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Effects of information in road transport networks with recurrent congestion

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Abstract. This paper aims to gain more insight into the implications of information provision to drivers on the performance of road transport networks with recurrent congestion. For this purpose, a simulation program consisting of three components has been written. The first component is the traffic simulation model, the second component is the information provision mechanism, and the third component monitors the behavioural decision-making process of the drivers, which is modelled using a utility-based satisficing principle.

Three types of information provision mechanisms will be considered: information based upon own-experience, after-trip information and real-time en route information.

The findings in this paper, obtained in a hypothetical context, underline the important relationship between *overreaction*, the *level of market penetration* and the *quality of the information*. High quality information allows a high level of market penetration, while low quality information, even when provided at low levels of market penetration, induces overreaction. Furthermore, real-time en route information is in particular beneficial during the process leading to a steady state; it reduces the variance in travel time considerably. The paper concludes with a discussion on the market potential of motorist information systems when commercially marketed.

1. Introduction

Congestion is one of the most pressing problems for transportation research. Today, road networks of major city centres are heavily congested. Furthermore, the congestion problem is not confined to the transportation sector, but has a substantial impact on the economy as a whole. The Confederation of British Industry (CBI), for example, estimates that road congestion costs British industry approximately 15 billion pounds a year. Expansion of the existing road network to meet the existing and future mobility demand is generally regarded as being infeasible, as the social and environmental consequences of building new roads could be far more severe than the beneficial effects to motorists (Boyce 1988). Moreover, in some urban areas it is physically impossible to enlarge the current road infrastructure with undue expense. As a consequence, transportation research is giving more emphasis to using existing road networks as efficiently as possible. It is envisaged that the introduction of new advanced technologies, Road Transport Informatics (RTI),[1] will help by increasing the road capacity and network efficiency (Stergiou & Stathopoulos 1989). In addition, these technologies have a potential of increasing road safety and decreasing pollution (Shladover 1993). However, in this paper attention will be focused on network efficiency, thus leaving aside the other potential beneficial effects of RTI.

One of the approaches in the RTI set, and addressed in this paper, is to provide drivers with information on the situation on the road network.[2] It is hoped that supplying information will affect key elements of travellers' journeys (speed, route, cost, accessibility) and the relative attractiveness of different travel modes, which in turn will have its effect on travel decisions and activity patterns (Bonsall, Pickup & Stathopoulos 1991). This is based upon the assumption that in general drivers possess little or no reliable information concerning travel and route alternatives and may be uninformed of road conditions on any specific day. Such lack of awareness leads to misperceptions on the part of the drivers as to the relative desirability of alternative travel decisions. Information provision thus has the potential of reducing or eliminating poor route choices and consequently diminishing excess travel time (Ben-Akiva, de Palma & Kaysi 1991). This is underscored by the empirical evidence that, according to a sample of trips in the United Kingdom, the inefficiency of trips taken over unfamiliar roads is about 20 to 25 per cent (Jeffery 1988). However, some researchers have addressed potential negative effects of providing information to drivers and argued that the implementation of motorist information systems does not necessarily generate benefits (Arnott, de Palma & Lindsey 1991; De Palma 1992; Emmerink, Axhausen, Nijkamp & Rietveld 1993b).

In this paper a simulation approach is used to analyse the potential effects of information provision to drivers. The work follows Mahmassani and coauthors, summarised in Mahmassani and Herman (1990). Attention is confined to one specific mode of travel: the private car. However, rather than analysing either the day-to-day dynamics (cf. Mahmassani & Chang (1985)) or the within-day travel dynamics (cf. Mahmassani & Chen (1991), Mahmassani & Jayakrishnan (1991)), this paper attempts to integrate these processes. A greater understanding of the interaction of these processes taking place at different levels is important, in particular with respect to the application of information provision to drivers in road transport networks.

The simulation model built consists of the three components, *driver behav-*

iour, *control system* and *network model*, suggested in Watling & Van Vuren (1993). In this paper, the control system component reflects the information collecting and information supplying process, which is described in Section 2. The driver behaviour component is incorporated in our simulation model by a number of simple behavioural models[3] and is addressed in Section 3, while the network model component represents the traffic flow which, combined with the simulation model, is presented in Section 4. Section 5 presents the results of the simulation experiments conducted. The experiments focus upon the following issues:

- Performance of boundedly rational model for driver's behaviour in an environment without information.
- Effectiveness of the provision of after-trip and real-time en route information in relation to the level of market penetration.

The first issue expands the current literature on boundedly rational behaviour. The implications on the overall network performance of different values for the bound are assessed in a combined day-to-day and within-day context, while past research concentrated on modelling and estimating the boundedly rational model seen from an individual perspective. The second issue expands the literature in that it focuses upon both after-trip and en route information, and links the day-to-day dynamics and the travel dynamics within a day. Past research concentrated either on after-trip information in a day-to-day travel environment (Iida, Akiyama & Uchida 1992; Mahmassani & Herman 1990) or en route information within a day (Mahmassani & Chen 1991; Mahmassani & Jayakrishnan 1991; Mahmassani & Peeta 1993).

