

Effects of Anticipatory Control with Multiple User Classes

Henk Taale* and Henk van Zuylen**

* Faculty of Civil Engineering and Geosciences

Delft University of Technology

Delft

The Netherlands

E-mail: h.taale@citg.tudelft.nl

** AVV Transport Research Centre

Rotterdam

The Netherlands

EJTIR, 3, no. 1 (2003), pp. 61-76

Received: February 2003

Accepted: May 2003

In this paper the integrated traffic control and traffic assignment problem is studied. This problem can be considered as a non-cooperative game in which the traffic authority, that controls the traffic signals, and the road users are the players, who use their own strategy and seek their own optimum. The game theoretical formulation leads to several different control strategies in which users' reactions to traffic control decisions are taken into account. Users' reactions can be the choice of route, departure time or even mode, but here only route choice is considered.

In this paper some of these control strategies for traffic signal control are described: Webster control, Smith's P_0 , Anticipatory Control and System Optimum Control. The first two control strategies are well known and described in the literature. The anticipatory control strategy can be formulated as a bi-level optimisation problem and this problem is solved using genetic algorithms. Also the system optimum solution can be found using genetic algorithms, simultaneously optimising route flows and green times.

In the paper the assignment method, together with the traffic model, is formulated. In the assignment several user classes, each with its own perception of route costs, are defined and taken into account. For several simple example networks the traffic control methods are tested and it is shown that taking route choice into account is beneficial to the network performance. Further research will focus on the improvement of the traffic model used in the control optimisation, realistic networks and the problem of departure time choice.

Keywords: *anticipatory traffic control, traffic assignment, genetic algorithms*

1. Introduction

Traffic control and traveller's behaviour are two processes that influence each other. The two processes have different 'actors' who may have different goals. The road manager will try to achieve a network optimum and will try to control traffic in such a way that this optimum is reached. Tools for controlling traffic are for example traffic signals, traffic information, ramp metering, etc. The optimum for the road manager can be minimum network delay or a preferential treatment for certain user groups, e.g. public transport or pedestrians (system optimum). The road users will search for their own optimum, e.g. the fastest or cheapest way to travel from A to B (user optimum).

Decisions taken by the road manager in controlling traffic in a certain way have an influence on the possibilities for travellers to choose their preferred mode, route and time of departure, and vice versa. A change in traffic control may have the impact that traffic volumes change. If, for example, traffic control is modified such that congestion on a certain route disappears and delays on intersections decrease, traffic might be attracted from other links where congestion still exists or which are part of a longer route. This might have the consequence that queues, which originally disappeared, return. Delays may reappear at the original levels (Van Zuylen, 2001). The question is then whether there still is a net profit for the traffic system as a whole. The same question arises with respect to new traffic that may emerge as a consequence of shorter travel times, due to either elastic demand or induced demand. Another example is that public transport gets priority in intersection control. The delay for other road users may increase and thus force these road users to search for faster alternatives, e.g. by using transport modes in the network (Mordridge, 1997).

If it is assumed that a modification in traffic control may give a change in travel behaviour, it is necessary to anticipate this change. If delays are optimised, it should be done for the traffic volumes that will be present after the introduction of the optimised traffic control and not for the traffic volumes that existed before the implementation. If the reaction of travellers is neglected in the optimisation of traffic control, the results may even be just opposite to the desired improvement. Mordridge shows with a simplified model that the improvement of the traffic condition for cars in a network with cars and public transport may cause a modal shift from public transport to the car, which at the end deteriorates the travel conditions for both modes (Mordridge, 1997).

Of course, it is possible to follow an interactive approach, where after each shift in traffic volumes the control scheme is adjusted until equilibrium has been reached, or one may use self-adjusting traffic control. However, it can be shown, for certain examples, that the process of the adjustment of traffic control, followed by a shift in traffic volumes, does not necessarily lead to a system optimum. It is even possible that the system oscillates between two or more states. The system optimum as chosen by the road manager for a given traffic pattern is good for the network as a whole, but the resulting travel times can be inconsistent with the assumption of the user equilibrium. The control problem is therefore to optimise traffic control in such a way that the system is at a certain, prescribed optimum, taking into account the reaction of travellers (anticipatory control). This problem is called the combined traffic assignment and control problem. More than 25 years this problem has been the subject of study. For an extensive overview of the available literature one is referred to Taale and Van Zuylen (2001).

In this article the focus will be on the comparison of several control strategies for a number of small example networks. The goal of the research is to determine the effects of anticipatory control for several small, artificial networks, in comparison with traditional control strategies. To make the route choice as realistic as possible, several user classes are defined, which differ in their route choice behaviour.

The article is structured as follows. First, in chapter 2 the control strategies tested are described. In chapter 3 the traffic model and the traffic assignment method are specified and the solution algorithm is given. In the next chapter the example networks are sketched together with their characteristics and the results for all examples and all control strategies are given. Finally, conclusions are drawn and items for further research are briefly mentioned.

2. Control Strategies

Optimisation of traffic signal control is one of the oldest research fields in traffic engineering. The subject has drawn the attention of many researchers. In this article several old and new control strategies are described and tested. The purpose is to study the interaction of these control strategies with route choice. Within all control strategies only the green times are varied between minimum and maximum values. The cycle time is not fixed, but is a result of the green times used. The results of all strategies are compared with the results of fixed-time control: fixed green times during the whole period. The fixed-time control strategy is optimised for the demand of the busiest time period, using Webster's strategy, described in the next section.

