this controller a competitive technique is employed in which a value for each phase representing the importance of giving it green time (henceforth referred to as 'urgency') is derived each second by means of several fuzzy control modules. The urgency values are derived from data supplied by inductive loop detectors on the junction approaches (upstream and at the stopline) and signal timing data. In a network environment, data relating to neighbouring junctions, which indicate the expected arrival of a platoon from upstream junctions and the possibility of spill-back at downstream junctions, can also be used. The individual phases compete for the available green time, since their respective urgency values are used as the basis for the decision whether to change the signals, and if so, which signals should be green next.

The behaviour of a fuzzy logic control system depends on a number of parameters which are often derived initially using an ad hoc rule of thumb method. While these may seem intuitively sound, it is necessary to ensure that they are having the desired effect on the operation of the controller by testing and optimisation. There are two main candidates for optimisation in a fuzzy

logic control system. These are the fuzzy set definitions (membership functions) for the input and/or output variables, and the rulebase, which constitutes the mapping between combinations of input variables and the output. These two components are related and changes to either (or both) can have a profound effect on the operation of the control system. In this study, the fuzzy set definitions are optimised as this permits wide variation in the performance of the controller, without losing the transparent and intuitive nature of the rulebase. The GA optimisation method was found to be suitable for this problem.

A GA is an optimisation and search tool that uses probabilistic search methods based on ideas from natural genetics and evolutionary principles (Goldberg, 1989). GAs are regarded as general purpose and robust. Various methods of using GAs to optimise fuzzy logic systems have been applied in a range of engineering fields with good results. For a bibliography of published work in the field of GA optimisation of FL systems see Cordón *et al* (1996).

The aim of this study is to optimise the signal controller off-line with respect to a number of diverse criteria, yielding a range of solutions with different attributes. For example, one solution might reduce vehicle delay at the expense of increased pedestrian delay, while another distributes the greentime more evenly. As the Delphi study showed, the relative weights of these criteria cannot be determined in advance in order to aggregate them into a single objective. An appropriate technique for multiple objective optimisation is the Multiobjective Genetic Algorithm (MOGA) which permits a range of optimal solutions to be found, rather than imposing an arbitrary weighting of the various criteria to be optimised to lead to a single solution (Fonseca and Fleming, 1995). Each optimal solution reflects a different trade-off between the desired objectives. This allows a set of solutions to be found, each of which is optimal with respect to some criteria, with a trade-off against the others. When implementing the controller in a particular context, the solution that performs best with respect to the desired objectives for that context can be chosen from the optimal set.

For each candidate solution (set of controller parameters) generated by the MOGA, the performance of the controller configured according to those parameters is evaluated by means of microscopic simulation. The simulator used is VISSIM (Fellendorf, 1996), a microscopic simulator operating in discrete time steps of 1s, and based on a psycho-physical vehicle driver model. It outputs a range of performance measures for each simulation run and is augmented by the MODEM model (available in the UK from TRL) which allows vehicle emissions to be estimated from the detailed vehicle-by-vehicle speed and acceleration profiles.

The aim of the optimisation of the parameters of the fuzzy logic signal controller is to identify a range of robust parameter sets which correspond to different policy objectives. To be considered robust, a given parameter set should perform well with respect to the chosen objectives in different simulated traffic scenarios, varying the flow profiles and traffic mix. In

consultation with traffic engineers at Newcastle City Council, a number of realistic strategies for an isolated junction will be identified and the appropriate parameter sets will be tested thoroughly against these criteria.

## THE FUZZY LOGIC SIGNAL CONTROLLER

### Introduction

Fuzzy logic is now well-established as a feasible method of controlling vehicle-responsive traffic signals and has been successfully implemented in a number of studies both theoretical and practical, as described in Hoogendoorn *et al* (1998). Algorithms based on fuzzy logic can be incorporated into traffic signal control systems at different levels and can be applied to different problems within the signal control context. At a level which requires little change to existing traffic responsive signal control systems, fuzzy logic modules can be integrated into conventional algorithms, as a substitute for functions describing complex and/or non-linear relationships between variables, such as the relationship between gap, occupancy and traffic density. The advantage of using fuzzy logic is that it is transparent and easy to modify, without sacrificing either the complexity of the relationship modelled or the accuracy of the model.

In a network context, fuzzy logic can be used to calculate cycle length, splits and offset, (Chiu and Chand, 1993) and also to determine when coordination of junctions is required in order to alleviate the traffic at critical intersections (Tzes *et al*, 1995). Fuzzy logic is often used to identify and recognise certain patterns of traffic flow, allowing the most appropriate signal timings to be defined and implemented as the traffic situation changes (Hoyer and Jumar, 1994 and Zhou *et al*, 1997). Many of these proposed systems have been tested on street (for example Hoyer and Jumar, 1994), and some are in full operation, such as the application described in Zhou *et al* (1997) and the system in operation in Posnan, Poland, developed by Kaczmarek and Rakiewicz (1980). The systems of fuzzy logic traffic signal control proposed by Niitymäki and Kikuchi (1998), and Niitymäki (1998), based on the fuzzy extension principle used in the seminal work by Pappis and Mamdani (1977), address the questions of bus priority at an isolated intersection, and varying degrees of friendliness to pedestrians and vehicles at a signal controlled pedestrian crossing.

More thorough reviews of the applications of fuzzy logic to traffic signal control can be found in Sayers (1997) and Hoogendoorn *et al* (1998).

### Competitive traffic signal control

The control of traffic signals is one of a class of problems where a limited resource is required

by a number of potential users, and the quantity of that resource is not always sufficient to meet demand. The users are competing against each other for a share of the resource and thus the control problem could be termed *competitive*. In the case of traffic signal control, the resource in question is green time, and the problem is made more complex by its temporal aspect and the ever-changing and stochastic nature of the demand. This means that the allocation of green time must be constantly reviewed as time passes and the traffic situation changes, in order to distribute it in the desired manner.

