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A multicriteria-based system dynamics modelling of traffic congestion caused by urban commuters.

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Abstract.

A framework combining system dynamics and group multicriteria decision aid is used to model the traffic crowding in cities. The basic model, which extends a congestion model described by K. Small, examines the behaviour of driving car commuters with respect to their home departure times to office during the morning rush hours. Several strategies for urban toll combined with working time flexibility are investigated

Keywords: Traffic, urban transport, congestion, system dynamics, multicriteria decision support system.

1. Introduction

Today, one of the major challenges for public decision-makers in Western countries in and around big cities is the solution of heavy congestion problems caused by the use of private cars. Especially the traffic jams in the morning and the evening on the highways leading to the central business district are getting out of control. It is clear that the capacity of the highways is getting too low for containing the ever increasing stream of car commuters driving to their job in the morning and back home in the evening. Furthermore, we observe an increase of the number of people leaving the city where they work in order to live outside in the green suburbs. This amplifying trend worsens the rush-hour issue as the number of commuters moving to and from the central business district with their private cars is growing.

Several solutions such as building new highways or preventing people to move out to the suburbs could be proposed. In a first thinkable approach of building new highways, however, past experience has shown that it will not solve the problem, because, after a while, the problem would come back in a even more acute form. Secondly, preventing people to move towards the green suburbs implies to have a comparable quality of life in the city districts. This is far from being the case, again partly due to the excessive use of cars. Though an improved quality is thinkable in the long-term, several social components such as security, cultural activities, environmental management, etc. have to be taken into consideration, however. Therefore, considering the specificity of this problem, we believe that solutions must be sought in changing the presumably bad habits of people with respect to their transportation means.

In this paper we will try to understand the effect of potential policies to reduce the congestion through the use of several techniques of operational research such as system dynamics and multicriteria decision aid. The purpose is mainly conceptual and methodological. It is planned to show how these techniques can be combined to provide new tools for investigating solutions and remedies to solve the congestion problem.

Our starting point is the simple traffic congestion model introduced by K. Small (1992). The latter is presented in section 2. It is based on the trade-off between two cost-functions representing the criteria: the time people spent on road when driving to the office, and the pressure of the schedule people are experiencing to arrive on time at the office. The major assumptions in this model are that each criterion can be represented by a cost-function, and that each car commuter is a rationally thinking being as he or she defines a personal commuting strategy. It is shown how the introduction of a urban toll during the peak hours and an increased flexibility in working hours can mitigate the congestion problem.

With this economic model in mind, an alternative behavioural approach is proposed in section 3. The solution of the latter requires a structural analysis of the causal relationships explaining the commuters' behaviours and also the solution to a multicriteria decision problem implying multiple decision-makers, i.e. commuters. The combination of system dynamics (SD) and Multicriteria Decision Aid (MCDA) proposed in the approach of Brans *et al.* (1998) provides the suitable working framework for that purpose. This approach will be applied in section 4 to investigate the benefits of an urban toll and flexible working hours on the congestion problem. Small's theory is used to define the initial conditions to this dynamic control problem.

A specificity of our model is the explicit inclusion of a MCDA-driver in the system dynamics model. This is absolutely necessary since the decision process of the individual car commuters lies at the heart of the problem. A new type of dynamic model, unusual in system dynamics, will be needed. In this model, the main feedback loop for the daily behaviour comes from the learning experience of the commuters on the road as they experience day after day the traffic conditions. The model is running for that reason on two different timescales and it is iterative till a convergence is achieved in the distribution of commuters' departure times.

2. An economic approach with the internalisation of social costs

A simple traffic congestion model has been described by K. Small in "Urban transportation economics" (1992). It was further elaborated in Mirabel (1997). In the following this approach will be labelled *"economic model"*.

A general setting of the model is the use of a unique highway by car driving commuters, which connects the green suburbs to the *Central Business District (CBD)*. In this idealised city, the car commuters get immediately from their houses on the highway and from there to their offices downtown. In a more advanced modelling the bottleneck effects rising up at the entrance and exit of the highway could easily be incorporated into the model. The existence of a unique highway is a large simplification though it seems to be sufficient for a first approximation of the congestion mechanism. This assumption could easily be relieved.

A second important (implicit) hypothesis of the model is the fixed number of car commuters day by day. In this paper we do not consider the leakage of a certain number of car commuters towards the public transportation means or vice versa, though we are well aware that this should be incorporated at a later stage of the model. In fact the influences of the public transportation means are absent in this model.

The result of commuting is a massive crowding in the morning (and symmetrically in the evening) on the connecting highway to (and from) the CBD (as confirmed by reality). Small's model examines the behaviour of commuters with respect to their home departure times to office during the morning rush hours only. There are two sub-models:

- The *individual sub-model* examines the commuter behaviour in the absence of any given specific policy. This model shows a sub-optimal solution regarding the collective interest. In the economic sense, the traffic crowding represents an externality for the society.

- The *collective sub-model* examines the modified commuter behaviour, assuming that a toll has to be paid for road use during the peak time. This time-dependent toll is supposed to optimise the collective interest, by internalising the congestion externality observed in the individual sub-model.

The basic idea behind both sub-models is that a car commuter chooses his (her) departure time from home to the office located in the CBD by making a trade-off between two time aspects:

- The *schedule time* imposed by the working hours in the CBD. The pressure imposed by schedule can be more or less dependent on the choice of the parameters in the model.