2.1 Webster

Already in the fifties Webster published his famous report on the optimisation of fixed-time traffic control (Webster, 1958). In his work Webster did a theoretical analysis and carried out a lot of simulations to derive a formula for the average delay due to signal control. Webster used this formula to derive a general, optimal fixed-time control plan. He found that the general formulas for an optimal cycle time and the accompanying green times are

$$C = \frac{1.5L + 5}{1 - Y}, \text{ where } L = \text{lost time per cycle and } Y = \sum_m y_m = \sum_m \frac{q_m}{s_m} \quad (1)$$

$$g_m = \frac{y_m}{Y}(C - L)$$

It is known that other coefficients than 1.5 and 5 can give better results for intersections with three or more phases (Van Zuylen, 1980), but in this article, dealing only with two-phase control, formula (3) is used to calculate new cycle times and new green times for every time period and every intersection for the flows entering that intersection. This means that the control plan changes due to changing route flows. In the algorithm used, minimum and maximum bounds for the green times are taken into account. This is done, not by simply increasing the green time for that particular movement, but by adjusting the cycle and all other green times in such a way that minimum and maximum bounds are met (Taale, 1995).

2.2 Smith's P_0

According to Smith three solution methods for the combined traffic assignment and control problem are possible: the iterative approach, the integrated approach and a generalisation of the iterative approach taking the control strategy into account (Smith, 1985). The control strategy P_0 is the result of this approach (Smith, 1980). Smith also showed that the P_0 control strategy complies with three conditions for equilibrium (flow, queues and control) and that using P_0 simplifies calculating a solution (Smith, 1987). It has capacity maximising properties, because it does not try to equalise the delays for every conflicting movement, but the product of average delay per vehicle and saturation flow.

The P_0 control strategy is implemented as a minimisation problem. For every intersection and every time period the product of delay and saturation flow for all conflicting movements is equalised and minimised. The saturation flow is given and the delay is estimated with the HCM 2000 delay formulas (TRB, 2000).

2.3 Anticipatory Control

The control strategies described above are reactive, meaning that they react on the current traffic conditions. It is also possible to anticipate on future traffic conditions, taking into account route choice. To that end, traffic assignment can be incorporated in the traffic control strategy. This can be formulated as a bi-level optimisation problem. In game theory this is called a Stackelberg game. The first two control strategies lead to a Cournot game. In the upper level problem the traffic manager tries to minimise the total travel costs

$$\min_{\mathbf{g}} Z_g = \sum_k \sum_{o,d} \sum_{r \in R^{od}} c_k^{rod}(\mathbf{g}, \bar{\mathbf{f}}) \bar{f}_k^{rod}, \quad \mathbf{g} \in G \quad (2)$$

In this formula is o an origin, d a destination, R^{od} the set of feasible routes between o and d , r a possible route, k the departure time interval, f_k^{rod} the route flow between o and d for route r departing during time interval k , c_k^{rod} the accompanying costs for this route flow (possibly travelling in more than one time interval) and G the set of feasible green times. The mark on the route flows f means that the route flows are in equilibrium, which is the solution to the lower level, dynamic traffic assignment problem (see paragraph on traffic assignment). So the road manager performs his optimisation for network flows that are constrained by the requirements of the user equilibrium.

The function Z_g is in general non-convex. Several local optima can exist so that a local search method is not sufficient to find the global optimum. To solve this problem, not an analytical, but a heuristic approach is used. Every feasible combination of green times can be seen as a point in the solution space G . To find the best combination, use is made of genetic algorithms. Genetic algorithms are part of the larger family of evolutionary algorithms. In general, evolutionary algorithms mimic the process of natural evolution, the driving process for the emergence of complex and well adapted organic structures, by applying variation and selection operators to a set of candidate solutions (population) for a given optimisation problem.

For this article a real valued genetic algorithm was used, implemented as a MATLAB[®] toolbox, which is named the Genetic Algorithms for Optimisation Toolbox (GAOT) (Houck *et al*, 1995). In the case of Anticipatory Control a member of the population (solution space) is a vector of green times of all intersections and time periods. Every member is evaluated

using traffic assignment and simulation in an iterative way (see also figure 1). Because it takes a lot of time to iterate towards equilibrium, the number of iterations can be limited. This can be considered as predicting a few days ahead in a day-to-day route choice process. In the calculations described below, a choice of one day has been used. The result of this process is a combination of green times that takes future traffic conditions, with respect to route choice, into account.

2.4 System Optimum Control

The system optimum control strategy is not really a practical one, but it is a kind of benchmark, useful to compare with other control strategies, because it represents the best that can be achieved if the traffic manager has total control over the signal settings and the route choice of travellers. In game theory this is called a monopoly game. In the general the route choice can only be partially influenced. In some cases the road manager is able to impose route choice to the road users by regulations (one-way streets and prohibition of turning movements). The system optimum strategy can give guidance for those situations. The optimisation problem is defined as

$$\min_{\mathbf{g}, \mathbf{f}} Z = \sum_k \sum_{o,d} \sum_{r \in R^{od}} c_k^{rod}(\mathbf{g}, \mathbf{f}) f_k^{rod}, \quad \mathbf{g} \in G, \mathbf{f} \in F \quad (3)$$

The flows don't have to be in equilibrium, but have to belong to the set of feasible route flows F . Again, genetic algorithms, implemented in the GAOT MATLAB® files, have been used to solve this optimisation problem. In this case a member of the population is a vector with route flows and green times for every time period. Genetic algorithms do not guarantee an optimal solution, but they will approach it fairly close, dependent on the number of generations and the size of the population. An advantage of genetic algorithms is that local optima are avoided; a disadvantage is the calculation time needed.