One approach to this type of problem is to derive a value for each user which reflects their claim on the limited resource, and to use these values to determine the appropriate balance of distribution of the resource. In the case of traffic signal control, a user can be defined as an individually controlled stream of traffic (vehicular or pedestrian). This value is henceforth referred to as the *urgency*, meaning the urgency with which the stream requires green. In the scheme of signal control, each of these streams is controlled by one *signal group* (or phase), and sets of non-conflicting signal groups can be defined, which are known as *stages*. Thus in competitive traffic signal control, an urgency is derived for each signal group and these urgencies are then used as the basis for the control decisions.

The use of an urgency measure for each signal group does not dictate the method of control, nor the frequency of the control decisions. It is a tool which can be used in different ways. For example, it could be used in a stage-based control system with fixed cycle time and variable stage extensions beyond the minimum green time of each stage, within a fixed sequence of stages. Whenever a decision needs to be made about whether to grant an extension of green time to the current stage, the urgency measures are calculated and used as the basis of that decision. At the more flexible end of the control spectrum, where the controller can combine the signal groups in any non-conflicting way with no fixed stage sequence or cycle time, the urgency values can be used to determine which signal group (or set of signal groups) requires green time most urgently, and the mechanism to give that signal group green time can be set in motion. In a system controlling a single intersection, the urgency values will feed directly into the single intersection control logic, whereas in a system governing a network, there may be further control levels determining the most appropriate overall control policy, which are informed by the urgency values throughout the network.

The urgency values are a buffer between the raw data and the higher levels of control logic, forming the basis of the main signal control decisions. This separation of the raw data from the higher level control means that if the nature of the available data changes, it is possible to cushion the control level from those changes, by adapting the interface between the two levels. This is of particular relevance if different methods of vehicle detection are to be introduced such as microwave, infra-red or video (Willott *et al*, 1998). These new detection methods result in the availability of different information about the traffic situation in addition to (or instead of)

the conventional values associated with inductive loop vehicle detection. For each different combination of inputs, an interface could be developed whose outputs present the same information to the controller. This results in a degree of independence between the controller and the input data, which reduces the need to modify or redesign the control strategy, thus facilitating the introduction of novel detection methods.

Using the concept of urgency in the control logic rather than the raw data received from the detectors and signals makes it possible to formulate the control logic in a general way, and makes it easier to encode. In a complex system, any reduction in complexity making the operation of that system easier to understand is likely to reduce errors and facilitate assessment and testing. In the controller described in this paper, the urgency values are derived from the raw data using a fuzzy logic interface. This method has also been used in the controller described in Sayers *et al* (1996).

**The derivation of urgency values**

The way in which urgency is derived depends on the data which are available to the controller. The configuration used for this fuzzy controller is one which is commonly found in signal controlled installations in developed countries, where the intersection has inductive loop detectors on the approach roads, at the stop-line and further upstream, and push button detectors for pedestrians to register their request for green. In a situation where the available data differed from this (for example if above ground detection equipment such as passive infra red or video image processing was installed), the urgency could be derived using those data in the most appropriate way. The interpretation of the detector data depends on the setting of the corresponding signal group. If a signal group is green, then the stop-line detector will register gap, count and occupancy which allow the nature of the traffic flow over the stop-line to be determined. The upstream detectors signal the quantity and density of the traffic which is expected to arrive at the stop-line after a certain number of seconds, or join the end of the queue. If a signal group is red, however, the stop-line detector can only register presence or absence of a waiting vehicle, thus allowing the time which that vehicle has been waiting to be calculated.

In the fuzzy controller, the urgencies are calculated in different ways depending on the current setting of the signal group and whether it controls vehicles or pedestrians. Table 1 shows how the data are used in the different situations.

| | Data | Type | Signal colour | Effect |
|---|---|---|---|---|
| 1 | Smoothed gap at the stop-line detector | Vehicle | Green | Indicates the departure rate. As it gets larger, the urgency decreases. |
| 2 | Smoothed gap at the upstream detector | Vehicle | Green and Red | Indicates the arrival of more distant approaching vehicles. As it gets larger, the urgency decreases. |
| 3 | Queue - estimated number of vehicles between stop-line and upstream detectors | Vehicle | Green and Red | Indicates likely presence or absence of a queue. Higher numbers of vehicles may cause the urgency to be increased. |
| 4 | Number of seconds since vehicle presence was detected waiting at stop-line in redtime. | Vehicle | Red | As it gets larger, vehicle waiting time increases causing urgency to increase. |
| 5 | Number of seconds since pedestrian request was received. | Pedes-trian | Red | Indicates pedestrian waiting time. As it gets larger, urgency increases. |
| 6 | Number of seconds since the last period of green for this signal group. | Pedes-trian | Red | The longer the period that has elapsed since the pedestrian signal was last green, the higher the urgency. |

*Table 1. Input data used to derive urgency values*

**The fuzzy logic component of the controller**

Each of the six inputs described in Table 1 is defined by three triangular fuzzy sets, denoted LOW, MEDIUM and HIGH, with the exception of the Queue input (number 3 in Table 1) whose MEDIUM set is trapezoidal. Graphical representations of the fuzzy sets defined for two of these inputs (numbers 5 and 6 in Table 1) are shown in Figures 1a and 1b.

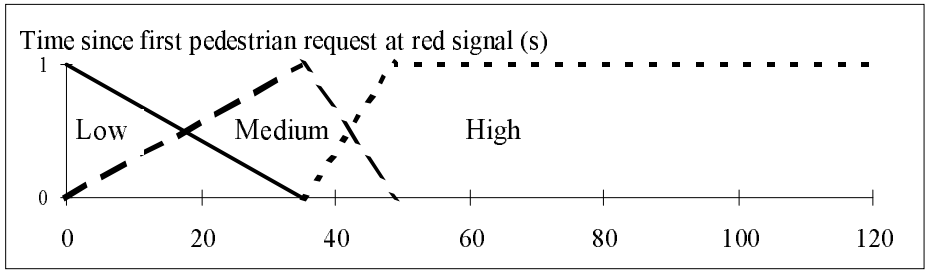


*Figure 1a. Fuzzy sets for the time since the first pedestrian request at a red signal*

