European Transport \ Trasporti Europei n. 44 (2010): 23-40

Rewarding instead of charging road users: a model case study investigating effects on traffic conditions

Michiel C.J. Bliemer [1,2*], Dirk H. van Amelsfort [3]

[1] *Delft University of Technology, The Netherlands*
[2] *Goudappel Coffeng BV, The Netherlands*
[3] *WSP Analysis and Strategy, Sweden*

Abstract

Instead of giving a negative incentive such as transport pricing, a positive incentive by rewarding travelers for 'good behavior' may yield different responses. In a Dutch pilot project called Peak Avoidance (in Dutch: "SpitsMijden"), a few hundred travelers participated in an experiment in which they received 3 to 7 euros per day when they avoided traveling by car during the morning rush hours (7h30–9h30). Mainly departure time shifts were observed, together with moderate mode shifts. Due to the low number of participants in the experiment, no impact on traffic conditions could be expected. In order to assess the potential of such a rewarding scheme on traffic conditions, a dynamic traffic assignment model has been developed to forecast network wide effects in the long term by assuming higher participation levels. This paper describes the mathematical model. Furthermore, the Peak Avoidance project is taken as a case study and different rewarding strategies with varying participation levels and reward levels are analyzed. First results show that indeed overall traffic conditions can be improved by giving a reward, where low to moderate reward levels and participation levels of 50% or lower are sufficient for a significant improvement. Higher participation and reward levels seem to become increasingly counter-effective.

Keywords: Pricing policies; Rewarding; Traffic conditions; Peak avoidance.

1. Introduction

Nowadays, increasing congestion levels, environmental pollution, and other external costs are experienced in most countries. Road pricing is seen as one of the most effective measures to battle these externalities. Road pricing does not need much introduction and for the interested reader we refer to Verhoef et al. (2008). An increasing number of countries has introduced some form of pricing, from simple local toll roads (e.g., Scandinavia, France), cordon charges (e.g., London, Singapore, Stockholm), and dynamic pricing (San Diego), to nation-wide kilometer charging

* Corresponding author: Michiel C.J. Bliemer (m.c.j.bliemer@tudelft.nl)

(Germany). The main principle is to let the user pay the costs for the 'damage' he or she causes, such as congestion costs, road maintenance costs, and pollution costs. In economic terms, pricing aims to internalize the external costs.

1.1. Charging versus rewarding

Charging, however, is a negative incentive and travelers' public acceptability of such a measure is typically low. Giving positive incentives is likely to have little resistance, while similar results may be expected. Prospect theory (Kahneman and Tversky, 1979) indicates that losses and gains are valued differently, and therefore also the magnitude of the responses between charging and rewarding is expected to be different. In this paper, we focus on rewarding instead of charging, by looking at a positive incentive for travelers when they show 'good behavior'. Furthermore, mainly the travelers' responses to a rewarding scheme and their impact on traffic conditions will be investigated.

Both charging and rewarding, also called push and pull measures, may be used to achieve the same objective, although in many perspectives they are different. In terms of acceptability, rewarding will be seen as more acceptable by most people than charging. With respect to effectiveness, it is not quite clear if charging is more effective than rewarding. Prospect theory would argue that losses have a more emotional impact than an equivalent amount of gains, such that charging should be considered as more effective. However, Schuitema et al. (2003) argue that some car drivers consider rewarding more effective, since punishment is bad for effectiveness and a positive incentive makes people happy, which contributes to its effectiveness. On the other hands, the effectiveness may be less with rewarding than with charging because of the induced demand that is higher with rewarding than under (optimal) tolling. From an economical point of view, charging (e.g., in the form of a tax) yields revenues, which has generally an indirect positive welfare effect, while for rewards such effects turn into a disadvantage.

The effects of rewarding on travel behavior has been tested by other researchers, and Nielsen and Sørensen (2008) for example find that providing rewards (as a proxy for testing road pricing schemes) does lead to travelers seeking other alternatives. Also, the levels of the rewards have an effect on the size of behavioral responses as well. The main behavioral responses found were new routes and for "occasional" trips new destinations, time of day (to non-peak) and to some extent, fewer trips.

Although interesting and also important, a description of a true business case is beyond the scope of this paper. In other words, it is assumed that the money for paying the rewards is available, and potential traffic effects of the rewarding scheme are analyzed, while not worrying about the source of the money. One can imagine that a Department of Transport could be interested in financing such a reward in order to alleviate congestion when road construction work yields significant additional congestion. Recently, the Dutch Ministry of Transport, Public Works, and Water Management has introduced two of such rewarding projects during construction works at two main motorway bridges.

1.2. Dutch Peak Avoidance project

In October to December 2006, a Dutch experiment called Peak Avoidance ("SpitsMijden" in Dutch) was conducted as a real life pilot study on the Dutch road network. In this experiment, 340 regular car driving commuters from the city of Zoetermeer to The Hague participated voluntarily. The A12 motorway is the main connection between these two cities and is heavily congested. The average trip distance is approximately 15 km and the trip takes between 10 minutes (free-flow) and 30 minutes (during congestion). During ten weeks, each participant was offered a reward if he or she avoided traveling by car during the morning rush hours (7h30–9h30). The reward was either monetary (systematically varied between 3 and 7 euros per peak avoidance), or one could save for a free smartphone and navigation system. In this paper, we focus on the effects of the monetary reward, however more information on the smartphone reward and their impacts can be found in Knockaert et al. (2007) and Ettema et al. (2008). Also, more general information of the project and many results can be found there. Car trips of participants were detected using transponder detectors and cameras with license plate recognition. Figure 1 illustrates the area and the location of the detection points. If a traveler is not detected on a working day, then the reward is given, relative to the average number of passages the participant made per week before the start of the pilot (license plate recognition was already in place for recruitment of the participants). Travelers could look at their gained rewards on a website. Additional questions about their trip were asked each day.

Figure 1: Zoetermeer – The Hague network with A12 motorway and detection points.

Since the detection points basically cover all routes from Zoetermeer to The Hague (and were known to the participants), route changes by the participants are not much expected. Mainly departure time shifts are expected, avoiding the morning peak by traveling earlier than 7h30 or later then 9h30. Also, shifts to other modes of transport can be expected. Some behavioral responses to the rewarding scheme are presented in Figure 2. First of all, the situation before and after rewarding is more or less the same (with some slight differences in public transport and bike use, which can be explained by cold weather conditions at the end of the pilot period). Hence, without rewards, there is no incentive to make any changes. With a reward of 3 euros per day, a significantly lower number of people travel during the morning peak (25% compared to 50%), and with a reward level of 7 euros this even decreases to 19%. Participants have a clear preference for departing earlier (before 7h30) than later (after 9h30). Also, public transport use increases under the reward scheme, from approximately 4% to 10%.1 Note that the difference in effects between a reward of 3 and 7 euros is actually not that large. Already with a reward level of 3 euros, many participants decided not to travel by car during the morning rush hours. For more details, see Knockaert et al. (2007) and Ettema et al. (2008).