- The *travel time* imposed by the current traffic conditions on the road on the way to the CBD, assuming a unique departure point.

Accordingly, two cost-functions are introduced for both time aspects. They represent penalties for each individual commuter. A potential toll charged during the peak hours gives an additional penalty. Commuters will make a trade-off between the cost components, including the possible peak-hour toll. The final result is to achieve a constant total marginal cost across the time board. In this way a unique distribution of departure times from home can be derived.

More formally, starting first with the individual sub-model, i.e. without considering a toll, assume that N (= fixed) commuters move to the CBD, and that the recommended arrival time is given by s_0. Mirabel (op. cit.) gives the private marginal cost C_{MC} of a car commuter as a function of the time t:

$$C_{MC}(t) = \alpha T_{road} + \beta(s_0 - t) \quad if\ s_1 \le t \le s_0 \qquad (1a)$$

$$C_{MC}(t) = \alpha\, T_{road} + \nu\,(t - s_0) \quad if\ s_0 \le t \le s_2 \qquad (1b)$$

s_1 is the arrival time of the earliest commuter [min.]

s_2 is the arrival time of the latest commuter [min.]

α is the unit cost associated to the travel time [arbitrary currency units/min.]

β is the unit cost associated with the arrival time before the recommended time s_0 [arbitrary currency units/min.]

ν is the unit cost associated with the arrival time after the recommended time s_0 [arbitrary currency units/min.]

T_{road} is the time spent on road [min.] given by

$$T_{road} = t_{\min} + t_{congestion}\left[\frac{A(t)}{R}\right]^{\gamma} \qquad (2)$$

t_{min} is the minimum commuting time achieved in $t = s_1$ and s_2 [min.]
$t_{congestion}$ is the congestion time achieved when the arrival rate becomes equal to the nominal road capacity [min.]
A(t) is the commuters' arrival rate at time t [cars/min.]
R is the nominal capacity of the lane [cars/min.]
γ is the elasticity of the travel time with respect to the commuters' arrival rate [-]

A unique equilibrium distribution of arrival times A(t) is obtained by considering the three following constraints:

- All N cars arrive between s_1 and s_2.
- There is no congestion in s_1 and s_2.
- The private marginal cost $C_{MC}(t)$ (1a or 1b) is constant at each time t.

The collective sub-model optimises the collective utility. It internalises the cost of congestion by applying a toll charge during the peak-hour period $[s_1,s_2]$. Using optimal control theory, the very important following result is obtained. The toll, while internalising the social cost of the sub-optimal individual solution, spreads out the peak-hour time, and therefore it significantly reduces the congestion amplitude expressed by the value of T_{road}.

These results are shown in the following four scenarios, numbered 1 to 4:

1. No toll imposition during peak-hours and relatively inflexible working time, i.e., high penalty in case of late arrival times.
2. Toll imposition during peak-hours and relatively inflexible working time, i.e., high penalty in case of late arrival time.
3. No Toll imposition during peak-hours and relatively flexible working time, i.e., low penalty in case of late arrival time.
4. Toll imposition during peak-hours and relatively flexible working time, i.e., low penalty in case of late arrival time.

For deriving the numerical results, the following numerical assumptions have been made regarding the values of parameters in Small's model:

There are $N = 10^5$ commuters. The chosen departure time lies between 6 a.m. and 12 a.m., i.e., between 1 and 360 minutes. The minimum travel time is t_{min}=15 minutes. Recommended arrival time in office is 9 a.m., i.e., at time $t = s_0 = 180$ min. The dimensionless elasticity between the arrival rate and the congestion time is • =1.4. Therefore one has the following values of parameters:

$s_0 = 180$ [min]
$t_{min} = 15$ [min]
$\gamma = 1.4$ [-]

The cost parameters are chosen to be:

$\alpha = 1$ [currency unit/min]
$\beta = 0.2$ [currency unit/min]
$\nu = 0.6$ [currency unit/min] for the "inflexible" working hours scenario
$\nu = 0.2$ [currency unit/min] for the "flexible" working hours scenario

Figure 1 shows the results of the four scenarios for the arrival rate in [inhabitants/min]. Calculations have been made with MATLAB® (see Kunsch et al., 2000).

As to be expected the influence of the toll is to spread out the relatively narrow time window of departures in the reference scenario 1. Of course this mechanism is largely enhanced towards later arrival times when combining the urban toll with more flexible working hours in scenario 4.

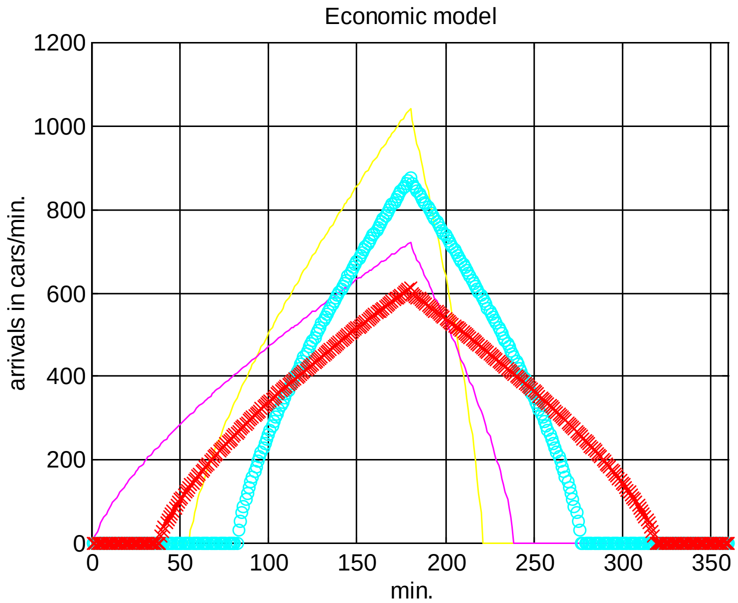

Figure 1: Arrival distribution rate in the economic model: scenarios 1(-), scenario 2 (- -), scenario 3 (o), scenario 4 (x) (from Kunsch et al., 2000)