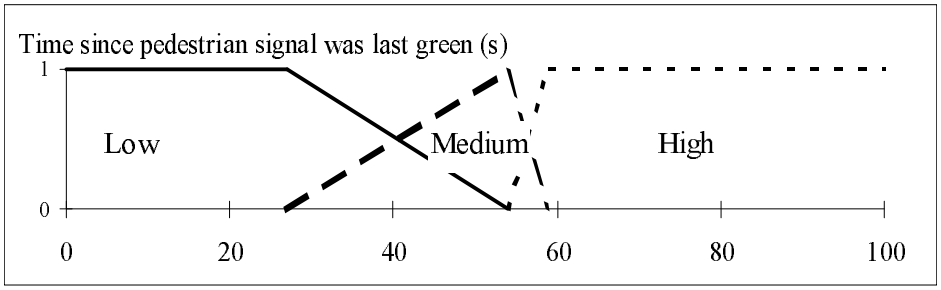


*Figure 1b. Fuzzy sets for the time since the pedestrian signal was last green*

The positions of the bases and apexes of the fuzzy sets shown are merely examples, being subject to change in the optimisation process. The vertical axis represents the degree of membership of each set, and the horizontal axis represents the number of seconds elapsed since the first pedestrian request when the pedestrian signal was red (Figure 1a) and since the pedestrian signal was last green (Figure 1b).

As each variable is defined by three fuzzy sets, each rulebase is a 3x3 matrix, and its output is the urgency of the signal group in question. A typical rulebase is shown in Figure 2. The output variable is defined by five fuzzy sets (VERY LOW, LOW, MEDIUM, HIGH and VERY HIGH), all triangular, and of equal size. In some cases, such as the red pedestrian signal shown in Figures 1 and 2, the urgency is derived simply using the two input variables and the rulebase whose output is the urgency. In other cases, such as a red vehicular signal, the process is 2-tiered, as shown in Figure 3.

| Time since signal was last green \ Time since first pedestrian request in red time | LOW | MEDIUM | HIGH |
|---|---|---|---|
| LOW | VERY LOW | LOW | MEDIUM |
| MEDIUM | LOW | MEDIUM | HIGH |
| HIGH | MEDIUM | HIGH | VERY HIGH |

*Figure 2. Rulebase to derive urgency of pedestrian signal group that is red.*

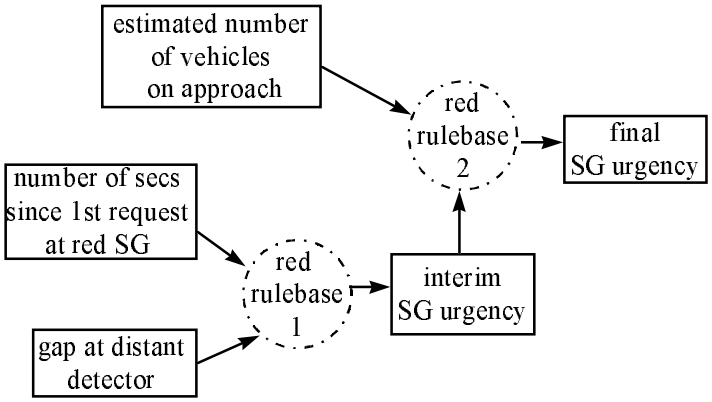


*Figure 3. Derivation of urgency for red vehicular signal.*

## EVALUATION OF THE FUZZY LOGIC SIGNAL CONTROLLER

### Evaluating the Signal Controller

The evaluation of a vehicle-responsive traffic signal controller is not a simple matter, due to its dynamic and adaptive nature. The controller's response to the approaching traffic affects the subsequent flow of traffic which in turn affects the operation of the controller, and the control of the signal for each approach is determined not only by the traffic it controls, but also by the traffic on opposing approaches. These factors mean that the most practical and satisfactory way to test the controller is using microscopic simulation, which models a junction with a given topology and other parameters such as input flows, turning movements, traffic mix and desired speeds. Pursula and Niitymäki (1996) discuss the rôle of microscopic simulation in the evaluation of traffic signal control. It is also important to take into account both a range of typical flow patterns and the inherent variability within each flow pattern when assessing the controller performance, as discussed by Fox *et al* (1998).

The simulator used for this study is VISSIM (Fellendorf, 1996), a microscopic simulator operating in discrete time steps of 1s, and using a psycho-physical vehicle driver model. Factors used in the MODEM model (available in the UK from the Transport Research Laboratory) allow vehicle emissions and fuel consumption to be estimated from the detailed vehicle-by-vehicle speed and acceleration profile, which can be part of the VISSIM output. The MODEM model has factors for 12 different categories of car covering various engine sizes and fuel types. When estimating the emissions and fuel consumption from the simulation runs, a typical traffic mix derived from the Vehicle Licensing Statistics 1996 (DOT, 1996) was used.

In order to test the signal controller in a realistic environment, the four arm intersection described by Allsop (1992) is used, with the addition of two conflicting bus lanes. This intersection has 13 phases (including four for pedestrians), which can be combined in up to 16 different ways (16 possible stages), although the signal controller under test only uses six stages, of which five are vehicle only and one is pedestrian only. Upstream of the junction on each approach is a fixed-time signal controlled junction, which gives a more realistic platoon-like flow of vehicles approaching the junction than a random generation of arrivals at a given flow rate. Detectors are placed on each approach lane just after the upstream signal (approximately 125m from the main stop-line) and at the stop-line. Figures 4a and 4b show the intersection in detail.