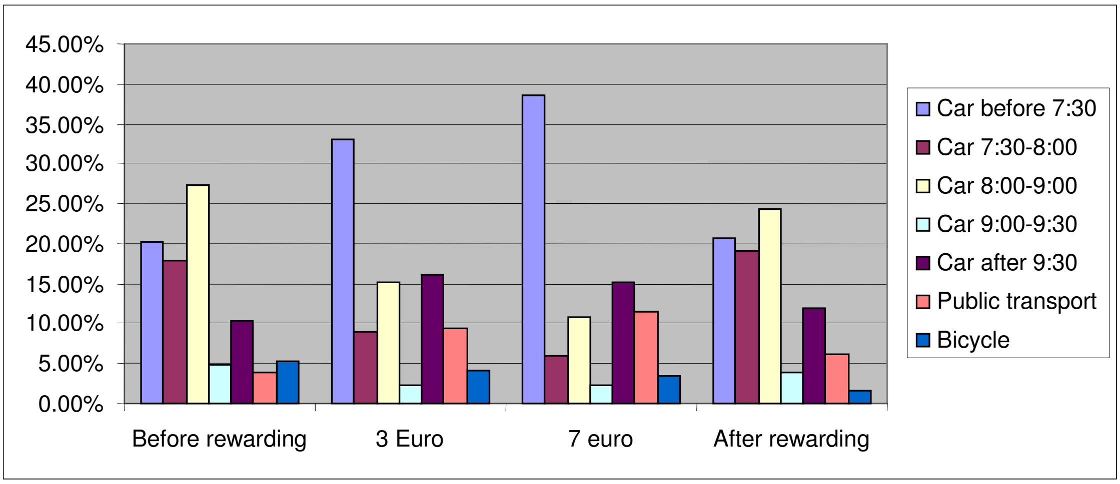


Figure 2: Behavioral responses to rewarding for avoiding the morning peak.

1.3. Aim of the model study

The behavioral changes observed in the pilot study are very interesting and offer insights into the sensitivities of travelers to a reward, at least in the short term. Long term effects on the traffic conditions could not be investigated due to the low number of participants in and the short run of the experiment. In order to assess such a rewarding scheme in terms of congestion levels and overall network performance, a mathematical transportation model is proposed in this paper, taking into account decisions of trip makers, such as trip choice, mode choice, departure time choice, and route choice. Higher numbers of participants can be simulated in the model. Since we are mainly interested in long term effects, feedback loops exist in the model such that travelers may change their decisions based on their experience. For example, if the rewarding scheme pushes participants away from the morning peak, the peak hours may become less congested, attracting other (non-participants) travelers possibly towards the peak period. All these interactions are included in the model.

1.4. Paper outline

In the next section, the model framework and methodology will be described, and each model component will be discussed in more detail. Then in the following section the Peak Avoidance rewarding scheme will serve as input for the model and different reward strategies will be analyzed using the proposed model. Results on total network travel time savings for different reward strategies will be presented, along with some

[1] During the pilot, the public transport was not operating at intended levels of service due to technical problems, which may bias the mode choice results in the pilot.

other results. Finally, the last section concludes with a discussion and directions for further research.

2. Model framework and methodology

In this section, the methodology and models used in the remainder of the paper will be described. The described model is able to determine responses to general pricing measures (which can be location and time specific) and takes trip and mode choice changes, departure time changes, and route changes into account. The latter two are modeled in more detail than the first two. Instead of talking about 'pricing', we use 'rewarding', which is mathematically a negative price inside the model framework (although the parameters may be different). The model is multiclass in the sense that it can deal with different preferences for different groups of travelers. In our case study later, this will mainly be used to describe participants (user-class 1) and non-participants (user-class 2) of the (voluntary) rewarding scheme. Different vehicles classes (e.g., cars and trucks) will not be considered in this paper, although this would be a direction for future research. For a more detailed description of the model and the parameter estimates, we would like to refer to Van Amelsfort (2009).

2.1. Overall framework of the model

The model consists of different components, as illustrated in Figure 3. In the modeling sequence the (static) total car demand is distributed over user groups, departure time intervals, and the available routes based on network conditions. To reflect trip and mode choice changes, the level of demand also changes as a result of changes in generalized costs. Thus, the aggregation level as well as the demand level itself change within the model and in order to discuss properly we first define three different types of demand.

- The first type of demand we define $\overline{D}^{rs}$ as the total demand for car travel in a reference situation without rewards. In this case the demand is not user class specific;
- The second we define $\widehat{D}_m^{rs}(k)$ as the initialized dynamic demand. The demand is user class specific, it is dynamic, and it includes the primary effect of rewards on demand (given that traffic conditions have not yet changed);
- The third type $D_m^{rs}(k)$ constitutes the resulting dynamic travel demand after applying demand elasticity factors and departure time shifts.

As shown in Figure 3, the model process starts with an initialization model in which the total car demand is split up between the participants and non-participants, demand is distributed over different time periods according to preferred departure times, and initial elastic demand effects of introducing the reward are applied. This initialization model results in the initialized dynamic demand and is the starting point for the iterative equilibrium process. This iterative process starts with calculating new levels of demand based on changes in traffic conditions and costs. These demand changes result from simultaneous calculations of elastic demand effects and departure time choice adjustments. The new demand levels are input for new route choice calculations after which the new traffic conditions can be determined using a traffic simulation model. We will now discuss the details of each of these components in the model.