3. A behavioural model combining System Dynamics (SD) and MCDA.

The following paragraphs extend the discussion on Small's model from Kunsch et al. (2000). This associated paper remarks that in several respects the economic model described in the previous section 2 is not satisfactory:

1. The commuter is regarded as a "Homo oeconomicus" making arbitrage between cost-functions. Therefore the evaluation of preferences with respect to a particular departure time are neither explicit nor transparent in the model. (Note also that, as shown in figure 1, reference is always taken to arrival times rather than to departure times in the economic model). In the Real World arbitrage also takes place, but in a less artificial way between multiple incentive factors: mainly early wake up hour, waiting time in congestion, and penalties for late arrival.
2. Aggregating costs in the same arbitrary units is a sensible thing to do, but the enumerated incentives have different units or are measured on qualitative scales.
3. The model is inherently static. The equilibrium distribution of departures is established instantaneously as a mathematical artefact. In a real situation, the equilibrium distribution will result from trial and error, as experience of the road conditions in previous days will guide the commuters in making adjustments in their selection of a "best departure time".

Taking these criticisms into account, we believe that the problem has to be considered from a behavioural and dynamic point of view rather than from a static approach based on aggregated costs alone. Understanding the commuters' behaviour with respect to a distribution of departure times requires a deeper modelling of their basic incentives for leaving their homes at given times. Also the learning process they go through day after day by observing the changing road conditions is an important element. We of course have to make the generally reasonable assumption that stationary road conditions are achieved after some time.

To go deeper, let us analyse the actions taken in the morning by every car commuter. First he wakes up at a given time in the morning. This wake up time is chosen with respect to his departure time, which on itself is chosen in such a manner that he would arrive on time at his job. How does this cause the congestion? The situation is such that we have a peak density of people leaving their homes in the morning. Due to the shape of this density function, the number of people on the road will increase suddenly very fast, which will lead to an overload and thus congestion on the highway. This congestion will increase the time people spend on road, which on itself leads to an increase of the number of people on the road. It is clear that what we have described here is nothing but a vicious feedback loop which can be schematically represented as a causal-loop or influence diagram (Richardson and Pugh III, 1981) shown in figure 2.

A plus sign at the arrowhead indicates that the variable to which the arrow is pointing will grow if the variable from which the arrow is leaving increases. The plus sign at the centre of the directed graph denotes the sign of this feedback loop (i.e. the product of all the signs of the arrows included in the loop).

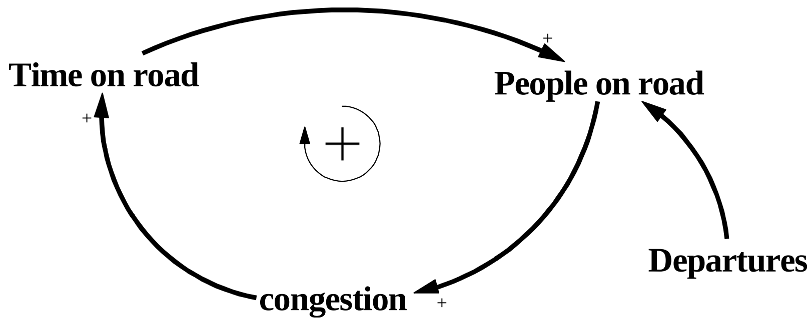

Figure 2: The positive feedback loop, which lies at the heart of the congestion problem.

Let us now outline the actions performed by the car commuters in the morning. As can be seen in figure 3 there is a certain number of people home (i.e. a fraction of N=100 000 in our model), and at every moment you have a given number of departures, which determines the number of people moving to the highway. This flow determines the number of people on the highway, which are staying there for a given time, called the "time on road". Afterwards they are moving from the highway and eventually they arrive at their job places, of which the cumulative sum gives the number of people at office. These last relations are represented in a flow-level diagram shown in figure 3.

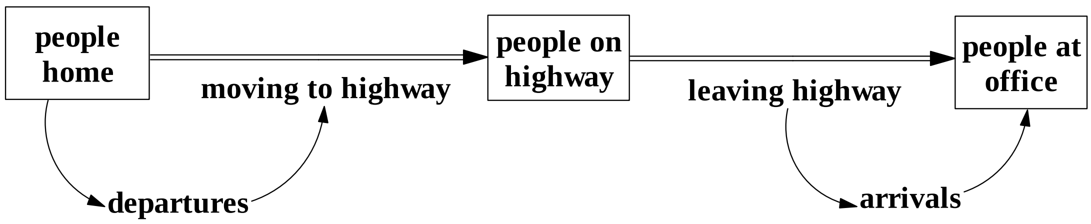

Figure 3: The flow-level diagram of the daily scheme, run through by every car commuter in the morning.