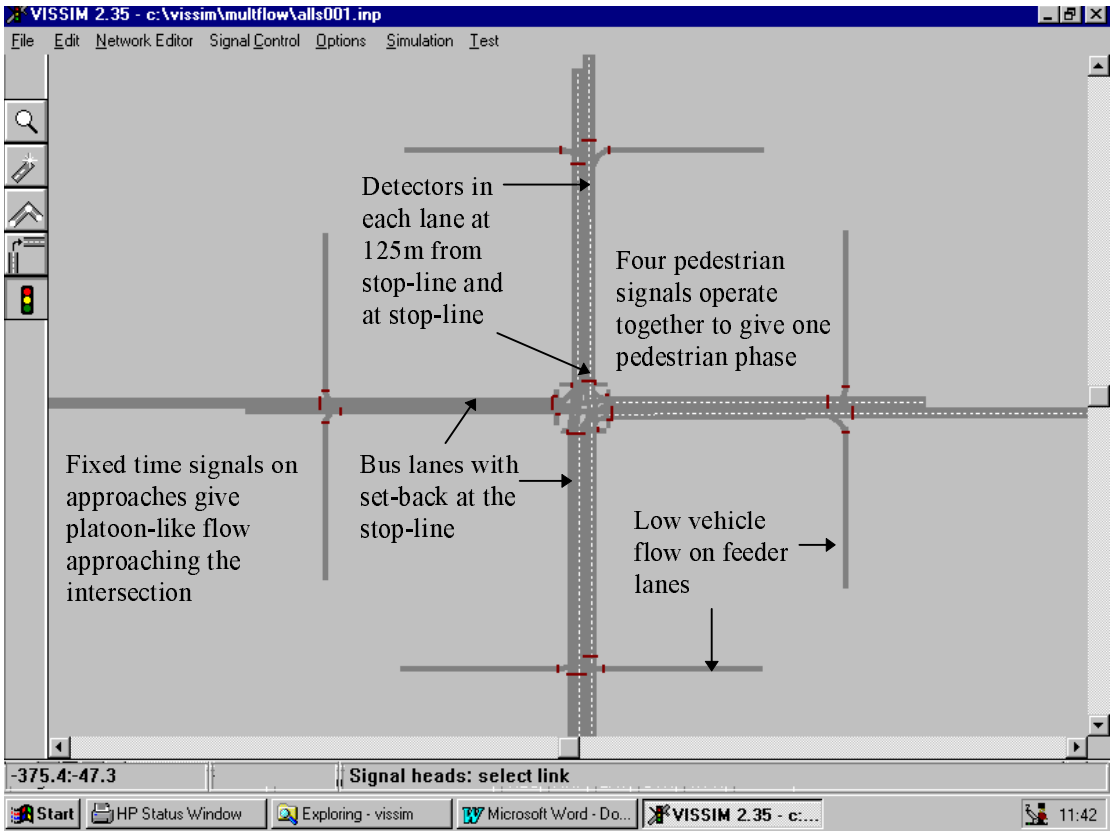


*Figure 4a. Plan of the test intersection*

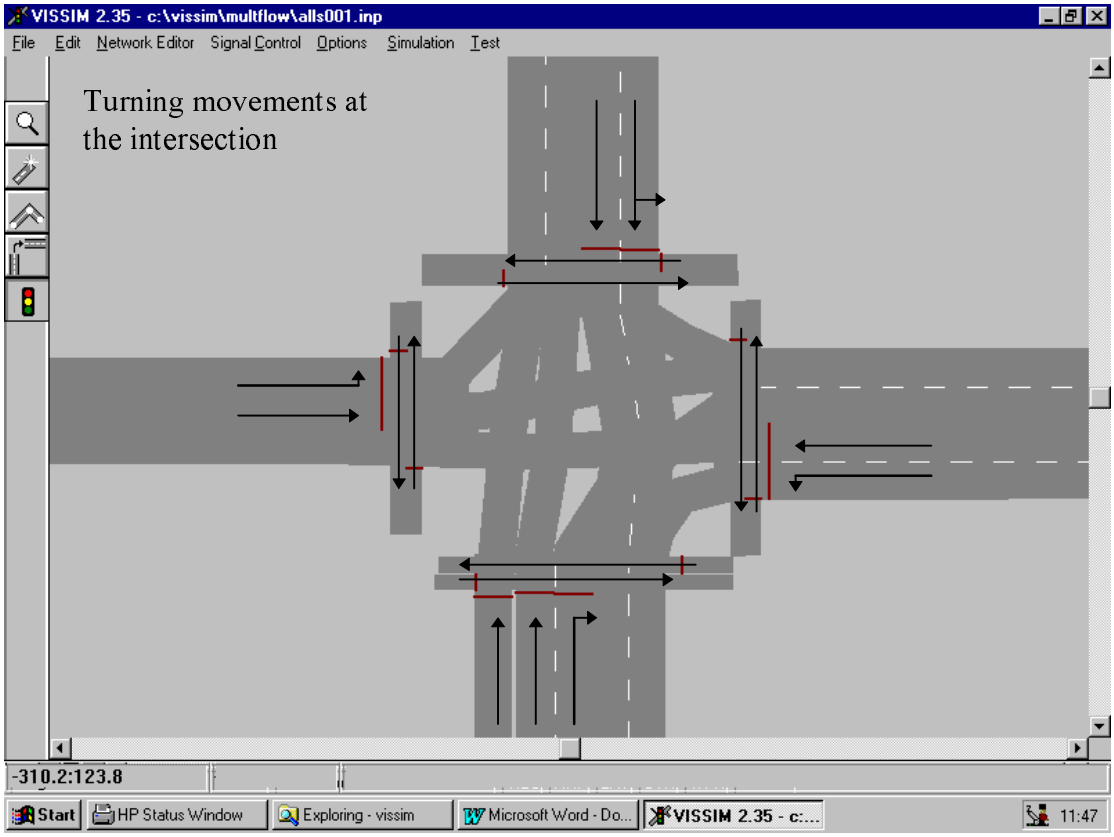


*Figure 4b. Close up of the intersection showing turning movements*

For the initial implementation of the MOGA, evaluation of each candidate solution is done using different constant flow rates in a 15 minute simulation. More realistic flow profiles incorporating peaks will also be used in subsequent tests, and the resulting optimum controller parameters will be compared with those derived previously.

For each parameter set to be tested, the controller is evaluated in a way that allows its performance to be monitored with respect to the different criteria under consideration. It is necessary to have measures of :

- specific vehicle emissions,
- waiting time for pedestrians,
- vehicle delay,
- vehicle stops, and
- delay to public transport vehicles.

The trade-offs between two groups of these objectives can be seen in Figures 5 and 6. Each line represents one controller configuration, with the objectives on the x axis and the performance of the controller shown on the y-axis. Trade-offs between adjacent objectives result in the crossing of the lines between them whereas concurrent lines indicate that the objectives are not in

competition. Thus Figure 5 shows that the pedestrian measures conflict with their vehicular counterparts, whereas Figure 6 shows that the minimisation of oxides of nitrogen is not compatible with the minimisation of the other environmental effects. Further details of some of the evaluation data acquired from the simulation runs can be found in Anderson *et al* (1998b).

