# OPTIMISATION OF A FUZZY LOGIC TRAFFIC SIGNAL CONTROLLER BY A MULTIOBJECTIVE GENETIC ALGORITHM

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## ABSTRACT

The increasing awareness of the importance of the wider objectives of traffic management and control has led to the work described in this paper. The aim of the study of which this is a part is to develop a flexible signal controller which may be configured so that it embodies the objectives appropriate for the situation in which it is to be used. This paper describes the investigation made into the feasibility of optimising a prototype fuzzy logic signal controller with respect to several criteria simultaneously. The controller's sensitivity to changes in the membership function parameters was demonstrated and it was not possible to minimise simultaneously even the limited set of performance measures explored (travel times and emissions). These results indicate that a multiobjective genetic algorithm (MOGA) optimisation technique is appropriate for further research.

## OUTLINE

The first section of this paper describes the context in which this study is being carried out. There follows a brief introduction to fuzzy logic and an outline of the prototype traffic signal controller used in this study. The use of Genetic Algorithms for optimisation problems is then described. The evaluation of traffic controllers using microscopic simulation and an emission model is then outlined. Having introduced the main components of the experiment, the study and its outcome are described.

## BACKGROUND

### New objectives of traffic signal control

The constant rise of car ownership, increasing congestion in cities, with concomitant increase in atmospheric pollution, the environmental impact of building new roads in an attempt to relieve congestion and many other factors have contributed to an awareness that it may be necessary to discourage people from using their car in order to limit the amount of traffic on the roads, as well as encouraging drivers to use certain routes, diverting them from areas which are prone to congestion, or which are heavily used by pedestrians. The advent of these new perspectives on urban traffic management and control has challenged the assumption that the main measure for judging the efficacy of a traffic signal control system is the extent to which it reduces vehicular delay and stops.

The Urban Traffic Management and Control (UTMC) initiative, launched in 1997 by the Department of the Environment Transport and the Regions, together with the Traffic Director for London, recognises and responds to these changing objectives (Routledge et al (1)). Flexibility and inter-operability are seen as key features of modern UTMC systems which can thus "achieve a wider range of transport and environmental objectives".

### Delphi study

As the preliminary part of the *policy-sensitive traffic signal control* project, 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. The first round questionnaire asked respondents to vote for given objectives, while the second gave the opportunity to discuss the respondent's chosen objectives in more detail. Detailed results from the two rounds are given in Sayers et al (2), but the general outcome was that it was unrealistic to try to reach consensus on the objectives of traffic signal control and their relative priorities, since every installation may have 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.

## FUZZY LOGIC IN TRAFFIC SIGNAL CONTROL

### Introduction

Since the seminal work of Pappis and Mamdani (3) describing a fuzzy controller for traffic signals, there have been many interesting applications of fuzzy logic control to traffic signals. A fuller discussion of these can be found in Sayers (4). Previous experience in TORG of developing a fuzzy logic traffic signal control system for an isolated intersection (Sayers et al (5)) demonstrated its potential to provide the required flexibility.

The heart of a fuzzy logic control system is a set of rules which describe the relationship between the inputs and the output in qualitative "natural language" terms. As in a knowledge-based expert system, these rules provide an easily understood scheme for explaining the input/ output mapping. In contrast to expert systems, however, a fuzzy logic rulebase can be relatively simple and concise, due to the mapping of the individual discrete input and output values onto user-defined fuzzy sets.

The simple building blocks of a fuzzy control system are fuzzy sets, which capture the significant categories of input and output values, and rulebases, which describe the relationship between inputs and output. These can be used to build a model which implements the desired non-linear mapping, and avoids unwanted "steps" in the output values caused by the simple use of thresholds in the input values. A thorough introduction to fuzzy control can be found in Lee (6).