The experiments are conducted in a network with recurrent congestion. This is a network congested due to under-capacity or, phrased differently, due to too much demand for mobility. Situations in which congestion is caused by accidents, bad weather or other incidents, i.e. non-recurrent congestion, is not addressed.[4] The paper concludes with a summary in Section 6.

2. Information provision

In this section the different kinds of information provision are presented. The four kinds of information provision shown in Table 1 are implemented. Throughout the paper, the code given will be used to refer to the specific types of information provision.

Information provision type A assumes that information on different routes is acquired solely through own experience. After a trip has been made, the expected travel time of the chosen route is updated, while the expectations of the other routes remain unchanged.

Information provision type B provides drivers with information on the unchosen routes after their trips have been completed. One could think of radio or TV reports that describe in detail the day's situation on the roads, or of in-home traffic information systems, for instance the Prestel or Minitel services. In the simulation model, the information given is based upon the densities realised on the links during the last travel period. These are the input for the travel time calculations of not chosen routes by a driver.

Table 1. Information provision types.

Code	Information
A	own experience
B	after-trip
C	real-time pre-trip
D	real-time en route

Information provision type C supplies drivers with real-time pre-trip information. This is information based upon the actual situation in the network just before the start of a trip, enabling drivers to change route before the trip according to the current situation in the network. As with type B, the information is based upon the prevailing densities on the links in the network. No attempt is being made to provide predictive information. Research in this direction is still in its infancy. Useful references are Ishtiaq & Hounsell (1993), Koutsopoulos & Xu (1993) and Lindveld, Kroes & de Ruiter (1992).

Finally, information provision type D is real-time en route information on the current situation in the network, enabling drivers to switch routes during the trip based upon the most recent information available. As with information types B and C, the information is based upon the prevailing link densities.[5] A prototype of such an advanced information providing system is currently being implemented in Illinois (ADVANCE 1990). In Europe research in this direction has been carried out within the LISB project in Berlin[6] and currently within the EC DRIVE programme.

New information provision types can be specified by combining the types given in Table 1. For instance, information provision type A+B implies that drivers base their travel choices upon both their own experiences and supplied after-trip information.

3. Behavioural models

This section presents the models of driver behaviour used. These models lie at the heart of our simulation approach, since they generate the drivers' decisions. In addition, these decisions determine the resulting traffic flows in the network completely. Section 3.1 addresses the way of updating information, while Section 3.2 deals with the decision-making process given the updated information. Throughout the section it is assumed that departure times are fixed. The only choice open to drivers is the route choice.

3.1. *Updating information*

Drivers' travel time expectations are updated after new information is available, and are dependent upon the information provided. Throughout this paper the term expectations rather than predictions is used to indicate that predictive information is not supplied. Subsequently, the updating processes associated with information provision schemes A, A+B, A+B+C, A+B+C+D and A+D are discussed.

The updating mechanisms are based upon the following linear equation, known as an exponentially weighted moving average.

$$\mathrm{ET}_r^{n+1} = \alpha * \mathrm{NewInformation}_r + (1 - \alpha) * \mathrm{ET}_r^n \qquad [1]$$

Here, ET_r^{n+1} denotes the expected travel time for route r in period $n + 1$, while the new available information on route r is embedded in $\mathrm{NewInformation}_r$. The parameter α lies in the closed interval [0, 1] and reflects the weight given to the last travel experience. An α-value close to 1 implies that the driver's expected travel time for the next travel period is largely based upon his last experience with a route. On the other hand, a value close to zero means that future expectations strongly rely upon past experiences. A similar mechanism has been applied by Horowitz (1984) and more recently in a sequential route choice context by Iida et al. (1992) and Vaughn, Abdel-Aty, Kitamura, Jovanis & Yang (1992).

Iida et al. (1992) estimated the parameter α and found large discrepancies among different individuals, ranging from 0.3 to 0.7. Vaughn et al. (1992) estimated an equation similar to [1], and it appeared that an α-value of 0.2 led to the largest log-likelihood. However, the differences in log-likelihood for varying α-values were small.

3.1.1. *Informntion provision type A*

Under information provision type A, it is assumed that drivers update the chosen route (r) using equation [1], and that the expectations for the other routes (j) remain unchanged. In mathematical terms this can be expressed by equations [2] and [3]

$$\mathrm{ET}_r^{i,n+1} = \alpha * \mathrm{ExperiencedTravelTime}_r^{i,n} + (1 - \alpha) * \mathrm{ET}_r^{i,n} \qquad [2]$$

$$\mathrm{ET}_r^{i,n+1} = \mathrm{ET}_j^{i,n} \quad [3]$$

in which index i refers to the driver. For simplicity it is assumed that α is equal for all drivers. A more realistic approach would have been to assign α randomly.

3.1.2. *Information provision type A+B*

Under information provision type A+B it is assumed that drivers' experience is used to update the expected travel time of the chosen route (the driver thus ignores the information on this route) while the provided information is used to calculate the expected travel times of the unchosen routes for the next travel period. The same updating formula as used in information mechanism A, formula [2], is applied if route r was chosen in period n. However, the expected travel times of the unchosen routes are now updated following [4],

$$\mathrm{ET}_j^{i,n+1} = \alpha * \mathrm{AfterTripInfo}_j^{i,n} + (1 - \alpha) * \mathrm{ET}_j^{i,n} \quad [4]$$

in which $\mathrm{AfterTripInfo}_j^{i,n}$ denotes driver i's travel time (according to the supplied information) in period n if route j had been chosen.