While running through this scheme day by day, every car commuter is somehow optimising his or her departure time in order to arrive on time at his or her job. As already mentioned in the previous section, every car commuter is taking into account several criteria to take the decision of a specific departure time. The wake-up time, the pressure of the schedule dictated by the more or less important working time flexibility, and the time spent on road from home to office give three criteria we can consider as being sufficient for explaining behaviours. As soon as a policy, like an urban toll to be considered later in this paper, is added to the system, it defines a fourth criterion, i.e. an additional incentive for the daily commuters.

Hence, each individual car commuter is making his multicriteria analysis in his own way in order to determine his departure time. The possible actions he is considering are the possible departure times in a restricted time window, say 6 a.m. to 12 a.m. In practice, each car commuter is determining the evening before at which time he plans to leave home in the morning. To do this he or she is using his or her experience from the previous days regarding the dynamic road conditions. This departure time will be optimised with respect to not only personal preferences, but also to the preferences of all other commuters on the road. The resulting iterative process considers two time dimensions: the departure time windows and the succession of departure days. The hope is to achieve the convergence towards a stationary distribution of departure times.

In the associated paper Kunsch et al. (2000) the authors present a first calculation of this iterative process expanding directly Small's model. The calculation of the mentioned incentives for choosing a particular departure time is calculated by comparing for each criterion two decisions, at each time step of 1 minute in the time window 6 a.m. to 12 a.m. The latter are (1) leave immediately and (2) leave later. The intensity of preference in a given criterion favouring the immediate departure is obtained as a discounted sum of the difference (gain-loss) realised with respect to choosing the second alternative. In this way normalised time-dependent incentive densities are obtained, which are then aggregated by a weighed sum over the three or four criteria. The results are very satisfactory and confirm, with much more transparency in the understanding of commuters' behaviours, the main results of Small's model in figure 1. This approach is however only applicable to the simplified case under analysis and extension capabilities to more complex settings are limited.

Therefore the authors have wished to develop a more general tool for policy-making in the congestion problem. Because the main purpose of any such policy shall aim at changing the habits of people, as we already mentioned in the introduction, we are dealing with a control problem. Some time ago, two of the authors (Brans et al., 1998) have developed a generic methodology for designing control policies in complex socio-economic systems, called Adaptive Control Methodology (ACM). It was fully indicated to develop an alternative approach within this more general framework.

As a short introduction to the ACM, we recall here that this framework combines two techniques, i.e. System Dynamics and MCDA, for the sake of controlling the analysed system. The ACM consists of four main phases comprising each several steps (11 steps in all):

1. Information system – Mental modelling phase;
2. System Dynamics modelling phase;
3. Strategy building and MCDA phase;
4. Monitoring and Control phase.

The purpose of phase 4 is to update the policy decisions as a function of the monitoring of their efficiency. So it is essentially where the iterative aspects set in during the day-to-day optimisation process, until stationary distributions of departure times are obtained.

In phase 3, in which strategies are fixed, a MCDA–driver shall trigger a myriad of individual departure decisions. This is based on the ideas explained in Macharis (2000), in which the author proposes the direct blending of the MCDA-calculations into the equations of the SD-model. As a matter of fact the system we are modelling incorporates the varying behaviour of car commuters in making their choice of a departure time.

The peculiarity of the transposition of this technique to the current problem is that it has to deal with a large number of decision-makers, i.e. car commuters. Hence, it is necessary to treat the problem by means of distributions of behaviours as pointed before. Nevertheless we show that applying a MCDA-technique in a rather straightforward way gives good results.

Considering the three or four criteria described above, all possible departure times by intervals of 6 minutes between 6 a.m. to 12 a.m. are compared pair-wise on the basis of a unique set of preference functions. The MCDA-driver produces outcome in the form of preference flows. This is explained in more detail below and in appendix 1. These flows can be interpreted as providing a measure for the incentive for picking up a specific departure time within the interval 6 a.m. to 12 a.m. A distribution of the incentives is obtained by renormalising, and it is then used as the relative distribution of departures. The assumption behind the pair-wise comparison is that all commuters are alike, i.e. they all have the same preference functions. With this assumption, the MCDA ought to be performed only once, rather than for a very large number of commuters N.

Taking a weighted average of the departure distributions of two successive days accelerates the approach to a stationary distribution: it is reasonable to assume that an optimal stable distribution exists under normal conditions (normal weather, no accidents, no holidays, etc.). The traffic situation on the highways appears indeed to be more or less the same every morning.

Let us now look more in detail to the MCDA-driver itself. We have used the well-known MCDA technique PROMETHEE (Brans *et al*., 1985 and 1994), suitably modified for our purpose. The general features of the approach are described in appendix 1. We first determine the ϕ^+ and ϕ^- flows for every departure time (being considered as actions), which are calculated in the usual way. Remark that in order to be able to do this, one must suppose that each decision-maker, i.e. the car commuter, has a sufficient knowledge of the road conditions within the complete departure time interval, drawing from the past days experience. Further it has to be assumed that the final choice taken previously to any departure is not changing later.