3. Algorithms

In the work described in this article, a choice has been made to use simulation, both in the evaluation of control strategies as in the traffic assignment procedure, which is basically an iterative approach. The iterative approach is used, because of the possibility to handle different control types realistically and more reliable. Also, with simulation, the problems with the analytical description of the complex, non-linear behaviour of traffic flow is circumvented (Abdelfatah and Mahmassani, 1998 and 2001). In the traffic assignment procedure the microscopic simulation model FLEXSYT-II- is used (Taale and Middelham, 1995) and for the evaluation of the control strategies a simple, analytical model is used, which is described in the next paragraph. After that the traffic assignment and solution algorithms are described.

3.1 Traffic Modelling

The traffic model is a simple demand/capacity model that uses travel time functions to calculate link travel times. For that purpose the travel time functions described by Akçelik (1981 and 1991) and functions from the HCM 2000 (TRB, 2000) are used. These functions

can be used for uncontrolled and controlled links. An advantage of the HCM 2000 formulas is that they take the initial queue into account. For uncontrolled links the travel time is estimated with

$$t = \frac{l}{v_{free}} + 0.25 \cdot T_f \left[(x-1) + \sqrt{(x-1)^2 + \frac{8 \cdot J_a \cdot x}{s \cdot T_f}} \right] \quad (4)$$

where l is the link length, v_{free} is the free speed on that link, s the saturation flow, T_f the analysis period for which the arrival rate q is constant, x the degree of saturation (q/s) and J_a the so-called delay parameter. This parameter is dependent on the type of road and has a small value for motorways and larger values for arterials or secondary streets. For controlled links with no initial queue the travel time is estimated with

$$t = \frac{l}{v_{free}} + \frac{C(1-g/C)^2}{2(1-\min(1,x)\frac{g}{C})} + 900T_f \left[(x-1) + \sqrt{(x-1)^2 + \frac{8 \cdot k \cdot I \cdot x}{Q \cdot T_f}} \right] \quad x > 1$$

$$t = \frac{l}{v_{free}} + \frac{C(1-g/C)^2}{2(1-\min(1,x)\frac{g}{C})} \quad x \leq 1 \quad (5)$$

where C is the cycle time in seconds, g the effective green time in seconds, Q the capacity of the signal controlled lanes in vehicles per hour ($Q=sg/C$, where s is the saturation flow in vehicles per hour) and x is the degree of saturation ($x=q/Q$). The additional parameters K and I stand for a parameter for the given arrival and service distribution (e.g. 0.5 for fixed-time control) and a parameter for variance to mean ratio of arrivals from upstream signals (e.g. 1.0 for Poisson arrivals) respectively.

If an initial queue is present an extra delay term d_3 is added, which is defined as

$$d_3 = \frac{1800W(1+u)t}{QT_f} \quad (6)$$

where W is the initial queue in the previous period (in vehicles), t the period (in hours) of unmet demand in T_f and u a delay parameter. Further details can be found in (TRB, 2000).

Input for the model is a network consisting of nodes and links, with their attributes. The nodes are described by their type (normal, origin node, destination node or controlled node) and their incoming and outgoing links. The links have attributes such as length, number of lanes, saturation flow and desired speed. Also different link types are distinguished: normal links, signal controlled links or metered links. Other input for the model is a set of general parameters, such as the number of time periods, the duration of these time periods and the length of the time step, which is used in the calculations. The length of the time step is maximised by the time a vehicle can travel the shortest link with free flow speed. Also origins and destinations have to be specified, including an OD table with the demands. Because a route based assignment is used, for every OD pair a set of feasible routes has to be specified. For the traffic model itself, the following algorithm is used:

Algorithm 1: Simple Traffic Model (T-Model)

- Step 1: Initialise
- 1.1: determine general parameters, link and node attributes;
 - 1.2: calculate incoming and outgoing saturation flows per node;
 - 1.3: give every link an initial flow according to the demand.
- Step 2: Main loop for every time step:
- 2.1: determine free flow travel time and capacity (depends on control) per link;
 - 2.2: calculate travel time and delay per link with Akçelik and HCM 2000 travel time functions
 - 2.3: compute the outflow and the remaining space for every link, taking into account downstream queues;
 - 2.4: for every node compute the inflows and outflows;
 - 2.5: determine the inflows for every link;
 - 2.6: calculate for every link the flows for the next time step.
- Step 3: Route delays and travel times:
- 3.1: initialise variables;
 - 3.2: calculate route delays and travel times per time step;
 - 3.3: calculate route delays and travel times per time period;
 - 3.4: calculate total time spent and total delay.

The T-Model is quit simple, but gives reasonable results and is very fast in calculations. Therefore, T-Model is used as the objective function in the genetic algorithms.

3.2 Traffic Assignment

The road user is assumed to obey the route-based discrete-time dynamic traffic equilibrium, which can be defined as:

For each origin-destination (OD) pair, the route travel costs for all users, travelling between a specific OD pair and departing during a specific time interval are equal, and less than (or equal to) the route travel costs which would be experienced (or perceived, in case of a stochastic assignment) by a single user on any unused feasible route (Chen 1999 and Bliemer, 2001).