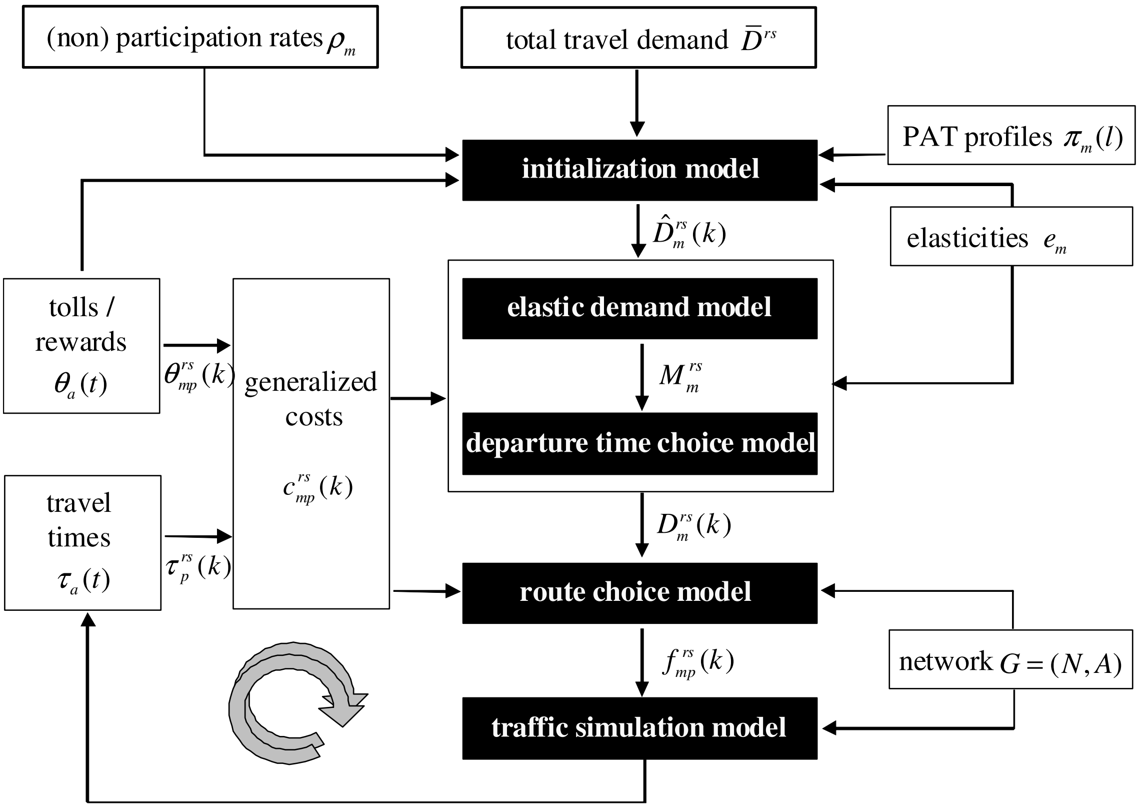


Figure 3: Overall framework of the model.

2.2. Initialization model

In the initialization model, the first step is to split up the total car demand into two user classes (participants and non-participants), according to $\bar{D}_m^{rs} = \rho_m \bar{D}^{rs}$ using participation rates ρ_m, where m represents user-classes 1 and 2. These participations rates are exogenous input into the model. Then the static user class specific demand is distributed over the different departure time periods k, using (calibrated) preferred arrival time (PAT) profiles $\pi_m(l)$ for each arrival period l. The profiles for the two different classes need not be the same, as participation of the rewarding scheme is voluntary and it is more likely that travelers that already travel very early or very late in the morning peak will participate. The dynamic initial travel demand, indicating the number of cars departing at time k, is determined as follows:

$$\bar{D}_m^{rs}(k) = \pi_m(k + \tau^{rs,0})\bar{D}_m^{rs}, \tag{1}$$

in which $\tau^{rs,0}$ is the (minimum) free-flow travel time between r and s. In other words, the free-flow travel times are used to convert the preferred arrival time, l, to a preferred departure time, k, where $l = k + \tau^{rs,0}$. We thus assume that travelers initially depart according to their preferred time of travel, not taking congestion into account. The former two steps together determine a first user class specific dynamic demand. Using this first dynamic demand we can run the route choice and traffic simulation model for the first time to get time dependent generalized costs. Let $c_m^{rs,0}$ and c_m^{rs} denote the flow-weighted (over routes and departure times) average generalized costs before and after the rewarding scheme, respectively (hence only primary effects are considered at this stage, as the travel demand is considered fixed; secondary responses will be dealt with in the elastic demand model). Then the initialized dynamic demand per user-class may be determined by

$$\hat{D}_m^{rs}(k) = M_m^{rs,0}\bar{D}_m^{rs}(k), \tag{2}$$

with

$$M_m^{rs,0} = \left(\frac{c_m^{rs}}{c_m^{rs,0}}\right)^{e_m}, \tag{3}$$

where $e_m \leq 0$ is an elasticity factor indicating the sensitivity of travelers to costs.

The elastic demand effects (factors) $M_m^{rs,0}$ are applied to the first dynamic demand $\bar{D}_m^{rs}(k)$ to arrive at $\hat{D}_m^{rs}(k)$ the initialized dynamic demand which enters the iterative process. The initialization model is completed by a final route choice and traffic simulation model. The resulting route travel times and travel costs are then input to the elastic demand model and departure time choice model in the next steps.

2.3. Elastic demand model (trip choice and mode choice)

Trip choice is the decision of travelers to make a trip or not. Pricing or rewarding may lead to a change in the number of trips, e.g. an individual may decide to work from home or not. It may also lead to changes in transportation mode, as car travel becomes more (in)expensive and travelers may decide to divert to public transport. Both trip choice and mode choice lead to changes in the car travel demand.

Denote the generalized costs for each user-class m, departure time k, and route p from origin r to destination s, described by the total costs of travel time and monetary costs, by

$$c_{mp}^{rs}(k) = \beta_m^T \tau_p^{rs}(k) - \beta_m^C \theta_{mp}^{rs}(k), \tag{4}$$

where $\tau_p^{rs}(k)$ is the corresponding route travel time, and $\theta_{mp}^{rs}(k)$ is the reward received by user-class 1 (and is zero for user-class 2, the non-participants). Furthermore, β_m^T and β_m^C are behavioral parameters to be estimated.

In the elastic demand model, the secondary responses of travelers are taken into account, which include departure time choice and route choice. Let c_m^{rs} now denote the current flow-weighted (over routes and departure times) generalized travel costs for OD pair (*r*,*s*). The elastic demand effects, which are again multiplication factors denoted by M_m^{rs}, are now determined by comparing the generalized costs from the reference alternative (in the same iteration) which the current generalized costs similar as in Equation (3). These factors are applied to the new dynamic demand that results from departure time choice mode.

2.4. Departure time choice model

The dynamic initial travel demand, derived in Equation (1), assumes that free-flow conditions hold. In practice, free-flow conditions typically do not hold as congestion occurs. Travelers may adjust their departure time from their preferred departure time to another departure time in order to avoid congestion or to gain a reward. Let $c_m^{rs}(k)$ denote the flow-weighted (over routes) average generalized travel costs. Then the utility of a traveler of class m of choosing departure time k, while the traveler prefers arrival time l, will be defined as

$$\begin{aligned} U_m^{rs}(k \mid l) = -c_m^{rs}(k) + \beta_m^{DE}\left(l - \tau^{rs,0} - k\right)^+ + \beta_m^{DL}\left(k - l + \tau^{rs,0}\right)^+ + \\ \beta_m^{AE}\left(l - k - \tau^{rs}(k)\right)^+ + \beta_m^{AL}\left(k + \tau^{rs}(k) - l\right)^+ + \varepsilon_m^{rs}(k). \end{aligned} \tag{5}$$

where $(x)^+ \equiv \max\{0,x\}$.