The MCDA-driver has several criteria data as input, which evolve over time. Instead of using the time-dependent PROMETHEE net flow:

$$\phi = \phi^+ - \phi^- \tag{3}$$

used in the determination of a ranking of several policies or actions, we propose to use rather:

$$P = \phi^+ (1 - \phi^-) \, . \tag{4}$$

The relation (4) seems to be sensible, as it reads: “the incentive power of an action is given by its strength measure, represented by the dominating flow and weighted by its weakness measure, represented by one minus the dominated flow”. By renormalising this quantity over the complete time interval of the departure time window from 6 a.m. to 12 a.m. we obtain:

$$P_N(t) = \frac{P(t)}{\int_{6a.m.}^{12a.m} P(t)dt} \, , \tag{5}$$

$P_N(t)$ is the distribution of the commuters’ incentive for leaving from home at each time t.

Putting all previous elements together, the simplified causal stock-flow diagram presented in figure 4 is obtained. It displays the positive feedback loop, responsible for the congestion problem, and in addition a negative control loop stemming from the optimisation procedure of commuters.

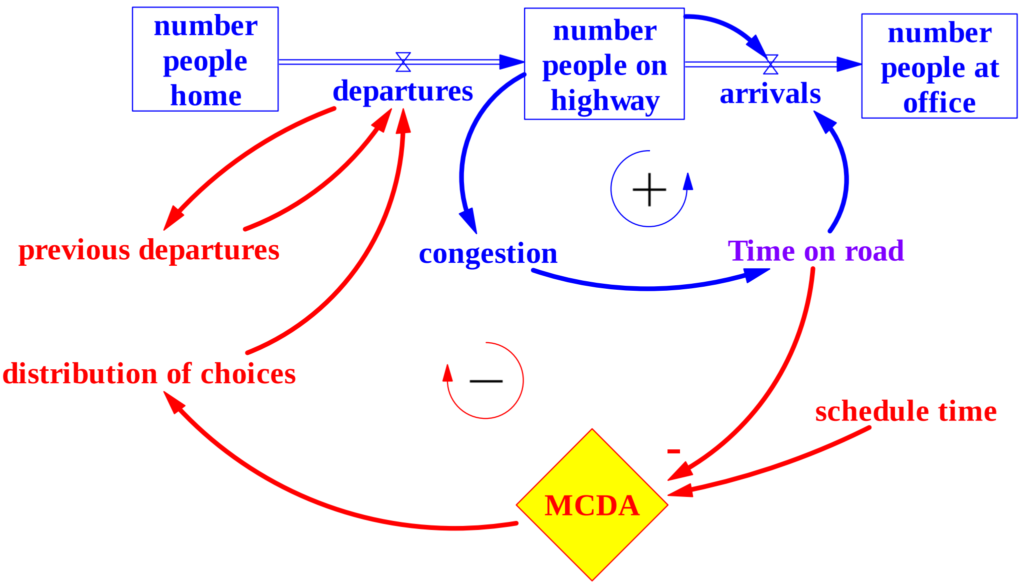

Figure 4: The causal loop/stock flow representation of the congestion problem and the commuters' optimisation.

The MCDA-driver triggers this decision process, as explained. The two input variables are "Time on road" and "schedule time". The latter variable represents the penalty people receive when they arrive too late at their job (i.e. after 9 a.m. in our model). Using the PROMETHEE analysis and the formulas (4, 5) we determine the variable "distribution of choices", which on itself determines the distribution of departures for the following day, since we supposed that car commuters are reacting on the present congestion with a time delay of one day.

As visible in the diagram "previous departures" are averaged with the result of the optimisation process of the car commuters' to calculate the actual departures, using a weighting parameter "obstinacy". The latter stands for the resilience of commuters in changing their minds. This parameter allows us to regulate the velocity of the convergence in the optimisation process.

The positive feedback loop is thought to be in most cases dominant over the negative damping loop (Ford, 1999), as the criterion "time on road" is relatively less important for most commuters. It is therefore given a rather low weight in the multicriteria analysis, to reflect this observation. Hence, this negative feedback loop has only a limited influence in practice in reducing the congestion amplitude. Remark that the congestion is defined in the same manner as in section 2 eq. (2) , i.e. by the difference between the total time people spend on road and the minimal time they have to spend on road.

Policies developed for tackling the congestion problem will therefore weaken the influence, and decrease the dominance of the positive feedback loop, responsible for congestion. This requires implementing structural measures, i.e., by changing the structure of the system. In addition these changes must be such that they force a change in the "distribution of choices". It is why the ACM has adopted the concept of "control by structure".

A first policy can simply be the introduction of flexible working hours, which would imply that the weight of the variable "schedule time" would decrease, increasing in turn the importance of the "time on road" and, consequently, the dominance of the negative feedback loop.

A second possibility is the introduction of new negative feedback loop, in order to exert a controlling effect on the positive feedback loop. This is achieved by introducing the urban toll. This toll is calculated and imposed when the congestion exceeds a certain threshold, i.e. when the dominance effect of the positive feedback loop is at its maximum value. It should be large enough to achieve its goal in the MCDA decision process. In the presented model the toll is calculated starting from the results of the basic run and implemented on the hours corresponding to the peak hours of the basic simulation.