In formulas this definition can be expressed as

$$(f_k^{rod} > 0 \Rightarrow c_k^{rod} = \pi_k^{rod}), \quad \forall o, d, r \in R^{od}, k \quad (7)$$

where

$$\pi_k^{od} \equiv \min_{r \in R^{od}} c_k^{od}, \quad \forall o, d, k \quad (8)$$

The traffic assignment problem can be formulated as a discrete time (finite dimensional) variational inequality problem: find an $\bar{\mathbf{f}} \in \Omega$ such that

$$\sum_{o,d} \sum_{r \in R^{od}} \sum_k c_k^{rod}(\mathbf{g}, \bar{\mathbf{f}}) (f_k^{rod} - \bar{f}_k^{rod}) \geq 0, \quad \forall \mathbf{f} \in \Omega, \quad (9)$$

where Ω is defined as the set of all \mathbf{f} satisfying the following constraints:

$$\begin{aligned} \sum_{r \in R^{od}} f_k^{rod} &= q_k^{od}, & \forall o, d, k, \\ f_k^{rod} &\geq 0, & \forall o, d, r \in R^{od}, k \end{aligned} \quad (10)$$

q_k^{od} is the demand between origin o and destination d for time interval k and R^{od} is the set of feasible routes between origin o and destination d . In a stochastic assignment the perceived route costs \hat{c}_k^{rod} can be represented by

$$\hat{c}_k^{rod} = c_k^{rod} + \varepsilon_k^{rod} \quad (11)$$

where c_k^{rod} are the real travel costs and ε_k^{rod} is the random component. If it is assumed that the random term is an independently and identically distributed Gumbel variate, than the multinomial logit model is obtained. Given actual travel costs, the route choice probabilities can then be described by (Sheffi, 1985 and Chen, 1999):

$$P_k^{rod} = \frac{\exp(-\theta c_k^{rod})}{\sum_{s \in R^{od}} \exp(-\theta c_k^{sod})} \quad \forall o, d, r \in R^{od}, k \quad (12)$$

where θ is a parameter that reflects the degree of uncertainty in the travel time knowledge of the road users. In the limit when θ approaches infinity, perfect knowledge is assumed and the deterministic user equilibrium solution is obtained. The parameter θ can be used to distinguish between different user classes with respect to the use of information. In general there are three user types: habitual users, partially informed users and perfectly informed users. Habitual users always take the same route, irrespective of the information, e.g. if they don't have any alternative or no access to any information. Partially informed users know something about the conditions in the network due to their experience, but they are not completely informed like the perfectly informed users, who know all about the network condition for now and in the future. Perfectly informed users are the main assumption of the dynamic user equilibrium assignment.

A logit model describes the stochastic assignment with mixed user classes. In this article the C-logit model, proposed by Cascetta *et al* (1996), is used. This logit model takes into account overlap in routes with the so-called commonality factor given, for route r of OD pair od per time period k , by

$$CF_k^{rod} = \beta \ln \left[\sum_{s \in R^{od}} \left(\frac{L_{rs}}{\sqrt{L_r L_s}} \right)^\gamma \right] \quad \forall o, d, r \in R^{od}, k \quad (13)$$

where L_r and L_s are the 'lengths' of routes r and s belonging to OD pair od . L_{rs} is the 'length' of the common links shared by routes r and s and β and γ are positive parameters. 'Length' can be the physical length or the 'length' determined by travel costs. In our case travel times are used. With this commonality factor CF_k^{rod} and the known travel costs, the probability to choice path r , for OD pair od , time period k and user class u , and flow f for that user class are given by

$$P_{uk}^{rod} = \frac{\exp(-\theta_u c_k^{rod} - CF_k^{rod})}{\sum_{s \in R^{od}} \exp(-\theta_u c_k^{sod} - CF_k^{sod})} \quad (14)$$

$$f_k^{rod} = \sum_u P_{uk}^{rod} \xi_u q_k^{od} \quad \forall o, d, r \in R^{od}, u, k$$

where ξ_u is the fraction of users belonging to class u .

3.3 Solution Algorithms

Using the control strategies, the traffic simulation model and the traffic assignment procedure described in the previous paragraphs, the solution algorithm for the combined dynamic control and assignment problem (DCAP), except for the system optimum control and assignment, is as follows:

Algorithm 2: Solution algorithm DCAP

- Step 1: Initialise
- 1.1: initialise general parameters;
 - 1.2: read network file with links, nodes, OD pairs, demands, routes and traffic signal control information;
 - 1.3: determine initial green times $g(0)$ and cycle times $C(0)$;
 - 1.4: initial assignment based on free flow travel times (or pre-specified) to calculate initial route flows $f(0)$ and link flows $u(0)$;
 - 1.5: calculate initial route costs $c(0)$ and total delay $TD(0)$ using FLEXSYT;
 - 1.6: set counter $M=1$.
- Step 2: Main loop
- 2.1: determine necessary intersection information (minimum and maximum timings, etc.);
 - 2.2: for all time periods and all intersections calculate new green times $g(M)$ and cycle times $C(M)$ with Webster, Smith's P0 or Anticipatory Control;
 - 2.3: calculate route costs $c(M)$ and total delay $TD(M)$ using FLEXSYT;
 - 2.4: calculate new route flows $f(M)$ and link flows $u(M)$ using stochastic assignment (formulas (17) and (18));
 - 2.5: calculate new δM with $\delta_M = a \cdot e^{-\eta M} + b / (M + 1)$;
 - 2.6: smooth route flows with $f(M) = f(M-1) + \delta M(f(M) - f(M-1))$;
 - 2.7: round flows on integers and make them consistent with demand;
 - 2.8: check convergence: if $f(M) - f(M-1) < \varepsilon \cdot q$ ($q =$ demand) then stop, otherwise set $M=M+1$ and go to step 2.1.
- Step 3: Final touch:
- 3.1: calculate route costs $c(M+1)$ and total delay $TD(M+1)$ using FLEXSYT;
 - 3.2: determine simulation time.