Besides the average generalized costs, capturing travel time (including congestion) and possible rewards, this utility includes an early and late departure schedule delay, and an early and late arrival schedule delay, respectively. For a detailed discussion on these schedule delays, see Small (1982) and Van Amelsfort and Bliemer (2006). Since l - τrs,0 is the preferred departure time, l - τrs,0 - k indicates an early (if positive) or late (if negative) departure. Similarly, since k + τrs(k) is the actual arrival time when departing at time k, then l - k - τrs(k) indicates an early (if positive) or late (if negative) arrival, where τrs(k) is the flow-weighted (over routes) average OD travel time. The parameters β_m^{DE}, β_m^{DL}, β_m^{AE}, and β_m^{AL} are behavioral parameters to be estimated. The unobserved random terms $\varepsilon_m^{rs}(k)$ denote all other factors not included in the utility function that may have an impact on departure time choice. Denote the observed part of the utility by $V_m^{rs}(k \mid l)$. If all terms $\varepsilon_m^{rs}(k)$ are independently and identically extreme value type I distributed, the probability of choosing departure time k, given the preference for arrival time l, is given by the following multinomial logit model (McFadden, 1974):

$$\varphi_m^{rs}(k \mid l) = \Pr\left(U_m^{rs}(k \mid l) \le U_m^{rs}(k' \mid l), \forall k'\right) = \frac{\exp\left(V_m^{rs}(k \mid l)\right)}{\sum_{k'} \exp\left(V_m^{rs}(k' \mid l)\right)}. \tag{6}$$

For each traveler with a certain preferred arrival time *l* there is such a probability distribution over departure times. In order to determine the new travel demand $D_m^{rs}(k)$, all travelers departing at the same time interval have to be aggregated, independent on what their preferred arrival time is:

$$D_m^{rs}(k) = \sum_l \varphi_m^{rs}(k \mid l) M_m^{rs} \bar{D}_m^{rs}(l - \tau^{rs,0}). \tag{7}$$

2.5. Route choice model

The route choice model consists of a route generation component and a route choice component. In the route generation the most likely routes are determined using a stochastic route selection procedure, described in Bliemer and Taale (2006). This procedure is able to generate a route set that includes all relevant routes (where irrelevant routes are for example routes with long detours) and filter out largely overlapping routes. Let P_m^{rs} denote the generated route set for origin-destination pair (r,s) for user-class m. Given this route choice set, travelers decide which route to choose, based on the utility of each route that comprises the generalized travel costs,

$$U_{mp}^{rs}(k) = -c_{mp}^{rs}(k) + \varepsilon_{mp}^{rs}(k), \tag{8}$$

where $\varepsilon_{mp}^{rs}(k)$ are an unobserved random terms, assumed independently and identically extreme value type I distributed, such that for each departure time k, the route choice proportions can be computed as

$$\psi_{mp}^{rs}(k) = \Pr(U_{mp}^{rs}(k) \le U_{mp'}^{rs}(k), \forall p') = \frac{\exp\left(-c_{mp}^{rs}(k)\right)}{\sum_{p'} \exp\left(-c_{mp'}^{rs}(k)\right)}. \tag{9}$$

Clearly, more advanced route choice models could have been used in which correlations between route alternatives are taken into account, such as the path-size logit (PSL) model or the paired combinatorial logit (PCL) model. However, the above simple multinomial logit model is at least robust (see Bliemer and Bovy, 2008) and largely overlapping route alternatives are mostly filtered out in the route generation process.

Given these proportions, the route flows can be determined as

$$f_{mp}^{rs}(k) = \psi_{mp}^{rs}(k) D_m^{rs}(k). \tag{10}$$

2.6. Traffic simulation model

Given the route flows $f_{mp}^{rs}(k)$, many different kinds of traffic simulation models can be used, either microscopic simulators (e.g., PARAMICS, VISSIM, AIMSUN2, etc.) or macroscopic models (VISUM, INDY, MADAM, etc.). In this paper we use the dynamic network loading procedure in the INDY model which runs in the OmniTRANS environment, as it is easy to add scripts in OmniTRANS to include elastic demand and departure time choice, and because it is a fast model (given the fact that the traffic simulation procedure will be called many times in an iterative procedure, computation time is an issue). INDY combines the above described route choice model and traffic simulation model, and is extended with the elastic demand and departure time choice models. For the interested reader, more information about INDY can be found in Bliemer et al. (2004) and Bliemer (2007).

3. Case study: Peak Avoidance rewarding scheme

As mentioned in the introduction, the Peak Avoidance project is a local initiative, investigating what the potential effects of rewarding travelers for good behavior are, in this case rewarding for not traveling during the morning rush hours (7h30–9h30).

Behavioral responses have been measured as indicated in the introduction, but impacts on traffic conditions could not be measured due to the low number of participants. In a model study we are able to increase this number of participants, even to 100%, and try to forecast what the network effects will be.

First, we will describe the input for the model, being (i) a description of the network and travel demand, (ii) behavioral parameters, and (iii) reward strategies. Then, some modeling results will be presented, which include (i) departure profiles, indicating how travelers change their departure time on aggregate, (ii) travel time savings, and (iii) reward payments, indicating how much the authority will pay when applying such a reward system.

3.1. Description of the model input

Transportation network and travel demand

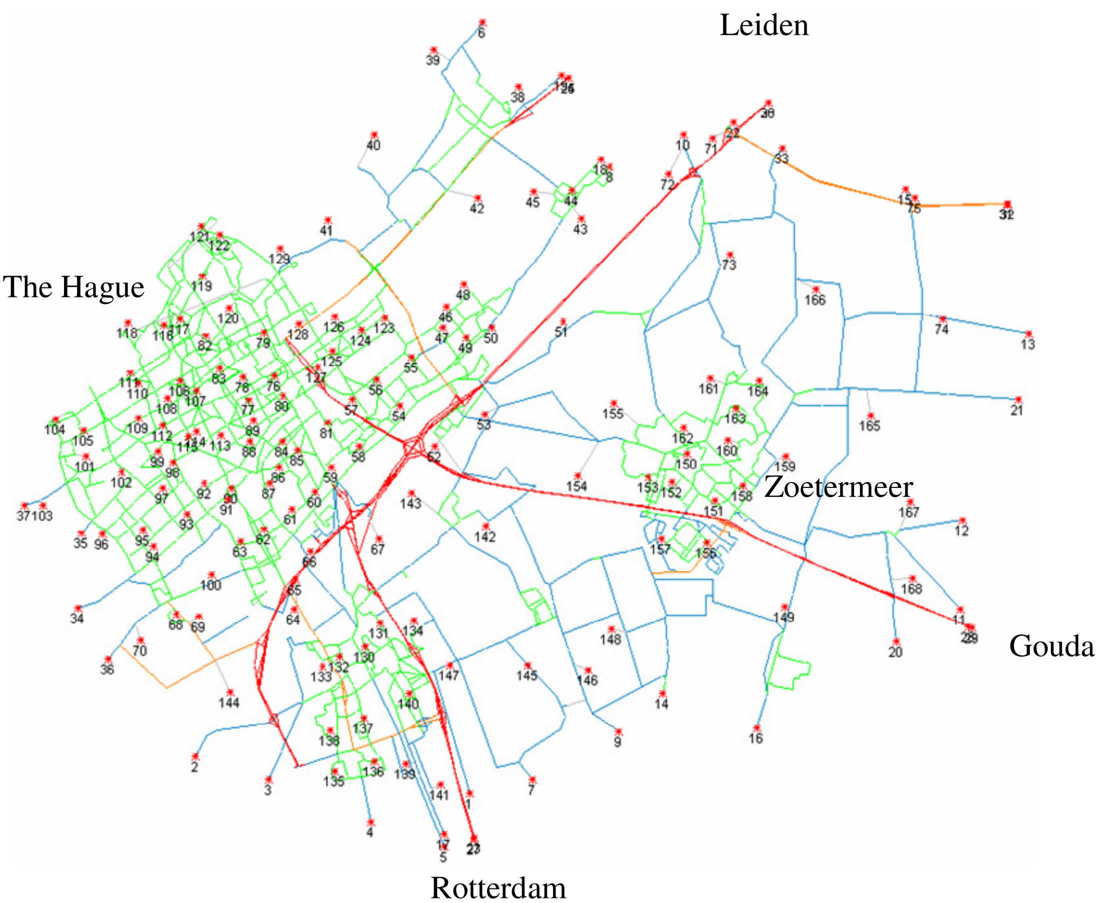


Figure 4: Transportation network and zones.