**Prototype controller**

The signal control methodology described in Lee et al (7) was chosen as a starting point. This controller employs a competitive technique in which a weight for each phase (or signal group) at the junction is derived each second by means of several fuzzy control modules. The weights are derived from count data supplied by inductive loop detectors on the junction approaches, signal timing data and data relating to neighbouring junctions which signal the expected arrival of a platoon from upstream junctions and the possibility of spillback at downstream junctions. These weights are combined to give a weight for each possible stage, including the current one, and are used as a basis for the decision to change stage or retain the current stage.

**Optimisation of Fuzzy Logic Controllers**

One criticism often levelled at the principle of fuzzy logic control is the subjectivity of the fuzzy set definitions and the rulebases. These are the fundamental building blocks of a fuzzy logic control system and as such determine its performance. Much work has been carried out on the derivation and optimisation of these components, some details of which are discussed in (4).

There are two main candidates for optimisation in a classic 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. There has been much work on the optimisation of fuzzy logic systems, looking at both rulebases and membership functions, with promising results.

## GENETIC ALGORITHMS FOR OPTIMISATION

**Introduction**

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. For the problem under consideration, an enumerative method was not viable due to the number of possible solutions, bearing in mind that in the simplified controller under test there were four different input variables whose membership function definitions could be varied simultaneously. The shape of the search space was not known in advance, although it was likely that it had many peaks of different forms and sizes. In this context, a classical hill-climbing algorithm was not suitable due to its tendency to stop at local maxima.

In the light of these difficulties, the optimisation method of Genetic Algorithms (GAs) was 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 (hopefully) converging on 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 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. A full explanation of GAs in all their diverse forms is found in Goldberg (8).

**Multiobjective Genetic Algorithms**

The goal of the project is to optimise the signal controller with respect to a number of diverse criteria, and the Delphi study showed that the relative weights of these criteria could not be determined in advance. An appropriate technique for such multiple objective optimisation is the recently developed Multiobjective Genetic Algorithm (MOGA) which permits a range of optimal candidate 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 (9)). 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, the solution that matches most closely the desired objectives for each implementation can be chosen from the optimal set.

The MOGA uses the Pareto ranking method to rank the solutions of each generation by the number of other solutions which dominate them and this ranking is then

used to determine the fitness (and thus expected number of offspring) of each solution.

## EVALUATION OF A TRAFFIC SIGNAL CONTROLLER

### Introduction

The evaluation of a vehicle-responsive traffic signal controller is not a simple matter, due to its dynamic and adaptive nature. Its 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 only realistic 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. The simulator used in this case is VISSIM.

### Traffic Simulations

**VISSIM.** The VISSIM (standing for Verkehr in Städten Simulation) microscopic simulator is a discrete, stochastic, time step based (1s) microscopic model with driver-vehicle-units as single entities. The model contains a psycho-physical car following model for longitudinal vehicle movement and a rule-based algorithm for lateral movements (Fellendorf (10)). The model parameters have been calibrated through image processing (Hoyer and Fellendorf (11)). The simulator uses a DDE (Dynamic Data Interface) to exchange information with the signal controller. Every second data from vehicle detectors are passed to the controller which then sends back signal setting for the coming second.

Data about each simulation run may be stored in files for later analysis. The types of data that can be stored include:

- vehicle position, speed and acceleration at each time step of each vehicle;
- travel times;
- signal changes;
- list of vehicles as they were generated; and
- saturation flow.

These output files can be processed to give various performance measures relating to each simulation run.

**Emissions.** Emissions are not calculated within VISSIM, so some further processing is required to obtain these data. In order to calculate the emissions from the vehicles as they travel through the simulated network, the emissions factors from the MODEM computer programme can be used in conjunction with the VISSIM output file which gives the speed and acceleration of each vehicle at each second during the simulation. The MODEM programme was developed from data collected during the DRIVE V1053 project "Modelling of emission as and fuel consumption in urban areas" from typical urban driving and is available in the UK from TRL. It calculates the exhaust emissions from a number of vehicle categories, based on the second by second speed of the vehicle. The pollutants calculated are carbon monoxide (CO), hydrocarbons (HC), oxides of nitrogen ($NO_x$) and carbon dioxide ($CO_2$). The consumption of fuel is also calculated.