In steps 2.6 and 2.7 the method of successive averages (MSA) is used to smooth the flows. The convergence of the MSA is slow, because the step size quickly becomes small and slowly

decreases. Therefore, the step size δ_M is chosen in such a way that in the first few iterations the step size is larger than the size normally used ($1/n$), and smaller in the next iterations to speed up convergence. The necessary conditions (Sheffi, 1985) $\sum_{i=1}^{\infty} \delta_i = \infty$ and $\sum_{i=1}^{\infty} \delta_i^2 < \infty$ are fulfilled for every choice of $a>0$, $b>0$, $a+b=1$ and $\eta>0$. For this article $a=0.8$, $b=0.2$ and $\eta=0.2$. Convergence is obtained if the difference in flows is smaller than a threshold value (ϵ) times the demand. For ϵ a value of 0.001 (0.1%) was chosen.

For anticipatory control the algorithm is also sketched in figure 1. Note that in the anticipatory control strategies T-Model and the stochastic assignment are used frequently as an objective function, to evaluate the vector of green times. In the calculations for this article, n was set to 1.

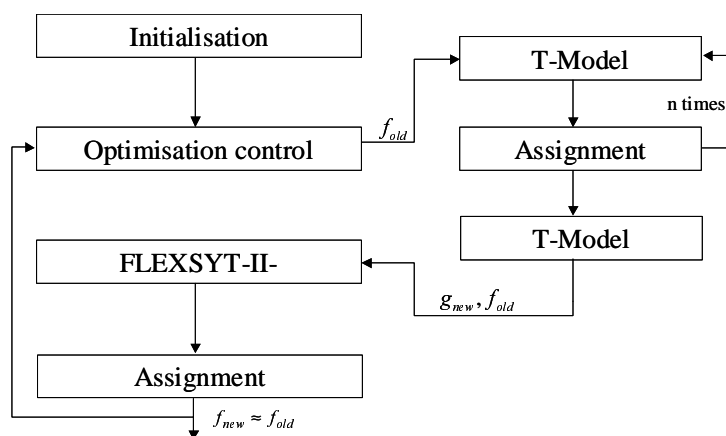


Figure 1. Solution algorithm for anticipatory control

The solution algorithm for the system optimum control and assignment problem (SOCAP) looks more or less the same, but has only one iteration in the main loop, which uses a genetic algorithm to determine best green times and route flows simultaneously. This algorithm is:

Algorithm 3: Solution algorithm SOCAP

- Step 1: Initialise
- 1.1: initialise general parameters;
 - 1.2: read network file with links, nodes, OD pairs, demands, routes and traffic signal control information;
 - 1.3: determine initial green times $g(0)$ and cycle times $C(0)$;
 - 1.4: initial assignment based on free flow travel times (or pre-specified) to calculate initial route flows $f(0)$ and link flows $u(0)$;
 - 1.5: calculate initial route costs $c(0)$ and total delay $TD(0)$ using FLEXXSYT.
- Step 2: Main loop:
- 2.1: determine necessary intersection information (minimum and maximum timings, etc.);
 - 2.2: for all time periods calculate new green times $g(1)$, cycle times $C(1)$, route flows $f(1)$ and link flows $u(1)$.

Step 3: Final touch:

- 3.1: calculate route costs $c(1)$ and total delay $TD(1)$ using FLEXSYT-II-;
- 3.2: determine simulation time.

In step 2.2 all variables all calculated in one round, using genetic algorithms. The outcome is evaluated in step 3 using FLEXSYT-II-.

4. Case Studies

4.1 Case description

The solution algorithms described were used to test the different control strategies for several small road networks, depicted in figure 2. The black dots represent signal-controlled intersections, the grey dots represent ramp metering locations.