The transportation network is given as a connected graph with 1,133 nodes and approximately 3,500 directed links, see Figure 4. For each link, the length, maximum speed, number of lanes, capacity, and speed at capacity are known. In the model we do not take delays at intersections into account, data on signalized intersections is not used. In total there are 168 zones that serve as an origin and/or destination, indicated in Figure 4. The total (initial) travel demand is 473,868 car trips in the morning time period 6h00-

11h00, of which 40,722 originate from Zoetermeer, 8,475 have a destination in The Hague. This latter number is also the maximum number of Peak Avoidance participants.

Behavioral parameters

In order to determine the parameters of the participants and non-participants, stated choice experiments were conducted, in which respondents had to choose their preferred travel option from hypothetical choice situations, in which the travel times, departure times, rewards or tolls were varied systematically. For non-participants, the parameters are obtained a stated choice experiment described in Van Amelsfort (2009), and for participants from an experiment described in Knockaert et al. (2007). Table 1 lists the used parameter values. The departure schedule delay parameters are not significant for participants, indicating that they are flexible in departure time. Compared to non-participants, they also have lower values for arrival schedule delays, also indicating more flexibility with respect to arrival times. This seems a plausible finding, as participation is voluntary.

Table 1: Behavioral model parameters.

Parameter	*Non-participants*	*Participants*
β_m^T	-0.0247	-0.0220
β_m^C		0.2490
β_m^{DE}	-0.0791	*
β_m^{DL}	-0.0162	*
β_m^{AE}	-0.0292	-0.0147
β_m^{AL}	-0.0339	-0.0137
e_m	-0.2	-0.25

Note: * Not specified in the model.

Furthermore, PAT profiles for non-participants (at 0% participation) are calibrated from comparison between the network model output with several (dynamic) traffic counts and travel time measurements from loop detectors. For participants, the PAT profile was obtained from a pilot survey. Figure 5 shows the PAT profiles for both user-classes. For both participants and non-participants, most travelers seem to prefer to arrive around 8h30. The PAT profile for participants is much more concentrated around 8h30 than for non-participants, although some participants also prefer to arrive after 10h00. It is logical that the participants PAT profile is more concentrated around 8h30, as only travelers frequently traveling between 7h30 and 9h30 were asked to volunteer.

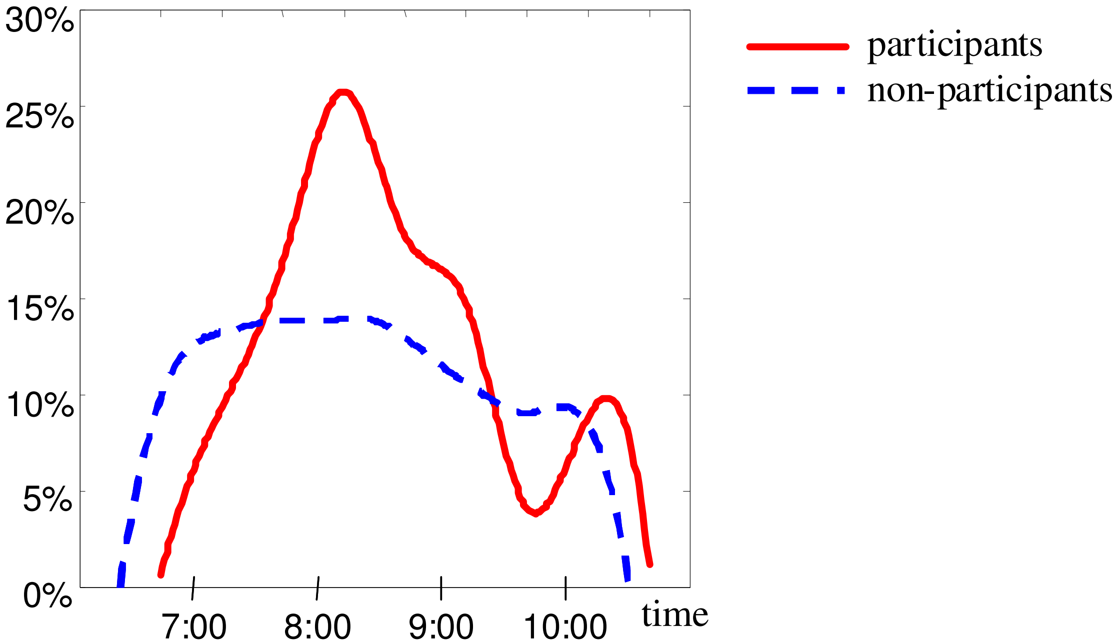


Figure 5: PAT profiles for (non) participants.

3.2. Reward strategies

Since in the real life pilot study only a few hundred travelers participated in the rewarding scheme, no changes in traffic conditions were expected. By changing the participation level in the model we are able to make a forecast about potential impacts on the traffic conditions (on a network level). Participation levels are chosen as 10% (848 travelers), 50% (4,238 travelers), and 100% (8,475 travelers). These strategies are compared considering a rewarding scheme of 5 euros per day when not traveling during the morning peak from Zoetermeer to The Hague. The reference strategies consider a reward of 0 euro, describing the current situation. Note that three different reference strategies are needed for making the comparisons, as participants and non-participants have different behavioral parameters and PAT distributions. Ideally, we would like to have an endogenous participation level, dependent on the reward level and the PAT distributions. To this end, the behavioral parameters could be described as continuously distributed population parameters. The participation model would explain which travelers would participate under which rewarding schemes. However, adding this participation level adds another significant complexity to the model and is left for future research. In order to be able to redistribute the population in participants and non-participants with different behavioral parameters, different reference scenarios are needed with different levels of participation. The non-participant PAT profile was adjusted such that the combined PAT profile is equal to the reference PAT profile (participation 0%) for which the model was calibrated. Since not the absolute outcomes are of interest, but mainly the comparisons between the strategies, our assumption of two groups of travelers is likely to give good indications about the differences between strategies.

Not only the participation level is varied, but also the role of the reward level is investigated by considered the levels 1, 3, 5, and 7 euros in different strategies, assuming a participation level of 50%. The rewards are fixed over the morning peak, time-varying rewards over the morning peak will be dealt with in future research. In total nine model runs have been performed, including three reference strategies. These model runs are indicated in Table 2. To give an indication of the computation time, each model run takes approximately 2.5 days on a desktop computer with an Intel Xeon 3Ghz dual core processor. Model results and analyses are presented in the next subsection.

Table 2: Overview of model runs.