In figure 5 it is shown how these policies can structurally be implemented in our model:

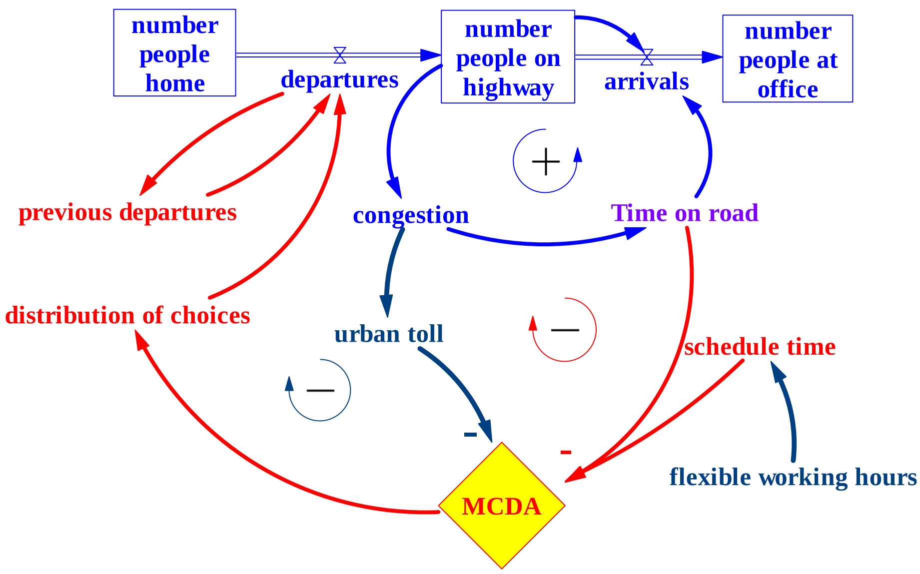

Figure 5: Structural modifications to control the congestion problem: introduction of an urban toll and flexible working hours. The former creates a new negative control loop. The latter reinforces the effect of the existing control loop.

4. Results using the behavioural congestion modelling

To analyse the impacts of an urban toll and flexible working hours and to compare our system dynamics/MCDA model with Small's model, we have simulated the analogues of the four scenarios presented in section 2.

Simulating the basic model (cf. figure 4) with the same general assumptions as in Small's model and with the same values of the parameters •, t_{min}, etc., we obtain the results presented in figure 6. The weights of the criteria "schedule time" and "time on road" have the respective values 0.9 and 0.1, which are used in the MCDA-driver. These results were obtained after several consecutive iterations performed by the model until the system has sufficiently reached the social optimum. The time interval from 1200 till 1259 represents the interval from 6 a.m. till 12 a.m..

It is clear from this figure that while the number of departures rise, the congestion on the highway increases. As observed in reality, we notice that the congestion peak is situated between 8.30 a.m. and 9 a.m.. Due to this congestion a lot of people arrive too late at their job in spite of the possible penalty they might suffer, which is also reflected in these simulation results: most of the car commuters arrive between 8.30 a.m. and 9.30 a.m., though there is still an important number of car commuters arriving after 9.30 a.m. In practice, the latter often work later in the evening in order to compensate the hours of their late arrival, which is somehow already a form of flexible working hours.

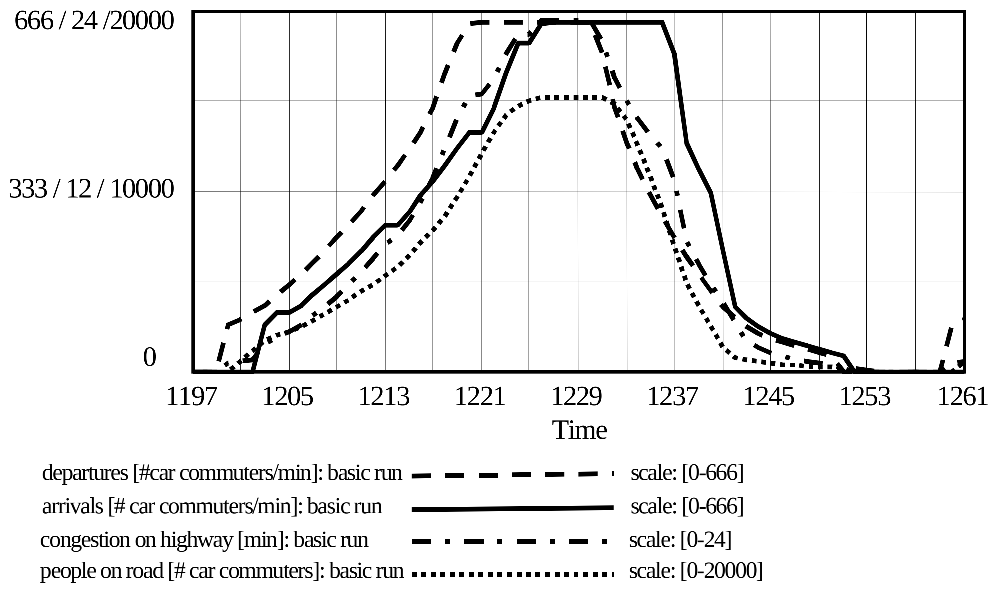

Figure 6: Simulation results of the basic model for several key variables.

The second scenario consists in implementing flexible working hours by lowering the weight of the "schedule time" from 0.9 to 0.4 and by increasing the weight for the "time on road" to 0.6. Furthermore, the penalty for arriving too late is weakened, creating an additional incentive for later departure times. Due to the higher importance of the "time on road" with respect to the basic scenario, the influence of the negative control loop (see figure 4) is strengthened.