It is important to note that in our model drivers regard provided information as reliable as own experience, since equal weights are given to both. An extension of the model is to (1) give different weights to own experiences and supplied information, (2) weigh the information according to its (perceived) reliability. A reliability measure could, for instance, be the difference between the experienced travel time of the chosen route and the information provided for this route. The driver, for instance, could perceive the information being reliable if the difference is relatively small. Although investigating drivers' attitude and reaction towards information is very important it is far beyond the scope of this paper.

3.1.3. *Information provision type A+B+C*

This mechanism is based upon two sequential phases. The first phase is the application of information mechanism A+B after the trip:

$${}^{\mathrm{A+B}}\mathrm{ET}_r^{i,n+1} = \alpha * \mathrm{ExperiencedTravelTime}_r^{i,n} + (1 - \alpha) * {}^{\mathrm{A+B+C}}\mathrm{ET}_r^{i,n} \quad [5]$$

if route r was chosen in period n by driver i and

$${}^{\mathrm{A+B}}\mathrm{ET}_j^{i,n+1} = \alpha * \mathrm{AfterTripInfo}_j^{i,n} + (1 - \alpha) * {}^{\mathrm{A+B+C}}\mathrm{ET}_j^{i,n} \quad [6]$$

for all the remaining routes j. Here, ${}^{X}\mathrm{ET}_j^{i,n}$ denotes driver i's expected travel time for alternative j in period n after information mechanism X has been applied.

In the second phase the pre-trip information is being processed. It is assumed that drivers adjust expected travel time according to formula [7].

$$ {}^{A+B+C}ET_j^{i,n+1} = \beta * \text{PreTripInfo}_j^{i,n+1} + (1 - \beta) * {}^{A+B}ET_j^{i,n+1} \qquad [7] $$

This equation is used for all the available routes j. The parameter β lies in the closed interval [0, 1] and reflects how much weight is given to the pre-trip information.

3.1.4. *Information provision type A+B+C+D*

Pre-trip travel time expectations are made using information mechanism A+B+C. During the trip, en route real-time information is given on the expected remaining travel time for the different routes. The en route decision-making process is discussed in Section 3.2.

3.1.5. *Information provision type A+D*

Pre-trip travel time predictions are made using information mechanism A. During the trip, en route real-time information is given on the expected remaining travel times for the different routes. The en route decision-making process is discussed in Section 3.2.

3.2. *Decision-making*

The previous section dealt with the updating mechanism of information, leading to travel time expectations. The current section explores how these expectations are used in the decision-making process of drivers. The section consists of two parts. In Section 3.2.1 general model principles are presented, while in Section 3.2.2 the models for the information provision types described in Section 2 are specified.

3.2.1. *General model principles*

In this section different behavioural models for the driver's route choice problem are discussed. The discussion is restricted to route choice.

In the simulation experiments it is assumed that drivers behave according to the models described in this section. These models consist of two components, a utility maximisation component and a satisficing component.[7]

Utility maximisation component. The models described in this section, have the utility principle as corner stone. The decision-making process of the individual consists of comparing utilities associated with the available route options, and choosing the one with highest utility. The utility of a route is calculated using a utility function. A general utility function has the following form,

$$U_j^i = \beta_1^i * x_{1j}^i + \beta_2^i * x_{2j}^i + \ldots + \beta_n^i * x_{nj}^i + u_j^i \qquad [8]$$

in which U_j^i denotes the utility individual i associates to alternative j and x_{kj}^i the kth attribute of alternative j of individual i. Furthermore, u_j^i represents the random error term of alternative j of individual i. In the simulation experiments of Section 5, these will be omitted for simplicity. In the simulation experiments the β_k^i are assumed to be equal among the individuals, although it is more realistic to assign the values β_k^i stochastically to the individuals.

A similar methodology of modelling drivers' behaviour has been applied by Van Der Mede & Van Berkum (1991).

The utility function used in route choice decision-making is generally assumed to be dependent upon the following attributes (Bovy & Stern 1990): (1) travel time, (2) distance, (3) desired arrival time at destination, (4) schedule delay,[8] (5) travel time uncertainty, (6) individual's socio economic characteristics. For simplification it is assumed throughout this paper that the utility function is dependent upon travel time only. Under this assumption model [8] collapses into model [9].

$$U_j^i = -\text{TravelTime}_j^i \qquad [9]$$

Since a decision has to be made every period (day) model [9] is expanded to

$$U_j^{i,n} = -\text{TravelTime}_j^{i,n} \qquad [10]$$

where n denotes the period. Furthermore, since the travel time in period n is unknown at the moment the decision for period n is made, it is estimated. The estimated travel time of driver i in period n for alternative j will be denoted by $ET_j^{i,n}$. Hence, model [10] turns into [11].

$$U_j^{i,n} = -ET_j^{i,n} \qquad [11]$$

The travel time is estimated using updating mechanism [12],

$$ET_j^{i,n} = \alpha * \text{TravelTime}_j^{i,n-1} + (1 - \alpha) * ET_j^{i,n-1} \qquad [12]$$

which has been explored in Section 3.1.