Reward / participation	*10%*	*50%*	*100%*
0 euro	reference	reference	reference
1 euro	--	X	--
3 euro	--	X	--
5 euro	X	X	X
7 euro	--	X	--

3.3. Model results and analyses

Departure profiles

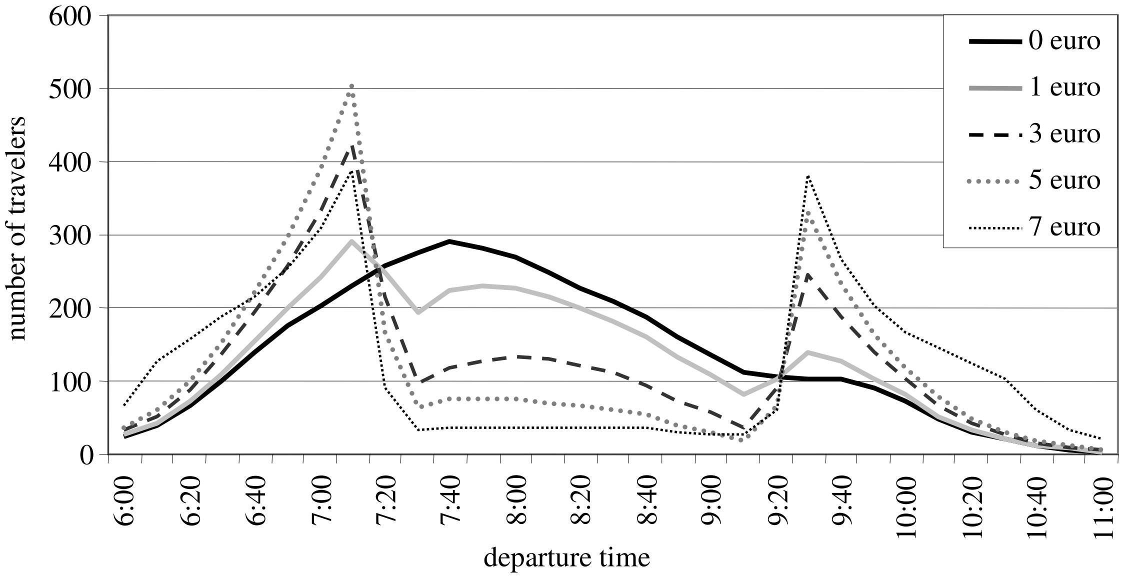
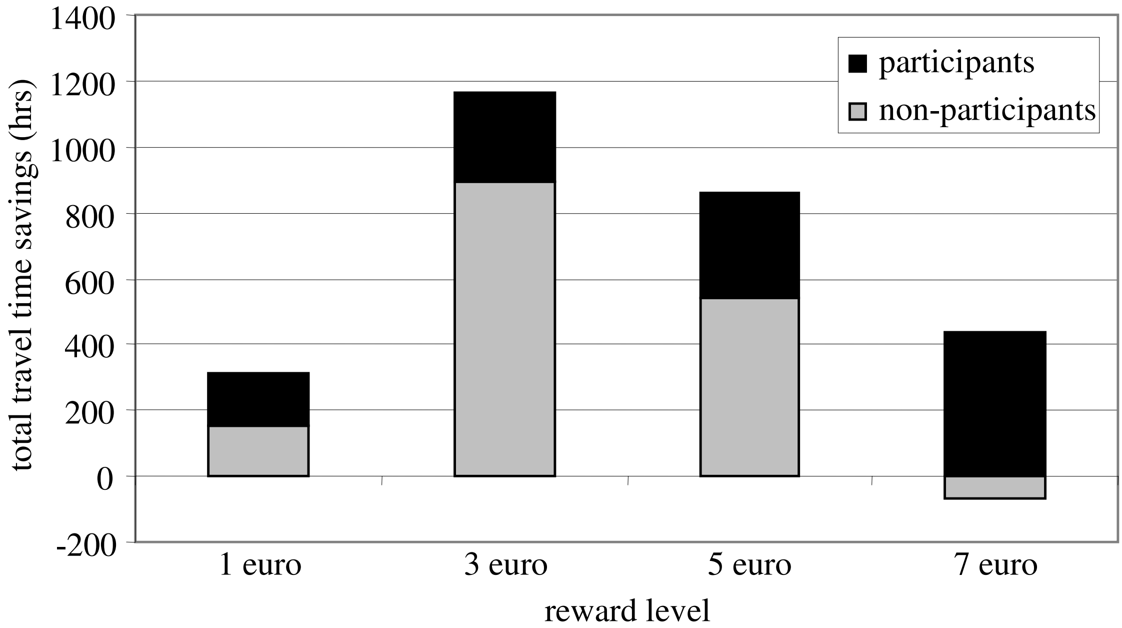


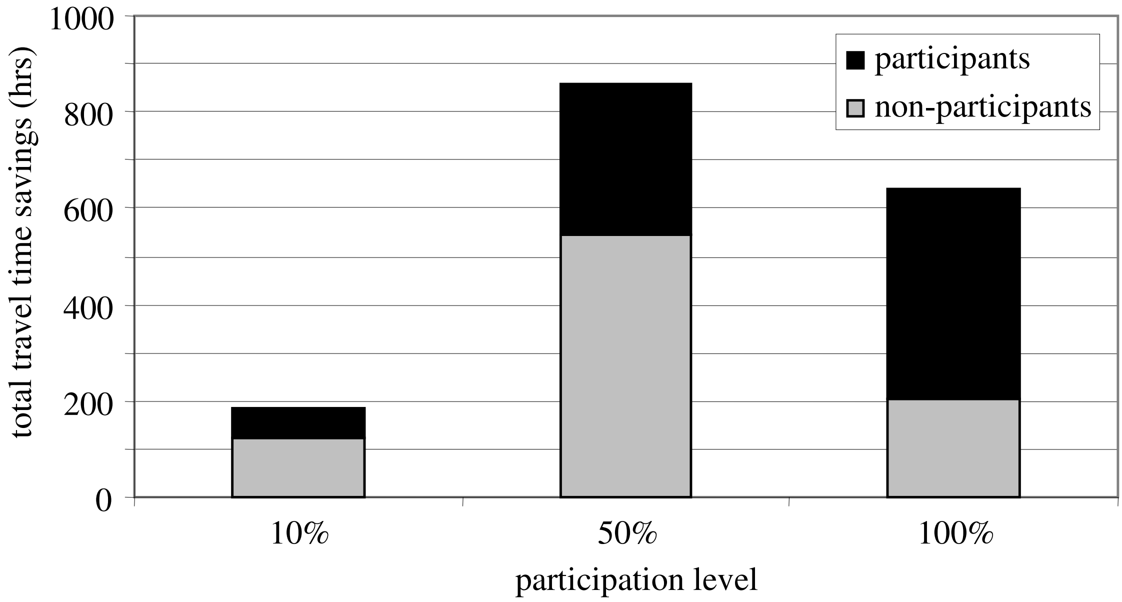
Figure 6: Departure profiles of participants for different reward levels (50% participation).