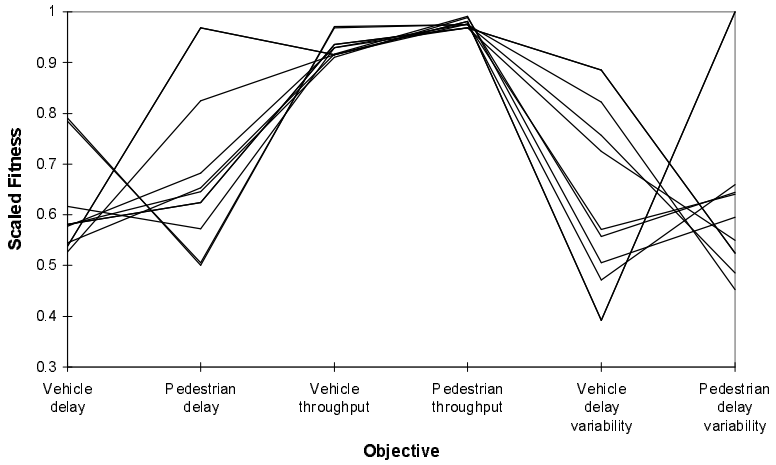


*Figure 5. Trade-off graph for measures of vehicle and pedestrian delay.*

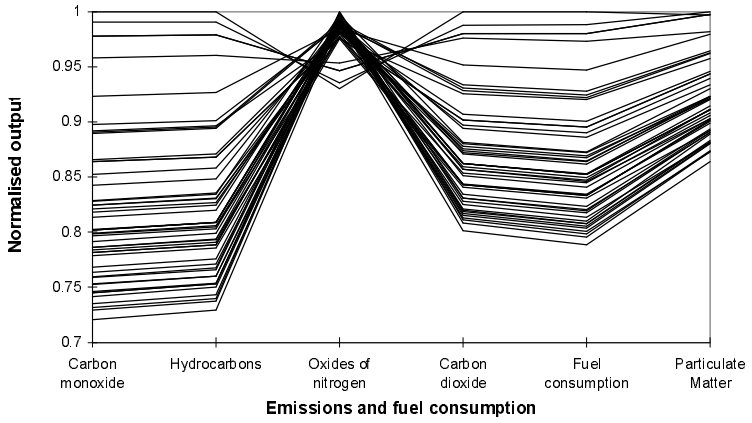


*Figure 6. Trade-off graph for emissions and fuel consumption.*

## The Effect of Changing the Controller Parameters

Before embarking on the MOGA, a feasibility study was carried out to determine the controller's sensitivity to changes in its membership function parameters. This involved evaluating a signal control program fifty times, each time using a different random set of membership function parameters. It was shown that altering these parameters could significantly affect the operation of the controller (Anderson *et al*, 1998b).

A different set of membership function parameters for an input variable results in differently shaped fuzzy sets for that input variable. This results in a different urgency being assigned to the signal groups affected by that input variable which in turn will result in the signal controller making a different decision about how to set the signals during the simulation, thus affecting the controller's overall performance (judged by the various criteria) for better or worse.

Taking the example illustrated in Figures 1 and 2, the urgency of a pedestrian signal group that is currently red is determined by the number of seconds that have elapsed since the first pedestrian was detected waiting at the crossing and the number of seconds since the signal group was last green. There are a number of rules such as "if *waiting time* is HIGH and *number of seconds since last green* is HIGH then *urgency* is VERY HIGH" which map the input data to a particular urgency. With different membership function parameters, the degree to which given inputs are considered high will alter, and thus alter the output of the rule. One set of parameters might have the effect that a pedestrian wait of 30 seconds is considered HIGH, whereas with a different parameter set, the same waiting time could be considered MEDIUM, with HIGH only reached when the pedestrian wait reaches 60 seconds. One would expect the pedestrians to have to wait for shorter times before getting green in the former case, all other things being equal.

Figure 7 (below) shows the performance of the controller configured using four different parameter sets, each of which was tested in simulation using ten different random seeds. The two lines show vehicle delay (diamond markers, solid line) and pedestrian delay (square markers, dotted line).