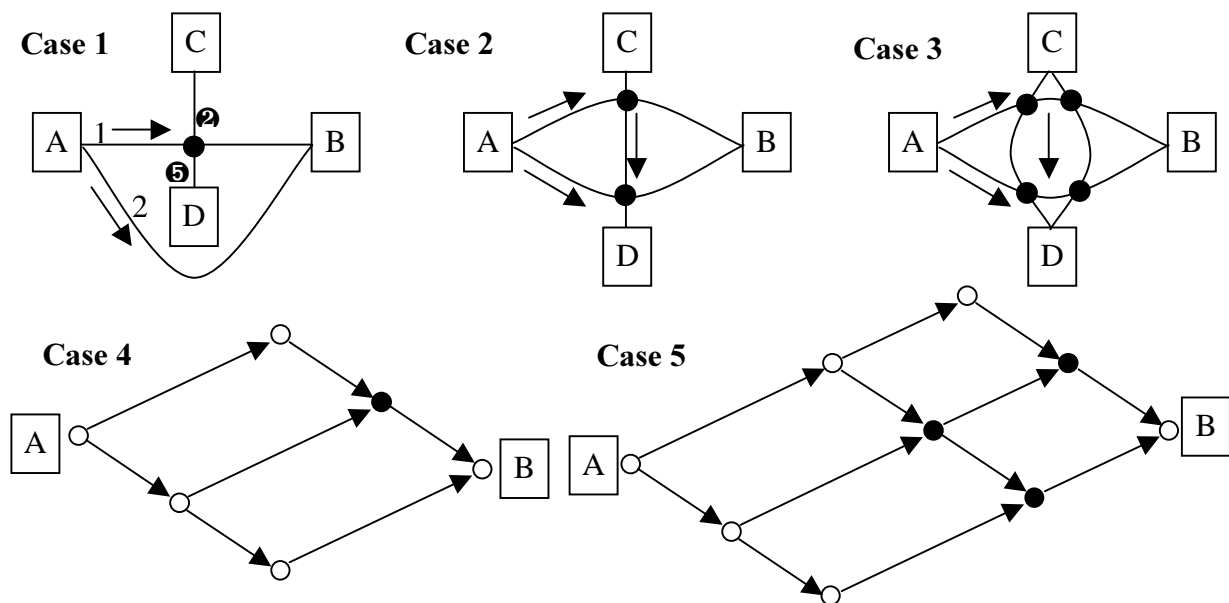


Figure 2: Several small road networks

The networks are hypothetical, but show a lot of variation in structure, demand and other characteristics. Due to the limit in size of the article, not all characteristics (e.g. length and capacity of links) of the networks can be given. At this point it is sufficient to show that a variable demand is used. The number of time slices and the demand for all cases and OD pairs in shown in table 1.

For all cases the time periods have a length of 15 minutes. For the fixed-time control strategy the green times for all cases are based on the busiest time period of the initial assignment. For the control strategies the green times are allowed to vary between 7 and 40 seconds. The cycle time is not pre-fixed, but based on the green times and the intersection lost time, which is always 10 seconds.

Table 1. OD demands (veh/hr)

	OD pair (# routes)	Time period				
		1	2	3	4	5
Case 1	AB (2)	1200	2400	1200	1000	1000
	CD (1)	400	1000	400	300	300
Case 2	AB (2)	1200	2400	1200	1000	1000
	CD (1)	400	1000	400	300	300
Case 3	AB (2)	900	1700	1000	700	-
	CD (2)	400	1500	400	300	-
Case 4	AB (3)	2000	4000	2000	1500	-
Case 5	AB (6)	2000	3800	2000	1500	-

Following Chen (1998) the parameters for the C-logit algorithm are chosen to be $\beta = 1.0$ and $\gamma = 2.0$. Three user classes are defined: class 1 are habitual users (10%), class 2 users (70%) have the perception parameters $\theta_2 = 1.0$ and class 3 users (20%) have $\theta_3 = 3.0$. These values were used for all cases. For case 1 extra runs were made with one user class with the perception parameter $\theta = 1.0$ to compare with the results with three user classes. The results for one user class only and using only T-Model are given in Taale and Van Zuylen (2003).

For Anticipatory Control the number of generations for the GA is set to 75, with a population size of 25 and for the System Optimum Control the population size is set to 20 and 1000 generations should lead to a near optimal solution.

It is well known that different initial assignments can lead to different equilibriums (Van Zuylen and Taale, 2000). For three cases (case 1, 4 and 5) the initial assignment was based on the free flow travel times. For cases 2 and 3 the distribution of the initial route flows was specified beforehand and non-symmetric: most of the traffic demand on one route and the rest on the other. The effects of other initial flows were not studied. All results were obtained within 35 iterations.

4.2 Results

The results for all cases and for all control strategies are shown in figure 3. The result is given in terms of the total delay of the equilibrium solution, shown as a percentage of the total delay of the equilibrium solution for fixed-time control (the base strategy, not shown, but set to 100%). The results show that in 4 out of 5 cases anticipatory control is better than traditional, local control strategies (Stackelberg game gives better results than Cournot game). For case 3 Smith's P_0 is the best control strategy. Probably, this is due to the fact that this is a symmetric case. All strategies strive for an equal distribution of the traffic on the available routes, so route choice is not really the problem, but finding the best local green times, in which Smith's P_0 is doing the best job. The results presented here similar to the ones presented in Taale and Van Zuylen (2003), using only T-Model and one user class.

On average, for the example networks and initial assignments studied, Webster control gave an improvement of 18% compared to fixed-time control, the same improvement as Smith's P_0 . The average improvement for Anticipatory Control was 25% and for System Optimum Control 39%. For all cases, the system optimum solution was the best, as it should be. Of course, this strategy will be difficult, if not impossible, to implement in real life, because it supposes complete cooperation of all road users, even when the decisions the road manager makes are not beneficial to them.