The departure time shifts of participants, presented in Figure 6 for 50% participation, account for the strongest behavioral responses that occur as a result of rewards. The morning peak is shown by the reference case of 0 euro reward. As the reward level increases, more travelers will change their departure time to the shoulder periods of the morning peak (before 7h30 and after 9h30). A large reward level may push almost all participants outside the morning peak. Although not depicted here, the departure profiles for the non-participants also change, as a reaction on the departure time changes of the participants. The morning peak period will become less congested; therefore some non-participants decide to return to the peak while they first traveled outside the peak period. The area underneath the departure profiles indicates the total travel demand for participants. Approximately 200 less travelers make a trip when they can gain a reward of 1 euro, increasing to about 550 less travelers when a reward of 7 euros can be gained.

Travel time savings



a. Total travel time savings for different reward levels (50% participation).



b. Total travel time savings for different participation levels (5 euro reward).

Figure 7: Total travel time savings depending on reward and participation levels.

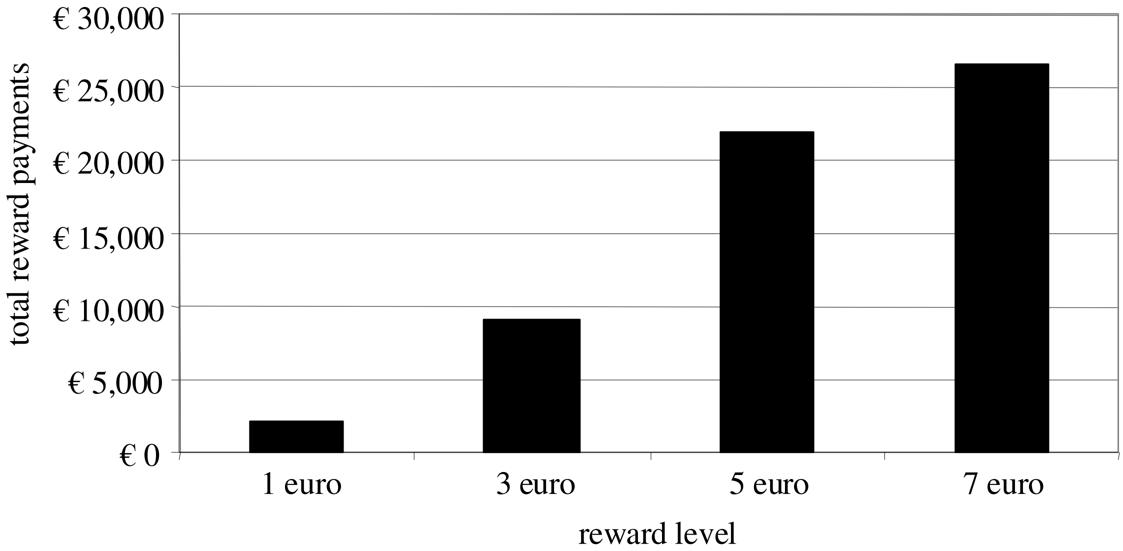
As seen in the previous subsection, the rewards result in lower numbers of travelers in the morning peak period. Then congestion will decrease in the peak hours and the total travel time experienced by all users in the network in the morning peak will decrease, while the travel times just outside the peak period will increase. The aim of the rewarding scheme is to have a positive net total travel time savings for the whole morning for all travelers. Depending on the reward and participation level, different total travel time savings result.

In Figure 7(a) the total travel time savings are indicated for different reward levels, and also split between savings for participants and non-participants, assuming a participation level of 50%. The total travel time savings are largest for the 3 euro reward level, while higher rewards are less effective. The reason for this is that the total travel time savings for the non-participants become smaller and smaller (and even negative), while the participants experience more and more travel time savings (since they avoid the morning peak, mainly by departing earlier). The total travel time savings for the non-participants decreases since they experience more and earlier congestion with higher reward levels due to increased travel demand from the participants just before the morning peak. This indicates that higher reward levels do not necessarily yield better system wide traffic conditions. On the contrary, if the departure time shifts are too large, then the morning peak just shifts to the shoulders of the peak, leading to an earlier breakdown of traffic performance for the non-participant traveling in the early peak. A low reward level (1 or 3 euros) seems to perform best.

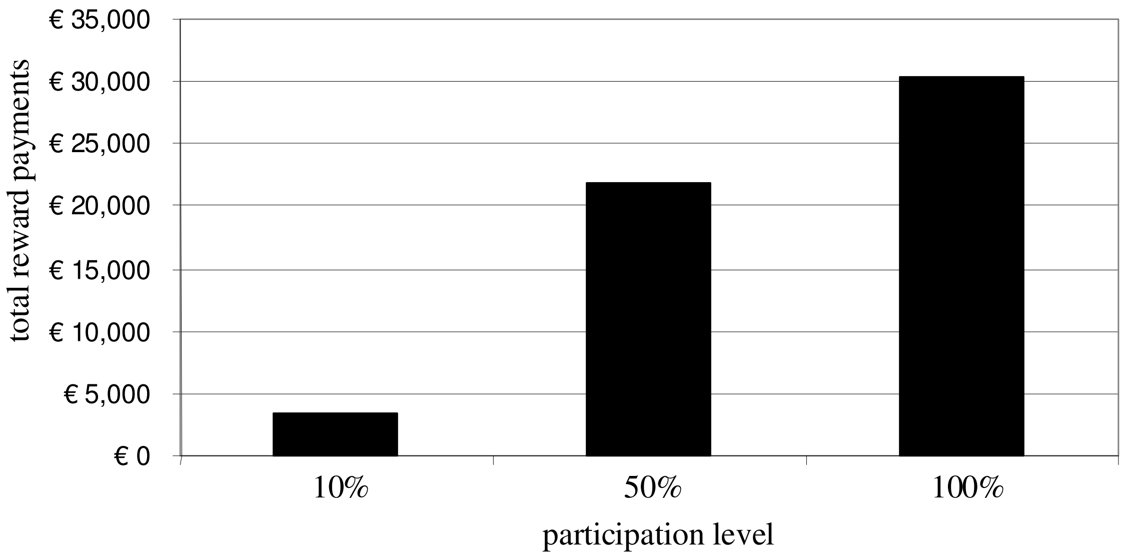
A similar result is found by looking at the different participation levels. In Figure 7(b) the total travel time savings are depicted for varying participation levels, assuming a reward level of 5 euros. Higher participation levels lead to increased numbers of travelers shifting their departure time to the shoulders of the morning peak, increasing congestion at these time periods. Therefore, a mandatory reward scheme (100% participation) does not seem a good option. A 50% participation level performs best.

Reward payments

The total travel time savings in the previous subsection give an indication of the effectiveness of the rewarding strategy. Another interesting question is: which rewarding strategy provides the highest bang for the buck? To this end, we investigate the reward payments for each of the reward strategies. Figures 8(a) and 8(b) show the reward payments for the different reward levels (assuming 50% participation) and for different participation levels (assuming a reward level of 5 euros). Clearly, payments go up as the participation level or reward level increases. Using a 1 euro reward level is cheap, but also not very effective according to Figure 7(a). Table 3 presents how much reward payments need to be made for each hour of travel time savings. The first euros (reward levels of 1 or 3 euros) lead to significant decreases in total travel time, spending less than 8 euros for one hour of travel time savings. Reward levels of 5 euros or higher lead to diminishing total travel time savings per reward increase.



a. Total reward payments for different reward levels (50% participation).



b. Total reward payments for different participation levels (5 euro reward).