Satisficing component. The satisficing principle stems from a paper by Simon

(1955) and has been introduced in the literature on route and departure time choice by Mahmassani & Chang (1985). Rather than using Wardrop's User Equilibrium (UE) principle (Wardrop 1952), they introduced a Boundedly Rational User Equilibrium (BRUE) theory. Properties of BRUE have been analysed in Mahmassani & Chang (1987). According to BRUE, individuals are trying to achieve a satisfactory outcome, rather than maximising utility. An intuitive argument backing the satisficing principle is based on costs. It is conceivable that an individual would like to avoid the costs (efforts) associated with finding the utility maximising solution, especially if a similar decision has to be made frequently as in our route choice context. Furthermore, if the costs associated with finding the optimal (utility maximising) solution were included in the utility function, it could well be true that the satisficing alternative coincides with the maximising utility solution. Or in other terms, the utility function is not correctly specified if the costs associated with finding the optimal solution are omitted.

The model presented below is an adapted version of the one used by Mahmassani and colleagues, for the first time described in Mahmassani & Chang (1985). In the present context this model needs to be adapted since in our simulation experiments the departure time is assumed to be fixed, so that the preferred arrival time is not relevant. In Mahmassani & Chang's model, the preferred arrival time and schedule delay are the key variables.

The boundedly rational model of Mahmassani & Chang (1985) assumes that drivers change departure time (and route) only if the schedule delay exceeds a certain threshold value, the so-called bound. The route and departure time decision at day $n + 1$ depends upon the schedule delay and bound at day n. In turn, the schedule delay is dependent upon the discrepancy between the predicted and actual travel time at day n. Therefore, in their model the decision of the previous day is altered, only if the difference between the predicted and actual travel time on the previous day exceeds the bound.

In a similar fashion the boundedly rational theory will be applied in our model. In this model the bound is an exogenous variable. However, Mahmassani and co-authors (see Mahmassani & Herman 1990) found some evidence that the bound is in reality dependent upon the past experiences. Nevertheless, we will omit these considerations for simplicity. In mathematical terms the decision-making process can be described as [13].

Assume route r has been chosen by driver i in period n.
Driver i's decision in period $n + 1$ is route r if the following expression holds:

$$\mathrm{ET}_r^{i,n} * (1 - \text{bound}) \leq \text{ExperiencedTravelTime}_r^{i,n} \leq \mathrm{ET}_r^{i,n} * (1 + \text{bound}) \qquad [13]$$

Otherwise the route with the highest utility will be chosen in period $n + 1$.

The ExperiencedTravelTime$_r^{i,n}$ denotes the experienced travel time of driver i for route r in period n. If the bound is larger than zero, this model does not contain a direct utility maximising incentive. The alternative having highest utility is chosen only if the individual is not satisfied with the previously made decision. Otherwise the driver sticks to his previous choice. If the bound is zero, however, this model collapses to a utility maximising model. Therefore, a satisficing model can be regarded as an extension of a utility maximising model. Model [13] will be used in the simulation experiments in Section 5.[9]

3.2.2. *Decision-making with information*

Decision-making with information provision types A, A+B and A+B+C is straightforward because route switching during the trip is not allowed. This implies that the route choice decision is made before the trip. Since it was assumed that the utility function has the form given in [10], decision-making consists of applying model [13] before departure. The decision-making process gets slightly more complicated if route switching during the route is allowed, which is the case for information provision types A+B+C+D, and A+D.

Below the decision-making mechanism corresponding to both information provision type A+B+C+D and A+D are discussed. However, the simulation experiments in Section 5 only make use of mechanism A+D for the following reasons:

- Applying mechanism A+B+C+D requires the estimation of an additional parameter, the β-parameter in equation [7], of which less is known in the literature.
- Interpreting the results obtained with mechanism A+B+C+D is extremely difficult, since they follow from the application of three (!) information provision types consecutively.

There are different ways to model route switching based upon real-time en route information provision of type A+B+C+D. The most logical way is to extend the sequential two-phase mechanism of information provision type A+B+C (see Section 3.1.3) with a third phase. Then, all the information acquired in the past is used during en route route switching. However, from a computational point of view this approach is very demanding. Since it is not correct to compare pre-trip expected travel time with en route expected remaining travel time, it would require to have, in addition to the expected travel time from the origin to the destination, the expected travel time from every link in the network to the destination. This in turn implies that the ET variable would need to have the form given in [14],

$$^{X}ET_{j,k}^{i,n} \qquad [14]$$

which defines driver i's expected travel time from link k to the destination (after having processed information X) in period n, if route j will be followed. It can be easily seen that the models previously described are encapsulated in this model; they follow by restricting the number of links k to one, the first link.