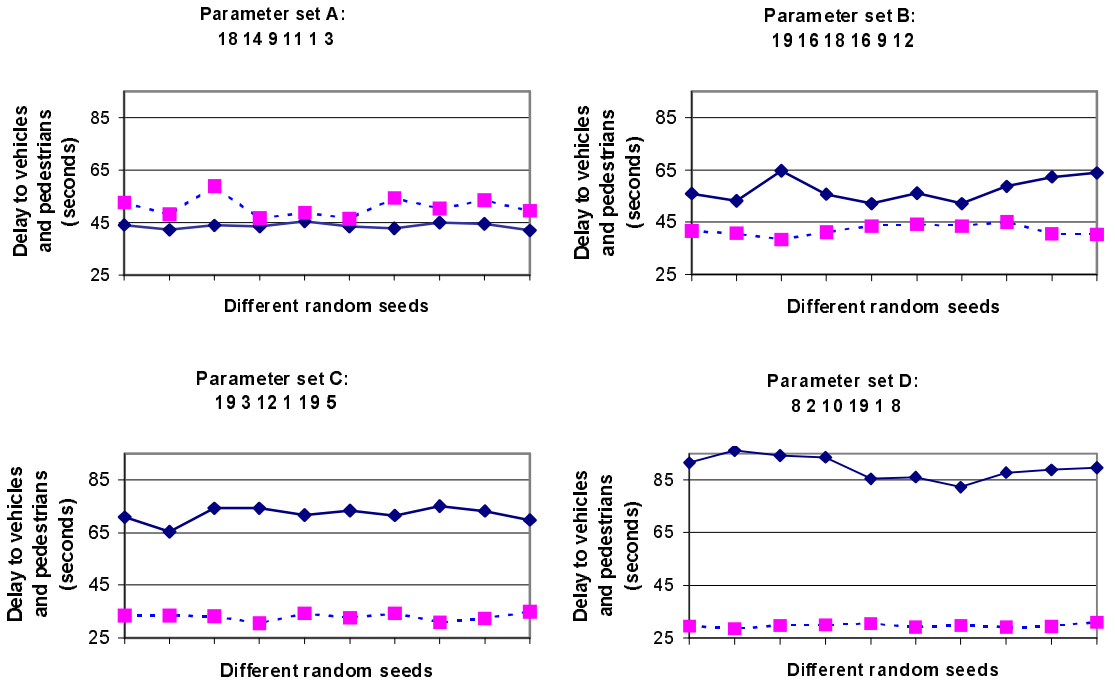


*Figure 7. Performance of controller using four randomly chosen parameter sets.*

### Smoothing the Impact of Different Random Seeds

Another factor affecting the performance of the controller is the choice of random seed which governs the arrival pattern of vehicles and pedestrian in the simulation for a given flow profile. These variations are small compared to those found when the parameter set is changed, but not insignificant. Figure 7 illustrates this point. Although the effect of changing the random seeds from one simulation run to another is not as great as that of changing the parameter set, it still has an impact on the comparison of different parameter sets and could lead to inconsistent evaluation. For example, when comparing the performance of two parameter sets with respect to pedestrian delay, one may be better when the simulation is run with a seed of 1, and the other may be better when the simulation is run with a seed of 2, although the overall flow rates are the same for both simulations. In order to minimise the bias that may result from comparing results obtained using a single seed, comparisons have been based on performance indicators averaged over simulation runs using three different seeds.

## OPTIMISATION OF THE CONTROLLER PARAMETERS

### Optimising Fuzzy Systems

One criticism often levelled at the principle of fuzzy logic control is the subjectivity of the fuzzy set definitions and the rulebases which determine the system performance. In the case where the desired output of the fuzzy logic control system is known for each combination of input values, the appropriate membership functions and/or the rulebase can be found using neural networks in a neuro-fuzzy framework, or tuned by some other method which uses the known output error as a guide. In the case of a complex, open loop system such as the road-user-responsive fuzzy logic traffic signal controller under discussion, the "right" answer can only be determined *a posteriori*.

### Choosing an Optimisation Method

The most appropriate optimisation method for a given problem depends to a large extent on the nature of the search space, in terms of its size and complexity, the method of evaluating each solution and the nature of the desired result.

Exploring the effects of changing the fuzzy logic signal controller parameters is not a small task, due to the number of parameters required to characterise the membership functions of the input variables. It is not possible to optimise the parameters for each variable in isolation because each affects the overall balance of urgency between the competing signal groups. The fuzzy logic signal controller has six input variables, as detailed in Table 1, which are used to derive the

urgency values. The shapes of the fuzzy sets characterising each input variable can be defined using three parameters, representing the following distances:

- from the origin to the apex of the MEDIUM set (which equals the third point of the LOW set);
- from the apex of the MEDIUM set to the apex of the HIGH set, and
- from the apex of the HIGH set to the maximum value in the universe of discourse.

Taking the example in Figure 1a, these three values would be 35, 13 and 72. Using three levels for each of these distances, a set of 19 different fuzzy set configurations was devised for each input variable. Thus the fuzzy sets which characterise these six variables can be defined using six parameters, specifying which of the 19 predefined parameter sets should be used. These parameters change during the optimisation process, and determine the way in which the signal controller functions.

There are thus $19^6$ different combinations of parameter values. It may be possible to search a space of this size if each solution can be evaluated quickly and easily, but in this problem each solution has to be evaluated using several microscopic traffic simulation runs, a processor-intensive and time-consuming operation. An optimisation technique which requires more sparing evaluation of solutions is necessary in this case.

Since the optimisation problem in question has multiple and possibly conflicting attributes (i.e. the range of different policy objectives outlined above), a search technique which yields many good solutions is preferable to one which attempts to find a single "best" solution. The collection of good solutions should contain solutions which excel for one or a few objectives, with a trade-off against conflicting objectives. There may also be solutions which balance the trade-offs to give reasonable performance with respect to all objectives, but outstanding performance with respect to none.

**Genetic Algorithms**

In this study the optimisation method of GAs has been adopted. This method has its roots in a simulation of the natural selection process, working on a population of possible solutions in parallel, combining them to produce successive generations and eventually converging to a group of near-optimal solutions. The technique has a stochastic element in that it makes small random changes (mutations) and also in the generation of the initial random population. However, it is also directed in that solutions which perform better (have a higher fitness) are more likely to produce offspring to take part in the next generation.

The main characteristic of the GA optimisation technique which makes it particularly suitable for the task of optimising the fuzzy logic controller parameters is that many different areas of the search space are considered simultaneously, due to the random selection of the initial population, and the crossover and mutation operations which operate on a probabilistic basis. The danger of becoming caught in local minima is thus reduced, as is the reliance on appropriate starting values.

**Multiobjective Genetic Algorithms**

In order to achieve the desired flexibility, the parameters of the signal controller must be optimised with respect to a number of diverse criteria. Traditionally, this kind of problem has been solved piecemeal by using a number of different weighting coefficients for each criterion, reflecting the relative importance of each criterion in determining the final solution. For each chosen set of coefficients, the weighted criteria are summed to give a single objective. These may then be optimised using an appropriate method, yielding a solution corresponding to each coefficient set. The MOGA eliminates the need to use weighting coefficients by permitting a diverse range of optimal candidate solutions to be found. Each optimal solution reflects a different trade-off between the desired objectives. When implementing the controller in a particular context, the solution that performs best with respect to the desired objectives for that context may be chosen from the optimal set by the user.

The MOGA uses the Pareto ranking method to rank the solutions of each generation by the number of other solutions which dominate them. For one solution x to dominate another, y, the value for at least one attribute of x must be better than the value for the same attribute of y, with the value for every other attribute of x better than, or equal to its counterpart in y. The Pareto ranking method is then used to guide the process of selecting parents for the next generation. Normally, a GA will converge to a single optimal solution, but when the problem has multiple attributes, the GA must be modified to maintain the diversity of the population, which then converges to a surface (the Pareto-optimal front) rather than to a single point. This front represents the boundary between the feasible and the infeasible solutions. This is accomplished using the mechanism of *niching* which assigns a relatively lower fitness to good solutions in over-populated areas of the search space, thus reducing their chance of being selected as parents. This technique is described more fully in Horn *et al* (1994).