Applying an urban toll creates an additional control loop (see figure 5), passing through the MCDA-driver and thus imposes a new constraint on the decision process. Consequently, the weights for the several criteria have to be redistributed. The respective weights of the "schedule time", the "time on road" and the "urban toll" were chosen to be 0.6, 0.1 and 0.3, reflecting the low importance of the "time on road" and the still dominating character of the "schedule time".

In the final scenario both policies: introduction of flexible working hours and an urban toll, are combined. The weights for the "schedule time", the "time on road" and the "urban toll" were then chosen to be respectively 0.4, 0.3 and 0.3.

The simulation results of the four scenarios can be found in figures 7 and 8. From figure 7 it is clear that flexible working hours lowers the peak in the number of arrivals and has a spreading effect on its distribution. Introducing an urban toll also lowers the number of people arriving at the same time. But while flexible working hours creates the incentive for people to leave their home later in the morning, the application of an urban toll without flexible working hours forces them to leave earlier. Hence combining both policies should have a flattening effect on the number of arrivals.

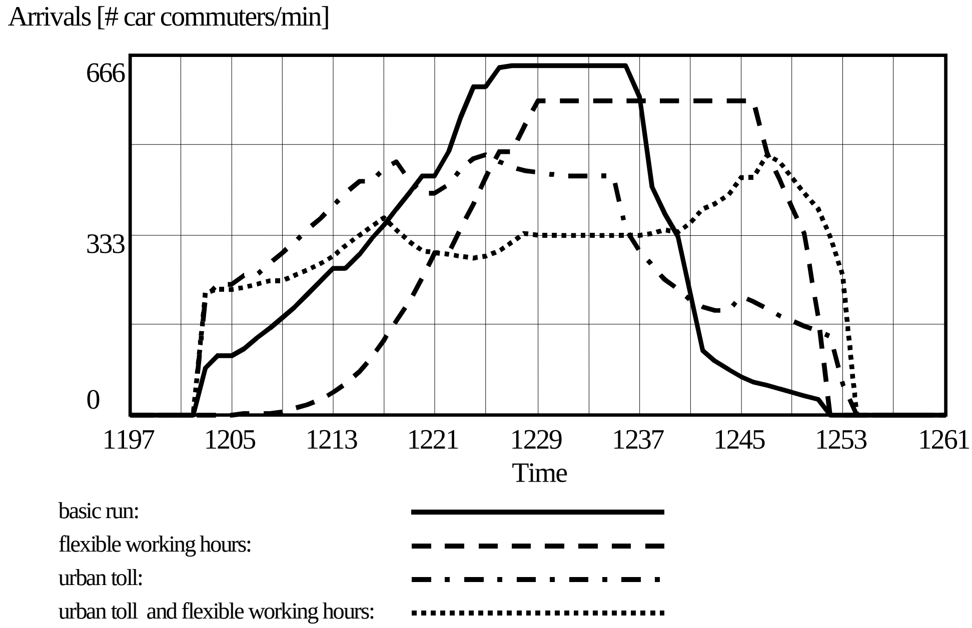

Figure 7: Simulation results for the four scenarios for the variable: "arrivals".

Remark that the shape of these distributions is less regular than those of the curves in figure 1 although the effect of the policies is comparable. This is essentially due to the incorporation of the MCDA-driver and the optimisation process through an averaging procedure, which, in our opinion, provides much more realistic results, despite the fact that we made the same general assumptions. But the final conclusion appears to be the same.

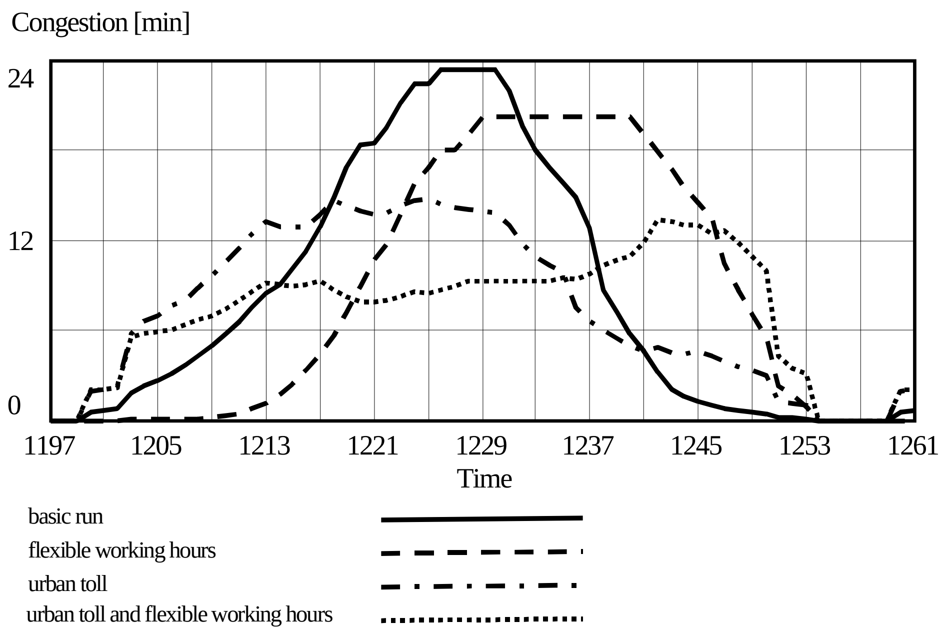

Figure 8: Simulation results of for the four scenarios for the variable "congestion on highway".