A, from a computational point of view, less demanding model is described below. Here, it is assumed that a driver regards pre-trip and en route decisions as being independent of each other. More precisely, en route decisions are made without taking into account travel time expectations made before the start of the trip. This approach has to be adopted with care, since in the extreme case it would imply that pre-trip decisions are of no importance at all, since if the driver starts the actual trip, the route switching decisions are completely based upon the current situation in the network. Therefore, the following modification is suggested. During the trip, route switching is carried out only if the improvement in expected remaining travel time compared to the expected remaining travel time of the route currently chosen exceeds a certain threshold value, and is in absolute value larger than the parameter τ. As Mahmassani & Jayakrishnan (1991) point out, plausibility is the main justification for this rule. The threshold values bound and τ may reflect perceptual factors, preferential indifference, or persistence and aversion to switching. The value bound is taken to be decreasing in time, dependent upon the remaining travel distance, to model a slowly decaying influence of the pre-trip decision during the trip. The specification of bound used in the simulation experiments is given in equation [18]. In mathematical terms the model is given in [15]

> Start driver i's trip according to the pre-trip decision. Calculate before entering a new link the expected remaining travel time of all the available routes k based upon the en route information. These travel times will be denoted by RTT_k^i. Calculate $\min_k \text{RTT}_k^i$ and suppose this occurs for $k = m$. Assume further that the current route is route r. If $\text{RTT}_m^i < \text{RTT}_r^i * (1 - \text{bound})$ and $\text{RTT}_r^i - \text{RTT}_m^i > \tau$ driver i will switch to route m. Otherwise driver i will continue on route r. [15]

The en route switching process in model [15] can be found in Mahmassani & Jayakrishnan (1991) and has recently been proposed by Bonsall (1992).

The decision-making model used for information mechanism A+D in Section 5 can almost be copied from model [15]. The only difference being that the driver's trip will be started according to information gathered by own-experience rather than pre-trip information. For clarity, the model is given in [16].

Start driver i's trip according to the decision based upon own experience. Calculate before entering a new link the expected remaining travel time of all the available routes k based upon the en route information. These travel times will be denoted by RTT^i_k. Calculate $\min_k RTT^i_k$ and suppose this occurs for $k = m$. Assume further that the current route is route r. If $RTT^i_m < RTT^i_r * (1 - \text{bound})$ and $RTT^i_m - RTT^i_r > \tau$ driver i will switch to route m. Otherwise driver i will continue on route r. [16]

4. Simulation framework

This section presents the set-up for the simulation experiments conducted in Section 5. Section 4.1 discusses methodological issues, while Section 4.2 describes the structure of the simulation model.

4.1. *Simulation methodology*

4.1.1. *Vehicle movement*

Following the MPSM model of Chang, Mahmassani & Herman (1985) traffic flows are modelled using a modified form of Greenshield's speed-density model. The speed of a vehicle on a link is calculated just before entering the link using formula [17].

$$v = (v_f - v_j) * \left(1 - \frac{k}{k_j}\right) + v_j \qquad [17]$$

v_f and v_j denote the free flow and jam speed; k and k_j denote the current and jam density. Two additional restrictions are imposed:

- Overtaking does not take place.
- The jam density cannot be exceeded.

With respect to the latter point, a driver wanting to move to a link that has reached the jam density remains on the current link. A (small) fixed amount of time later, Δ, the driver makes a new attempt to move to the next link.

4.1.2. *Network description*

The road network depicted in Fig. 1 is used for the simulation experiments. This network, containing one OD-pair, consists of many routes (25) and decision points (10) for providing an interesting framework for the analysis of the effects of information supplying.

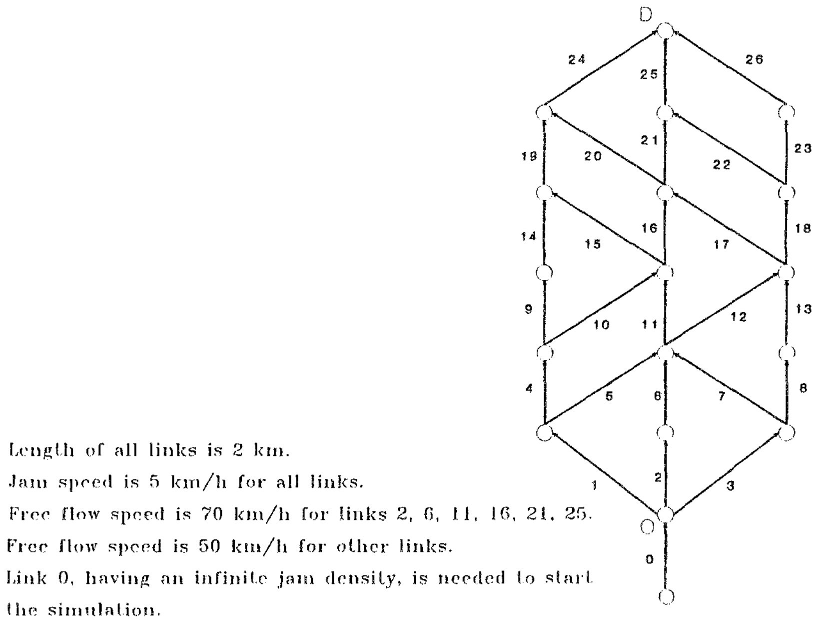

Fig. 1. Road network used in simulation experiments.

4.1.3. *Simulation parameters*

Number of drivers. The simulation experiments are carried out with 300 drivers. A larger number is, obviously, more realistic, but currently unmanageable with respect to computing time. An implication is that every driver in reality represents a bunch of drivers, or in terms of Chang et al. (1985), every simulated driver is a macroparticle of drivers.