In the example of a signal control program whose parameters were to be optimised against the conflicting criteria of reduction of delay to vehicles and to pedestrians, the outcome of the MOGA should be a collection of solutions from which the appropriate solution could be chosen according to whether the signal controller should reduce delay to vehicles or to pedestrians.

In addition to the primary criteria, such as delay to vehicles and pedestrians, there may be secondary criteria which allow the differentiation of solutions which appear to be similar when judged solely on the primary criteria. For example, measures of the distribution of the delay between the traffic streams could help to choose between two solutions whose overall mean vehicular delays were the same. This concept is also discussed by Chipperfield and Fleming (1997).

**The Mechanics of the Optimisation Process**

The complete optimisation process combines all of the processes described so far in a complex iterative loop whose end result is the set of Pareto-optimal fuzzy set parameters which govern the signal controller's operation. Figures 8a-8c illustrate the processes at work within the MOGA, with processes represented by rectangles and data storage represented by ellipses. The arrows indicate the sequence of events and the passage of data. The term "solution" means one complete set of fuzzy membership function parameters for each of the input variables.

The event loop shown in Figure 8a continues until either a fixed number of iterations (generations) has been completed, or until some other stopping criterion has been reached, such as the attainment of a minimum amount of improvement from one generation to the next. Figures 8b and 8c expand the two boxes in Figure 8a describing the main actions within the loop.

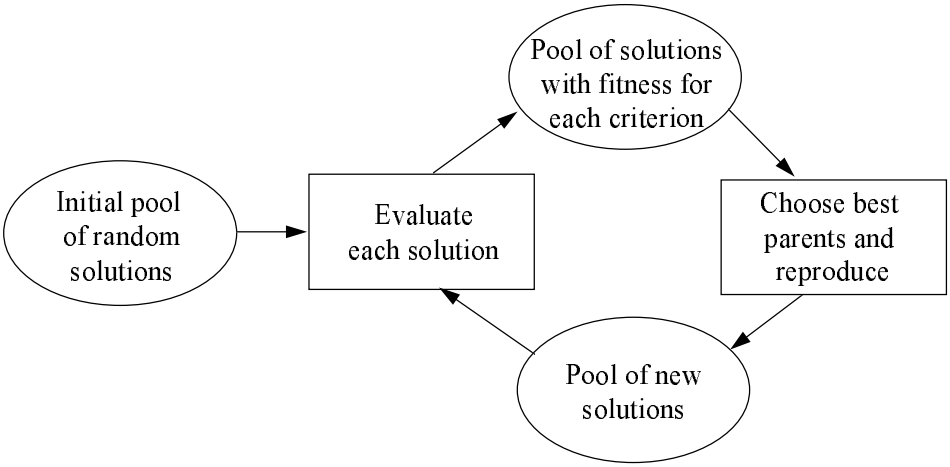


*Figure 8a. Sequence of events within the MOGA*

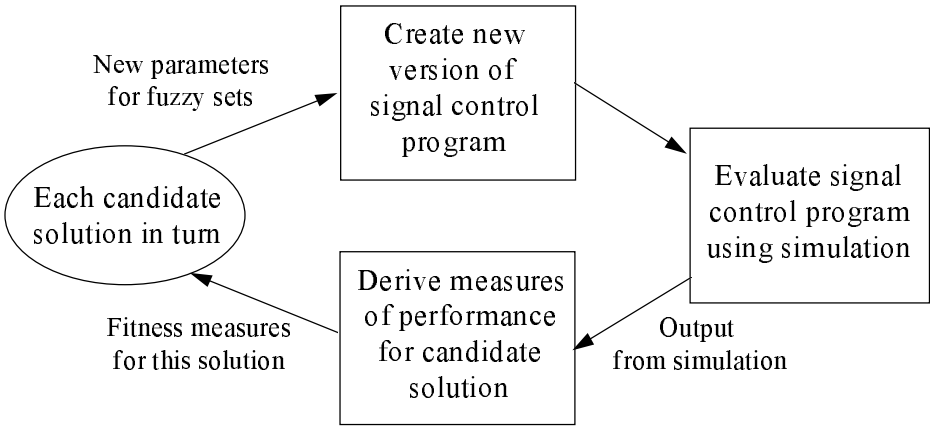


*Figure 8b. Process of evaluation of each candidate solution*

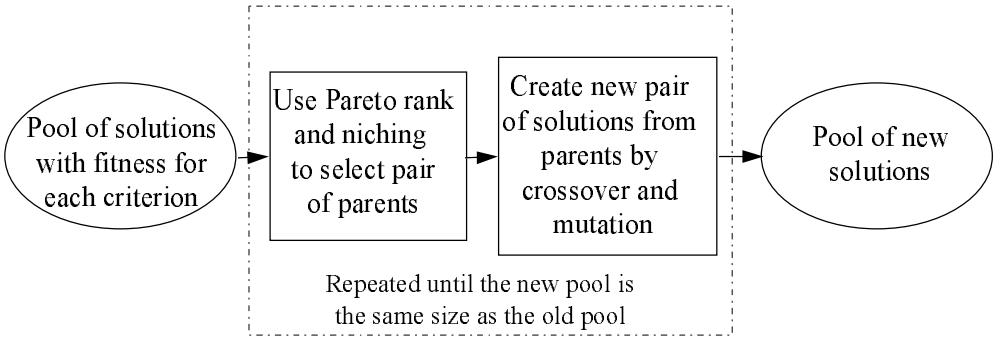


*Figure 8c. Process of creating successive generations in the MOGA*

**MOGA Parameters**

By trial and error it has been demonstrated that the following parameters governing the operation of the MOGA are suitable:

- a chromosome consists of 6 integers, each constrained to lie between 1 and 19,
- the population size is 100,
- two-point crossover is used to create two new chromosomes from two parent chromosomes,
- the mutation rate is 0.1, meaning that mutation has a 0.1 chance of occurring in each new chromosome created by crossover,
- the MOGA is run for at least 20 generations,
- elitism is enabled, permitting solutions of high rank (cut-off point can be specified) to pass directly into the next generation without modification,
- primary criteria:

  * vehicular and pedestrian delay, expressed as total number of seconds spent by the relevant type of road-user approaching and passing through the junction. In contrast to the method of recording the delay experienced by each vehicle/pedestrian that passes a travel time

measurement point, this method also takes into account the delay experienced by all road-users that have not yet passed through the junction,
    * vehicular and pedestrian throughput,
- secondary criterion, used to judge between chromosomes when values for primary criteria are not significantly different:
    * variability of delay across vehicle streams (pedestrian streams are treated as one),
- parents chosen by tournament selection using Pareto ranking against a randomly chosen group of five other solutions,
- niching implemented.