Figure 8: Total reward payments depending on the reward and participation levels.

Table 3: Reward payments per hour of travel time savings (euro/h).

Reward / participation	*10%*	*50%*	*100%*
1 euro	--	€ 7.01	--
3 euro	--	€ 7.83	--
5 euro	€ 18.96	€ 25.42	€ 47.29
7 euro	--	€ 72.40	--

4. Discussion, conclusions, and further research

In this paper we have proposed a methodology and mathematical model to assess the effects of rewarding (and pricing) on a car transportation network. It is general in the sense that many different types of pricing or rewarding strategies could be included, varying from a fixed cordon charge to a time-varying kilometer charge, but also (time-varying) rewards, which has been the focus of this paper. The model is applied to the The Hague region in the Netherlands, where in a small pilot study travelers could earn 3 to 7 euros per day for avoiding the morning peak period. In the model study, the participation level is increased such that it enables the analyst to determine effects of a reward strategy on the traffic conditions. Different reward levels have been analyzed. It turns out that with a relatively low reward level (3 euro per day), a large shift in departure time choice is established, such that the peak period becomes less congested and there are overall network benefits in terms of total travel time savings. In case of high reward levels (5 to 7 euros per day) too many participants may change by leaving just before or after the morning peak, causing congestion at these time periods. In case of low reward levels, the participation level could be higher to achieve the largest benefits, although full participation is likely to be less effective again due to too many travelers shifting to periods just before or after the morning peak period. Hence, an optimal combination of reward level and participation rate could be determined, with low reward levels and high participation rates, or higher reward levels and lower participation rates. From a financial perspective, higher participation rates with low reward levels may be less costly in terms of rewards paid to travelers, as travelers seem to change their behavior already quite significantly with a low reward level, while high reward levels only contribute marginally to that. Combining the effectiveness with the financial aspect, a (relatively) low reward level of 3 euros with 50% participation seems to be the best option.

Further research concentrates on two aspects: theoretical and empirical. From a theoretical and modeling point of view, the model proposed in this paper can be further improved by considering different classes of travelers with different VOT's and different schedule delay preferences. Furthermore, a participation model will be added in the future, describing which travelers would (voluntarily) participate, considering a certain reward strategy. Empirically, results from the pilot study have been obtained for a short period of time (ten weeks), and long term effects are still uncertain. In a follow-up experiment, a longer time period will be used to measure behavioral effects, and a time-varying reward level seems to be more effective as it may overcome problems that travelers decide to travel just before or after the peak hours. Instead, by offering a high reward level when avoiding driving during the most congested hour, and lower reward levels on less congested peak hours, travelers could be spread more in time. Additionally, a business case is proposed and offered to companies, in which their employees can participate in the Peak Avoidance project, while the companies contribute by paying the rewards. Such a scheme would no longer be a local measure on the corridor Zoetermeer – The Hague, but would be a country-wide implementation. Other business cases could be considered as well, such as a budget-neutral credit-based system, which is a combination of charging and rewarding, in which credits can be earned by avoiding the peak hours, while they can be spent by traveling during peak hours (Kockelman and Kalmanje, 2005).

Acknowledgements

The authors would like to thank Transumo and Next Generation Infrastructures (NGI) for their financial contributions. Furthermore, we are grateful for contributions from Kobus Zantema and other researchers in the SpitsMijden team.

References

Bliemer, M.C.J. (2007) "Dynamic queuing and spillback in an analytical multiclass dynamic network loading model", *Transportation Research Record*, 2029: 14-21.

Bliemer, M.C.J., and Bovy, P.H.L. (2008) "Impact of route choice set on route choice probabilities", *Transportation Research Record*, 2076: 10-19.

Bliemer, M.C.J., and Taale, H. (2006) "Route generation and dynamic traffic assignment for large networks", Proceedings of the *1st International Conference on Dynamic Traffic Assignment*, Leeds, UK.

Bliemer, M.C.J., Versteegt, H.H. and Castenmiller, R.J. (2004) "INDY: A New Analytical Multiclass Dynamic Traffic Assignment Model", Proceedings of the *TRISTAN V conference*, Guadeloupe.

Ettema, D., Knockaert, J. and Verhoef, E.T. (2008) "Using incentives as traffic management tool: empirical results of the 'Peak Avoidance' experiment", Proceedings of the *87th Annual Meeting of the Transportation Research Board*, Washington DC, USA.

Kahneman, D., and Tversky, A. (1979) "Prospect theory: an analysis of decision under risk", *Econometrica*, 47: 263-292.

Knockaert, J., Bliemer, M., Ettema, D., Joksimovic, D., Mulder, A., Rouwendal, J. and van Amelsfort, D. (2007) *Experimental design and modelling Spitsmijden*, Bureau Spitsmijden, The Hague, The Netherlands.

Kockelman, K.M. and Kalmanje, S. (2005) "Credit-based congestion pricing: a policy proposal and the public's response", *Transportation Research*, A 39: 671-690.

McFadden, D. (1974) "Conditional logit analysis of qualitative choice behaviour", In: Zarembka P. (ed.) *Frontiers in econometrics*, Academic Press, New York, USA.

Nielsen, O.A. and Sørensen, M.V. (2008) "The AKTA Road Pricing Experiment in Copenhagen", In: Jensen-Butler, C., Sloth, B., Larsen, M.M., Madsen, B. and Nielsen O.A. (Eds) *Road Pricing, the Economy and the Environment*, Springer, Berlin Heidelberg.

Schuitema, G., Steg, L. and Vlek C. (2003) "Prijsbeleid: effectief en aanvaardbaar voor veranderen van autogebruik?" (in English: Pricing policy: effective and acceptable for changes in car usage?), Proceedings of the *Colloquium Vervoersplanologisch Speurwerk*, Antwerp, Belgium.

Small, K.A. (1982) "The scheduling of consumer activities: work trips", *American Economic Review*, 72: 467-479.

Van Amelsfort, D.H. (2009) Behavioural responses and network effects of time-varying road pricing, *Ph.D. thesis*, Delft University of Technology, The Netherlands.

Van Amelsfort, D.H. and Bliemer, M.C.J. (2006) "Alternative specifications of schedule delay components: the effect of travel time uncertainty and departure time rescheduling", Proceedings of the *86th Annual Meeting of the Transportation Research Board*, Washington DC, USA.

Verhoef, E.T., Bliemer, M.C.J., Steg, L. and Van Wee G.P. (2008) *Pricing in road transport: a multi-disciplinary perspective*, Edward Elgar, Cheltenham.

Wismans, L.J.J., Van Berkum, E.C. and Bliemer, M.C.J. (2009) "Multi-objective optimization of traffic systems using dynamic traffic management measures", Proceedings of the *International Conference on Models and Technologies for Intelligent Transport Systems*, Rome, Italy.