Different levels of congestion. From the speed-density equation [17] it is clear that the speed on a link solely depends upon the ratio of current and jam density, or more precisely, upon the current and jam density in macroparticles. The size of a macroparticle is irrelevant, only the jam density, measured in macroparticles, is relevant. Throughout the paper the jam density per kilometre in macroparticles will be denoted by the constant K0. This constant then enables us to manipulate the level of congestion in the network. A low K0-value, and therefore a low jam density, implies a highly congested network since it assumes that only a few of the 300 drivers can occupy a link at the same time. On the other hand, a high K0-value implies an almost uncongested network. Thus, different K0-values could be interpreted as a network with different capacities. In this paper three different levels of congestion are analysed. These are shown in Table 2.

Table 2. Three levels of network capacity.

Level of congestion	K0 (macroparticles)
Practically uncongested	12
Congested	8
Very congested	5

Departure time structure. In the simulation experiments, departure times are assumed to be fixed. Hence, route choice is the remaining decision. The departure time structure is depicted in Fig. 2 and assumes that all drivers depart within one hour. The steeper the slope of the curve in Fig. 2, the higher the departure rate.

This structure assumes that:

- (3/17)th of the drivers departs between minutes 0 and 15.
- (12/17)th of the drivers departs between minutes 15 and 45.
- (2/17)th of the drivers departs between minutes 45 and 60.

Thus, the rate of departure is two times as high in the interval [15, 45] compared to interval [0, 15], and three times as high in [15, 45] compared to [45, 60]. A similar approach (using different figures) has recently been applied by Mahmassani & Peeta (1993).

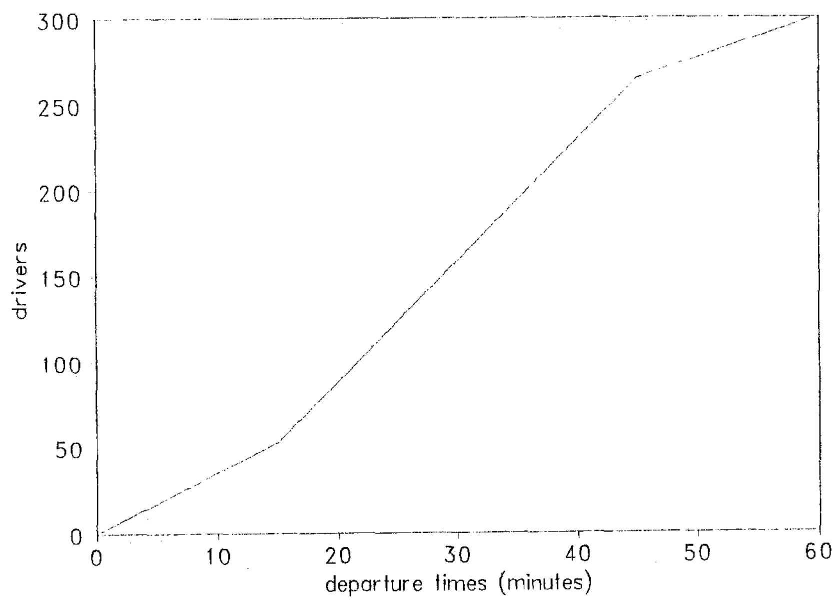

Fig. 2. Departure time structure.

Stochasticity of simulation. The initial ET-values of the drivers (see Section 3) are assumed to correspond to a speed of sixty kilometres per hour, thus equalling 12 minutes for every route. To force a route decision in the first travel period, a small random number taken from the interval [0, 1] is added to the ET-value of every driver for every route. This divides the drivers randomly over the available routes in the first period. However, as pointed out by Horowitz (1984), different initial distributions can lead to different simulation processes. Hence, the necessity to repeat each experiment a number of times to assess the significance of the results. According to the statistical theory, the more repetitions the better, but due to time limitations, the number of repetitions has been fixed at ten.

4.1.4. *Market penetration*

In Section 5, among other things, an analysis of the impacts of different levels of market penetration will be conducted. The different levels to be analysed are 0, 2, 5, 20, 50, 75, and 100 per cent. In all the cases, the drivers supplied with information will be spread homogeneously throughout the population. For instance, if twenty per cent of the 300 drivers are supplied with information, the drivers with information are respectively, driver 1, driver 6, driver 11, . . . , driver 291, and driver 296 of Fig. 2.

4.1.5. *Simulation run and steady state*

Simulation run. One simulation run consists of several subsequent simulated periods. A period represents a day of travel, and the words period and day will be used interchangeably. Every day, the same number of drivers carry out the same trip. The drivers can be considered being commuters. The route choice is the only decision open to them. The route choices lead to a certain traffic situation. The overall network performance will be measured in terms of travel time averaged over all drivers. During the next period, drivers will incorporate the experience gained during their last travel period in the next day's route choice decision which in turn will lead to a changed overall network performance etc. The overall network performance is taken as the sum of the drivers' travel times. This process will be repeated until either the system has reached a steady state[10] for at least ten subsequent periods, or the number of simulated periods exceeds 400. In the former case, the network performance at the end of the simulation process equals the steady state travel time, while in the latter case the network performance is taken to be equal to the average network travel time over the last twenty simulated travel periods, i.e. the average over the periods 381 to 400. Every simulation run will be repeated ten times (see Section 4.1.3), which will give an average network performance over the ten conducted runs. These averages will, unless stated otherwise, be used to draw inference from the simulation experiments.