## RESULTS TO DATE

In order to perform the optimisation described in this paper, it was necessary to go through the following steps:

- Code up a junction in VISSIM which would be used to test the controller. A 4-arm junction was encoded which had 9 signalised vehicle streams and 4 signalised pedestrian crossings, and detectors at the stop line and 130m upstream, as well as pedestrian push-button detectors;
- Devise a range of flow profiles for the VISSIM test junction, varying flow on the four vehicle approaches, the pedestrian crossings, and varying the proportion of heavy goods vehicles;
- Devise the fuzzy logic framework (using the SIEFUZZY toolbox from Siemens) for the derivation of the urgency values;
- Write the signal control program which uses the urgency values to inform the logic which determines whether the current stage should be retained, and if not, which stage should be switched next. This was extensively tested in simulation;
- Adapt the signal control program so that it could read the parameters defining the fuzzy sets from a file written by the MOGA program;
- Adapt the public domain source code of the SUGAL program so that it would evaluate the chromosomes with respect to a varying number of objectives, using Pareto ranking and tournament selection;
- Adapt the SUGAL code so that the evaluation of each chromosome was performed by spawning an instance of VISSIM and running three instances of the simulation with three different random seeds to determine the pattern of vehicle and pedestrian arrivals within a preset flow pattern;
- Investigate the effect of altering the GA parameters such as mutation rate, size of starting population and number of generations;
- Devise a suitable random initial population of chromosomes;

- Write programs which would read a number of output files from each simulation run and process the data contained to give the values to be used for the evaluation of the chromosomes.

The length of time required to perform one reasonably sized run of the MOGA (such as a population of 100 and 20 generations) is typically 3 days of continuous processing on a PC with 100MHz Pentium processor under the Windows 95 operating system, although run-time problems can lengthen the process.

As an illustration of a MOGA run which used a population of 100, 20 generations, and a different random seed to govern the precise vehicle flow for each generation, Figure 9 shows that the solutions found in the twentieth generation have moved towards the Pareto-optimal front for the two objectives of overall mean vehicle and pedestrian delay, by their shift towards lower values on both axes.

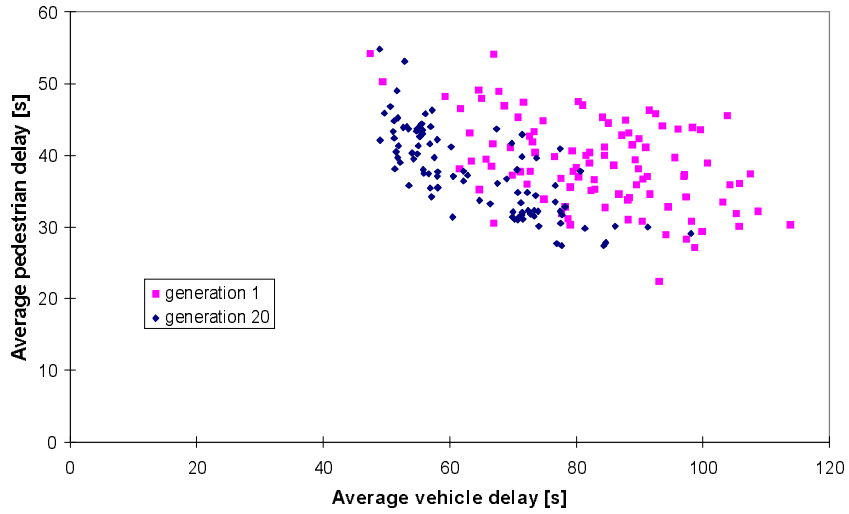


*Figure 9. Scatter plot showing performance of solutions in generations 1 and 20.*

## FURTHER WORK

Further iterations of the MOGA described above will be performed to determine the point at which no further improvement may be made. This will result in a set of controller parameters which perform well for the scenario in which they were tested. The next step is to investigate the possibility of finding parameters which can perform well in different simulation scenarios, varying the traffic flows and proportion of heavy goods vehicles. If no robust parameter sets are found, it will be necessary to optimise separately for different flow patterns.

The operation of public transport vehicles will be optimised separately from the other more general parameters, since analysis of the public transport data obtained from early simulation

runs showed no consistent pattern of correlation with the other objectives. The criteria used to evaluate the performance of the controller with respect to public transport vehicles are the extent to which they deviate from both their timetable and their scheduled headways.

Senior traffic engineers at the local city authority will be consulted in order to ascertain some realistic scenarios at a local isolated junction with pedestrian crossings and bus lanes, where different combinations of signal control objectives would be desirable. For example, "give priority to pedestrians, but with reasonably short delays to cars and buses", or "give absolute priority to buses". The appropriate parameter sets will be chosen for the controller and its performance under various realistic conditions evaluated.

There are many tasks which will not be able to be performed within the timescale of the current project but which would be useful and interesting enhancements to the work carried out so far. These include further investigation into the operation of the MOGA and the effect of alterations to its parameters, extending the controller to a network of autonomous intersections, and applying the fuzzy logic-derived urgency to other forms of signal control.

## CONCLUSIONS

This paper describes a flexible form of fuzzy logic signal control whose performance can be tuned off-line using a set of parameters which define the fuzzy set membership functions for the input variables. Not only can it be tuned for optimum performance in a particular intersection or network, but the criteria by which that performance is measured can be changed to match the prevailing policy objectives. This work also demonstrates the feasibility of using a MOGA to find a set of optimal parameters for a fuzzy control system with a range of possibly conflicting performance measures.

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