## OPTIMISING THE CONTROLLER

### Introduction

Before embarking on a MOGA which would be time-consuming to carry out due to the large number of simulation runs required in the evaluation stage, it was thought prudent to determine the controller's sensitivity to changes in its membership function parameters.

In the first instance the membership functions alone were optimised. A number of constraints were imposed in order to preserve the transparent and meaningful nature of the fuzzy control system.

### Constraints on Membership Functions

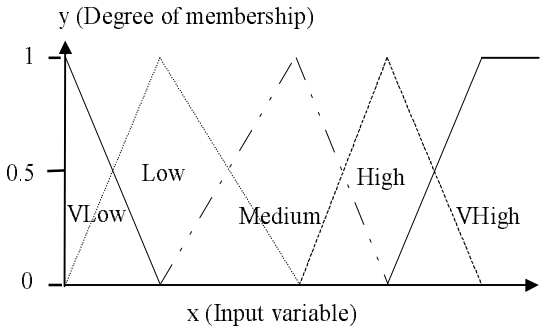


Figure 1. Illustration of fuzzy sets

The first constraint was to retain the ordering of the fuzzy sets over the range of each variable. In the example illustrated in Figure 1, where the input variable x has five input sets called 'VLow', 'Low', 'Medium', 'High', and 'VHigh', corresponding to consecutive overlapping sections of the input range, then it is not permitted to alter their definitions so that the set 'High' corresponds to lower values of the variable than the set 'Low'. This would make the resulting system rather counter-intuitive!

The second constraint was that the sets should be triangular and the bases of one set should be at the same points as the apexes of the two neighbouring sets. This had the effect of ensuring that neighbouring sets overlapped at a degree of membership of 0.5 and that for

any input value, the sum of its degrees of membership was always 1, giving an even coverage of the input ranges.

The number of sets could not be altered as this would affect the rulebase, either losing rules or requiring new ones. The minimum distance between the bases of any fuzzy set was set to 1.

Taking these constraints into account, the position and width of the base of each set could be altered, and the position of the apex could be anywhere between the base points, resulting in skewed sets.

**Method**

**Introduction**. In order to do test the controller's sensitivity to changes in the fuzzy set membership function parameters, 50 simulation runs were performed using different sets of randomly generated parameters. The results of these simulation runs were then analysed to determine whether altering the membership function parameters had much impact on the behaviour of the controller and if so, which output variables should be used as the performance criteria. If all output variables were strongly correlated, then a single criteria optimisation would suffice. A Pareto ranking of the results from the initial 50 runs using the most suitable criteria was performed.

**The network layout.** A left-hand drive test network was encoded in VISSIM, in which a central junction with four approaches was controlled by the fuzzy logic controller. At the periphery of each approach a fixed time junction regulated the flow of vehicles to the central junction, giving a more realistic platoon-like input flow than a simple random generation of vehicles. At the central junction all turning movements were allowed on all approaches, with two lane approaches flaring to three at the junction, giving a short lane for right-turners. The left hand lane of each approach was shared by vehicles turning left and vehicles going straight on, and the middle lane was for straight on only.

**The stage scheme.** Each approach was controlled by two independent phases; one for straight on and left turns, and one for right turns. This gave a total of eight phases, which may be combined in eight different stages, where each stage combines two non-conflicting phases. A transition was defined for each possible pair of stages, so that whichever stage was currently green, any of the others may be switched next, giving a high degree of flexibility to the controller.

**Modelled traffic.** Each of the fifty simulation runs carried out had the same characteristics. The traffic flow was constant, and the same on each approach. Each approach of the central junction received 1200 vehicles per hour, of which 15% turned left and 5% turned right. There were no heavy goods vehicles, buses or trams, because the current version of MODEM does not have emission factors for large diesel engines. The traffic mix was mostly MODEM type 1 vehicles (type ECE 15.03, engine size < 1.4l).