Steady state. The term steady state is used to indicate a situation (during a simulation run) characterised by the fact that none of the drivers has an incentive to change routes in future periods. The term steady state, rather than equilibrium, is employed to underline that a steady state in the simulation model does not necessarily coincide with Wardrop's user equilibrium (Wardrop 1952). It is important to note that if drivers did not change routes in the current period (compared to the last one), it does not necessarily imply that a steady state is reached. A steady state is reached only if the expected travel time equals the experienced travel time. This does not need to be the case if drivers did not change routes in the last period, and this is the reason for adopting the approach described above, which assumes that a steady state has been reached after the drivers did not change routes for ten consecutive periods. After ten periods without route choice changes, it is highly unlikely that drivers will change routes in future periods, since the difference between expected and experienced travel time will have become very small.[11]

4.2. *Structure of simulation model*

The simulation model is implemented in the language C and adopts an event based simulation approach. In such an approach, the simulation is conducted using an ordered list of events, the so-called event list. An event is an occurrence that alters the state of the simulated system. In our road network, an event corresponds to the potential movement of a driver (macroparticle) to another link. An event based simulation model proceeds by taking the first event from the event list, executing this event, and inserting newly generated events in their appropriate position in the event list. An empty list characterises the end of the simulation process. The flow of control in the simulation model is depicted in Fig. 3.

The model deals with information provision at two different levels. Firstly, the box *Update knowledge of drivers* updates drivers' travel expectations, and in addition gives information to drivers prior to their trip. One could think of either historic after-trip information, as described in Section 3.1.2, or pre-trip information on the current conditions in the network, as described in Section 3.1.3. Secondly, box *Provide real-time information* supplies the driver with real-time en route information before entering a new link, thereby enabling him to change his route dependent upon the prevailing network conditions.

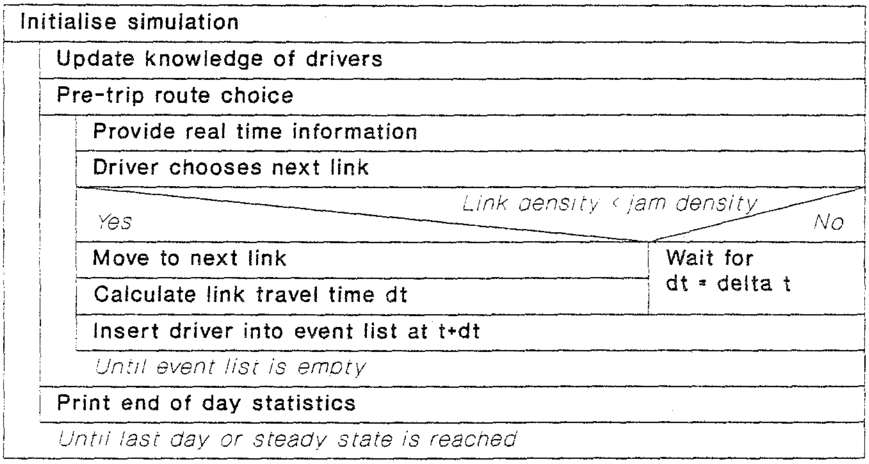

Fig. 3. Flow of control in simulation model.

5. Results of simulation experiments

The results of the simulation experiments will be explained in four sections. Section 5.1 describes some general characteristics prevailing in all the conducted experiments. Section 5.2 analyses the performance of the boundedly rational model using information based upon own-experience (information provision type A). Section 5.3 investigates the implications of providing after-trip information (information provision type A+B), while Section 5.4 focuses on real-time en route information (information provision type A+D).[12]

Before analysing the results, we would like to stress that these are obtained in a hypothetical setting: (1) Drivers behave according to a simple decision-making model, (2) There is only one OD-pair, (3) Traffic is simulated using a linear speed-density relationship, (4) Provided information is never ignored. Nevertheless, we think that this is an interesting environment to investigate the potential and properties of information provision.

5.1. *General characteristics of simulation experiments*

Throughout this paper, the parameter α (see equation [1]) is set equal to 0.4. Given the empirical evidence in Iida et al. (1992) and Vaughn et al. (1992) this seems a reasonable estimate.[13] The decision model used in the simulation experiments is model [13]. In Section 5.4 this model is combined with model [16].

The different congestion levels lead to large discrepancies in steady state travel time. Under congestion level K0 = 5, the average travel time is just under

40 minutes, implying an average speed of 18 kilometres per hour. Congestion level K0 = 8 leads to a travel time slightly over 20 minutes (average speed of 36 kilometres per hour), while congestion level K0 = 12 causes a travel time of approximately 15 minutes, reflecting an average speed of 48 kilometres per hour. The congestion level K0 = 5 leads to a heavily congested network, while congestion level K0 = 12 leaves the network relatively uncongested.

Different runs of the same experiment (differing only in starting values) lead to different steady state values. These findings underline the theoretical arguments given in Horowitz (1984).