The ultimate purpose of introducing the above policies is lowering the congestion. As can be seen in figure 8 the congestion on the highway is suppressed drastically and the peak distribution of the basic simulation has almost become uniform when introducing both flexible working hours and an urban toll. Hence, from these numerical results we may conclude that only an appropriate combination of flexible working hours with an urban toll will have favourable effects on the congestion.

5. Conclusions.

In this paper group multicriteria decision analysis and system dynamics have been combined into one model in order to analyse congestion problem in urban areas. A conceptual model has been set-up to the behaviour of the car commuters and their underlying decision process. By influencing the decision process one obtains a global effect on the distribution of choices of departure times, which is the key variable driving the process. This result is achieved by using "control by structure policies": the introduction of an urban toll and flexible working hours.

From the simulation results we conclude that the most appropriate policy would be a good matching combination of flexible working hours and an urban toll. Of course these results should be considered within the restrictions of our model, in which several relationships between variables and procedures are still under development. Several questions remain so far without answer:

- Is it sufficient to have one set of preference functions and weights in the PROMETHEE procedure on which the MCDA-driver is based?

- Should the MCDA-driver perform a full pair-wise comparison of all actions, as assumed in the present paper, or, on the contrary, a partial comparison of subsets of possible actions? For example commuters could change their mind just before they were supposed to leave as decided in the previous evening? In this case their decision process would be "will I leave now or will I leave later" (See Kunsch et al. 2000).

- Has the urban toll been calculated in an appropriate manner? Should the toll be dynamic: depending on the degree of congestion or should it be a well-optimised but fixed function?

- Has the iteration process been performed in an appropriate way? Does the social optimum for departure times really exist?

In addition to these open questions it is important to perform a sensitivity analysis on the technical parameters of preference of PROMETHEE like the weights of the criteria and the preference thresholds of the preference functions.

Furthermore, the model should be extended in such a way that the public transportation means are taken into account. This would broaden the spectrum of policies, and enable the policy-makers to influence the decision process of the commuters with respect to the choice of their transportation mean. Hence, policies could be introduced, to lower the number of car commuters itself, herewith decreasing the traffic congestion.

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APPENDIX The basic principles of the MCDA technique PROMETHEE-GAIA

Let $f_1(.), f_2(.), ... f_K(.)$ be the K evaluation criteria the decision-makers wish to take into account. Suppose, in addition, that all the evaluations are real numbers expressed on their particular criterion units or real number scores placed on numerical scales, such as 0 to 10 or 0 to 100, etc. The following evaluation table is set up for a set of considered strategies S_i, i=1,N.

Strategies	$f_1(.)$	$f_2(.)$	...	$f_j(.)$	...	$f_K(.)$
S_1	$f_1(S_1)$	$f_2(S_1)$	....	$f_j(S_1)$	....	$f_K(S_1)$
S_2	$f_1(S_2)$	$f_2(S_2)$	...	$f_j(S_2)$	...	$f_K(S_2)$
...	...	...	...	...	...	...
S_i	$f_1(S_i)$	$f_2(S_i)$	...	$f_j(S_i)$	...	$f_K(S_i)$
...	...	....	...	....	...	....
S_N	$f_1(S_N)$	$f_2(S_N)$	...	$f_j(S_N)$	...	$f_K(S_N)$

Table 1: Multicriteria evaluation table

First, preference functions $P_k(S_n, S_m)$ are defined for the sake of comparing strategy pairs S_n, S_m for all criteria $f_k(.)$, k=1, K. Each function for a given k is defined as being monotonously increasing, in function of the difference of the scores being obtained by the two strategies on each particular criterion. Different shapes of the preference function with the possibility of multiple preference thresholds can be chosen. Suppose now that all pairwise comparisons have been performed, providing all function values:

$$0 \leq P_k(S_n, S_m) \leq 1 \tag{A.1}$$

$$k = 1, 2, ...K; \; n, m = 1, 2, ...N.$$

An aggregated preference index over all the criteria is then calculated

$$\Pi(S_n, S_m) = \sum_{j=1}^{K} P_j(S_n, S_m) w_j \tag{A.2}$$

where w_j is a weight, measuring the relative importance allocated to criterion j. The weights are supposed to be normalized, so that

$$\sum_{j=1}^{K} w_j = 1 \tag{A.3}$$

The following positive and negative dominance flows express the dominating and the dominated character of a strategy S_n, respectively, over all the other strategies:

$$\begin{aligned} \Phi^+(S_n) &= \frac{1}{n-1} \sum_{m=1}^{N} \Pi(S_n, S_m), \\ \Phi^-(S_n) &= \frac{1}{n-1} \sum_{m=1}^{N} \Pi(S_m, S_n); \end{aligned} \tag{A.4}$$

while the balance of the dominance flow gives the net flow:

$$\Phi(S_n) = \Phi^+(S_n) - \Phi^-(S_n) \tag{A.5}$$

The two partial rankings can be obtained from both the positive and the negative flows. Their intersection provides the so-called *PROMETHEE I ranking*, in which incomparabities between strategies are made visible. Complete ranking, or *PROMETHEE II* ranking is obtained from the net flows.

The PROMCALC software (Brans and Mareschal, 1994) and its more recent Windows version (Visual Decision, 1999) allows sensitivity analysis on the weights.