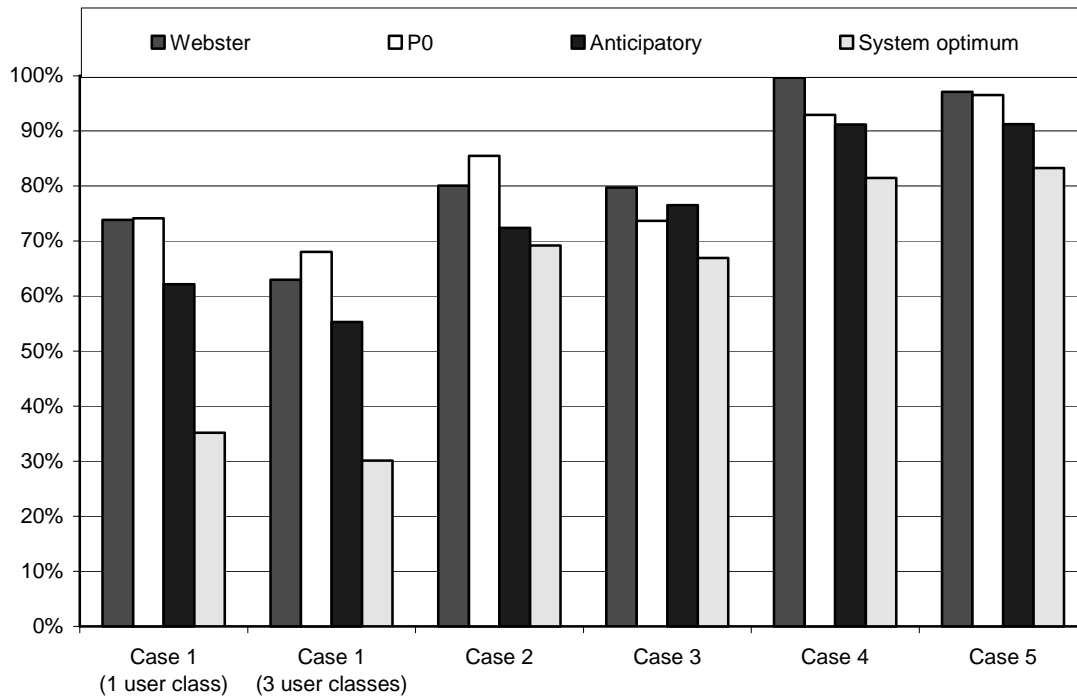


Figure 3. Percentages all control strategies in comparison with fixed-time control

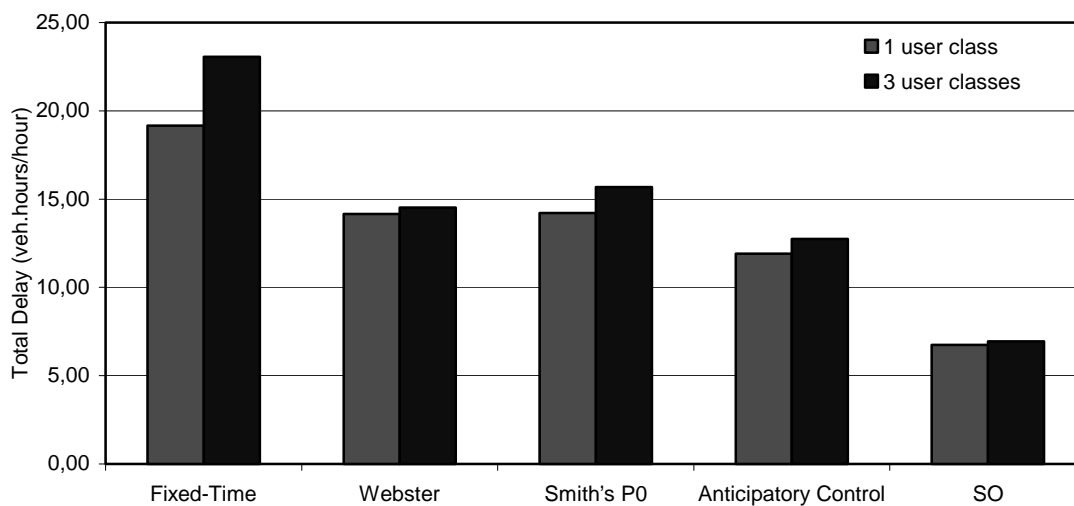


Figure 4. Total delay for the control strategies with one and three user classes

The influence of the existence of multiple user classes in the network on the results of the different control strategies is not so large. For case 1 the relative improvements compared with fixed-time control are shown in figure 3. From this figure it looks like if multiple user classes give less delay, but this is not true as is shown in figure 4, which gives the absolute values. For all control strategies the delay with three user classes is higher, which is

intuitively correct considering the assumptions for these user classes. The increase for fixed-time control is the highest, giving larger relative improvements for the other strategies compared with fixed-time control.

To show the differences between the equilibrium solutions for the different control strategies in table 2 the route flows and green times for time period 2 are shown for Case 1. The route and signal numbers are shown in figure 2.

Table 2. Equilibrium Solution Route Flows and Green Times

		Route Flows per route (veh/hr)	Time Period 2	
Case 1	Fixed-Time	Route 1	1352	
		Route 2	1048	
	Webster	Route 1	944	
		Route 2	1406	
	Smith's P_0	Route 1	949	
		Route 2	1459	
	Anticipatory	Route 1	841	
		Route 2	1559	
	System Optimum	Route 1	325	
		Route 2	2075	
			Green times (sec)	Time Period 2
	Case 1	Fixed-Time	Signal 2	30.0
Signal 5			40.0	
Webster		Signal 2	39.4	
		Signal 5	39.2	
Smith's P_0		Signal 2	22.6	
		Signal 5	22.0	
Anticipatory		Signal 2	34.1	
		Signal 5	24.2	
System Optimum		Signal 2	25.2	
		Signal 5	7.4	

As can be seen from this table the route flows for time period 2 (the busiest time period) are not so different between the local control strategies (Webster and P_0), but quite different for the other control strategies (Anticipatory and System Optimum). Anticipatory Control and System Optimum Control try to put as much traffic on route 2 (the fastest, but longest route) as possible. Therefore, the green times for signal 5 are remarkably different for this time period. To force traffic to route 2, Anticipatory and System Optimum Control give less green to route 1 (signal 5) than the other control strategies, resulting in better system performance. In the end System Optimum Control is better, because it doesn't have to obey stochastic user equilibrium and can put almost all traffic to route 2. Note that in the results the cycle time is not fixed.