**Output.** The travel times for each of the 12 turning movements in the main junction were collected, second-by-second, and the average, maximum and standard deviation of the travel times for each turning movement were calculated. In addition, the overall mean travel time for each simulation run was calculated. The total emissions of CO, $CO_2$, NOx, HC and fuel consumption were calculated from the VISSIM file giving details of each vehicle's speed and acceleration at each second during the simulation.

**RESULTS**

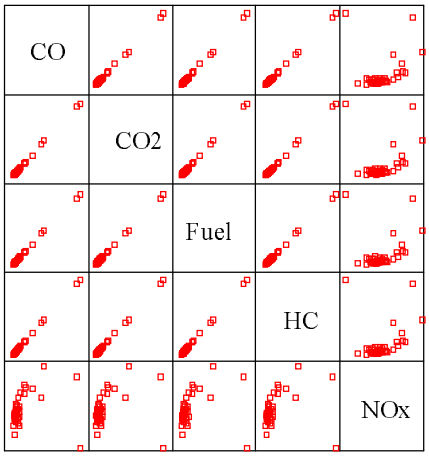


Figure 2. Matrix of scatter plots showing correlations between emissions and fuel consumption

A scatter plot matrix (shown in Figure 2) of the emissions and fuel consumption from the 50 runs showed that they were all strongly correlated except for NOx. A scatter plot matrix of the travel times showed that the travel times for each straight-on direction was representative of the three turning movements on the same approach. Thus the variables that were chosen for the Pareto ranking were CO, NOx, and the average travel times for the 4 straight-on streams at the central junction.

A Pareto ranking was performed by comparing the values for each of the criteria across all pairs of solutions. If all of the values for solution x were less than or equal to the values for solution y, and at least one of them was less that its equivalent value in y, then solution x was said to dominate solution y. The highest rank was awarded to the solution which was dominated by the least number of other solutions. There may be

several solutions with the same rank. A solution with a low rank is better than one with a high rank.

The values for the chosen criteria across the 50 test solutions were ranked using this method. Figure 3 is a scatter plot of travel time for one straight-on stream against the Pareto rank of each solution. The plot shows that the rank does not depend on any one variable but on a combination, since the solution with second-highest travel time is given rank 1.

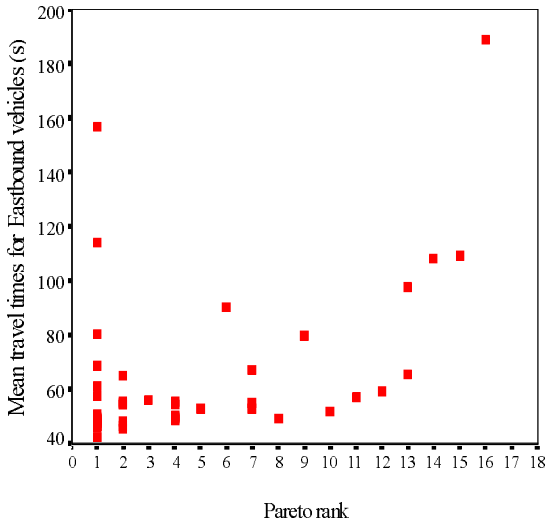


Figure 3. Scatter plot of travel time versus Pareto rank.

## CONCLUSIONS

The controller's sensitivity to changes in the membership function parameters has been demonstrated. In addition, it has not been possible to minimise simultaneously even the limited set of performance measures explored. These results indicate that a multiobjective optimisation technique is appropriate.

## FURTHER WORK

A MOGA will be implemented fully. The solutions of successive generations will be evaluated using different simulation parameters such as traffic flow patterns and traffic mix. Pedestrian delay will also be included in the evaluation criteria.

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