5. Conclusions and Further Research

Fairly large improvements are possible if route choice is taken into account in the control strategy. For the examples studied, Anticipatory Control showed an improvement of 25% in

comparison with optimised fixed-time control. In four out of five cases Anticipatory Control was better than the traditional control strategies.

From the traditional control strategies Webster control and Smith's P_0 appeared to be more or less equal, with an average improvement of 18%. These results are consistent with the results if also T-Model is used for evaluation in the main loop and for one user class (Taale and Van Zuylen, 2003).

Further research will focus on the use and optimisation of vehicle-actuated control. VA control is the normal Dutch strategy for all intersections and will be studied in combination with anticipatory control, especially for more complex intersections. Other important research topics are the assumptions made for this article. The question can be raised, what happens if the OD matrix is not known precisely or the assignment is not in equilibrium. Finally, the influence of departure time choice will be an interesting research field.

References

- Abdelfatah, A.S. and H.S. Mahmassani (1998) System Optimal Time-Dependent Path Assignment and Signal Timing in a Traffic Network, paper for the *TRB 77th Annual Meeting*, Washington D.C.
- Abdelfatah, A.S. and H.S. Mahmassani (2001) A Simulation-Based Signal Optimization Algorithm Within a Dynamic Traffic Assignment Framework, 2001 IEEE Intelligent Transportation Systems Conference Proceedings, Oakland (CA), pp. 430-435.
- Akçelik, R. (1981) *Traffic Signals: Capacity and Timing Analysis*, Research Report ARR No. 123, Australian Road Research Board.
- Akçelik, R. (1991) Travel time functions for transport planning purposes: Davidson's function, its time-dependent form and an alternative travel time function, *Australian Road Research* 21 (3), pp. 49–59. (Minor revisions: December 2000).
- Bliemer, M.C.J. (2001) *Analytical dynamic traffic assignment with interacting user-classes*, PhD Thesis, Delft University Press, Delft.
- Cascetta, E., A. Nuzzolo, F. Russo and A. Vitetta (1996) A modified logit route choice model overcoming path overlapping problems: specification and some calibration results for interurban networks, in: J.-B. Lesort (ed.) *Proceedings of the 13th International Symposium on Transportation and Traffic Theory*, Lyon, France, pp. 697-711.
- Chen, H.-K. (1999) *Dynamic travel choice models: a variational inequality approach*, Springer, Heidelberg, Germany.
- Chen, O.J. (1998) *Integration of Dynamic Traffic Control and Assignment*, PhD Thesis, Massachusetts Institute of Technology, Boston, USA.
- Houck, C.R., J.A. Joines and M.G. Kay (1995) *A Genetic Algorithm for Function Optimization: A Matlab Implementation*, NCSU-IE Technical Report 95-09, North Carolina State University.
- Mordridge, M.J.H. (1997) The self-defeating nature of urban road capacity policy; a review of theories, disputes and available evidence, *Transport Policy*, Vol. 4, No. 1, pp. 5–23.

- Sheffi, Y. (1985) *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods*, Prentice-Hall, Englewood Cliffs, NJ, USA.
- Smith, M.J. (1980) A local traffic control policy which automatically maximises the over-all travel capacity of an urban road network, *Traffic Engineering + Control*, Volume 21, Number 6, pp. 298-302.
- Smith, M.J. (1985) Traffic Signals in Assignment, *Transportation Research Part B*, Volume 19B, No. 2, pp. 155-160.
- Smith, M.J. (1987) Traffic Control and Traffic Assignment in a Signal-Controlled Network with Queueing, in: N.H. Gartner and N.H.M. Wilson (eds.), *Transportation and Traffic Theory. Proceedings of the 10th International Symposium on Transportation and Traffic Theory*, Cambridge, Massachusetts, USA.
- Taale, H. (1995) An algorithm for calculating the cycletime and greentimes for a signalized intersection, *Studies of the Faculty of Management Science*, University of Transport and Communications, Žilina, Slovakia, Volume 4, pp. 87-94.
- Taale, H. and F. Middelham (1995) Simulating Traffic and Traffic Control with FLEXYT-II-, in: M. Snorek *et al* (Eds.) *Modelling and Simulation 1995*, Society for Computer Simulation International, Istanbul, pp. 335-339.
- Taale, H. and H.J. Van Zuylen (2001) The Combined Traffic Assignment and Control Problem: An Overview of 25 Years of Research, paper for the *9th World Congress on Transport Research*, Seoul, Korea.
- Taale, H. and H.J. Van Zuylen (2003) Effects of Anticipatory Control for Several Small Networks, paper for the *Transportation Research Board 82nd Annual Meeting*, Washington D.C.
- Transportation Research Board (2000) *Highway Capacity Manual*, Transportation Research Board, National Research Council, Washington D.C., USA.
- Van Zuylen, H.J. (1980) *A Delay Minimizing Traffic Assignment for (Nearly) Congested Road Networks*, Verkeersakademie Tilburg, internal report.
- Van Zuylen, H.J. (2001) The assessment of economic benefits of dynamic traffic management, paper for the *9th World Congress on Transport Research*, Seoul, Korea.
- Van Zuylen, H.J. and H. Taale (2000) Traffic control and route choice: Conditions for Instability, in: M.G.H. Bell and C. Cassir (eds.) *Reliability of Transport Networks*, Research Studies Press Ltd, Baldock, United Kingdom, pp. 55-72.
- Webster, F.V. (1958) *Traffic Signal Settings*, Road Research Technical Paper No. 39, Road Research Laboratory, London.