A typical average travel time pattern (travel time averaged over all the drivers) during one simulation run is depicted in Fig. 4. Two conclusions can be drawn:

- The average travel time is a highly sensitive performance measure. A relatively small number of drivers taking the same route in a small time interval can cause a highly congested link, while at the same time the other links will be relatively uncongested, but nevertheless leaving the average travel time in the network excessively large.
- Figure 4 indicates that the particular simulation run depicted reaches a steady state. This is the case for most of the experiments. However, the number of days needed to reach a steady state varies strongly, depending upon the parameters chosen in the behavioural model and the kind of information provided.

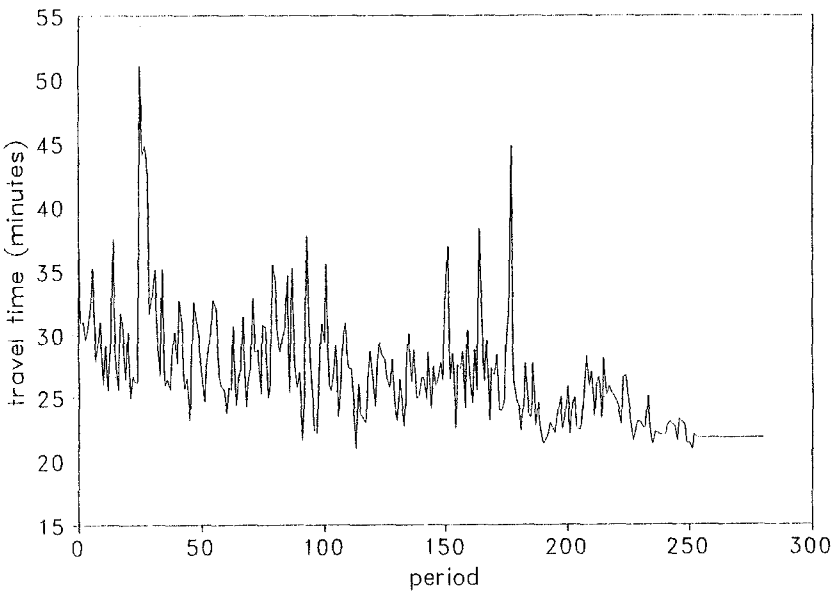

Fig. 4. Evolution of daily average travel time during a simulation run. K0 = 8, bound = 0.

5.2. Comparison of models with different bound

In this section the influence of the bound on the network performance is analysed under information provision type A (information based upon own experience). Model [13] is used and the bound varies between 0 and 0.4 in steps of 0.1. Combined with the three congestion levels of Table 2 this gives 15 different experiments.

Figure 5 depicts the travel time as a percentage of the travel time under the model with bound equal to zero, which is used as base case throughout this section. It can be seen that the models with bound generally outperform the base case, especially if the level of congestion is equal to 8. These results suggest a steady state travel time reduction of 7 per cent compared to the base case.

The number of routes used[14] decreases as the bound increases. This intuitively appealing result is shown in Fig. 6. The number of routes chosen decreases dramatically if the bound increases to 0.4. Furthermore, Fig. 6 shows that a higher level of congestion induces a larger number of routes used. This could be explained by noting that it takes longer to reach a steady state if the recurrent congestion is more severe, which is underlined by Fig. 7.[15]

As shown in Fig. 8, the switching propensity (percentage of drivers

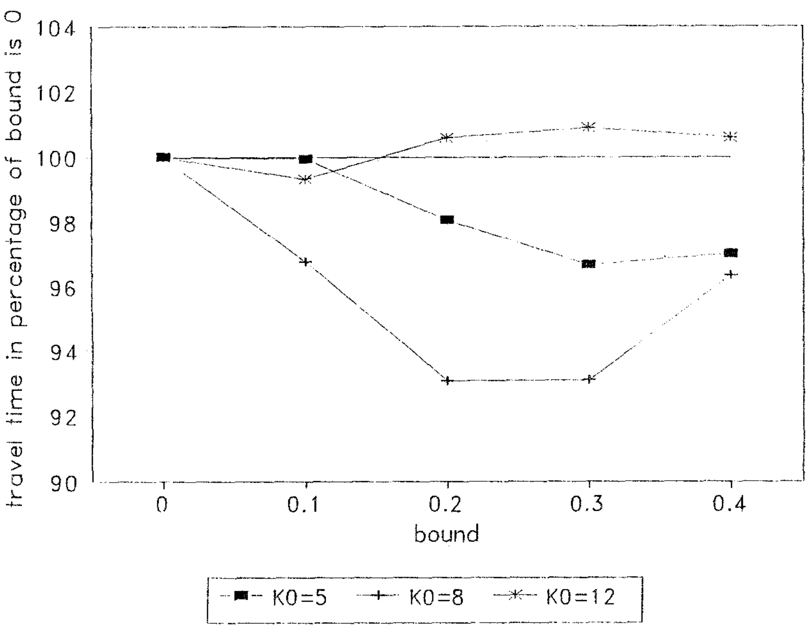

Fig. 5. Travel time as a percentage of the travel time under the model with bound = 0 for three levels of congestion.

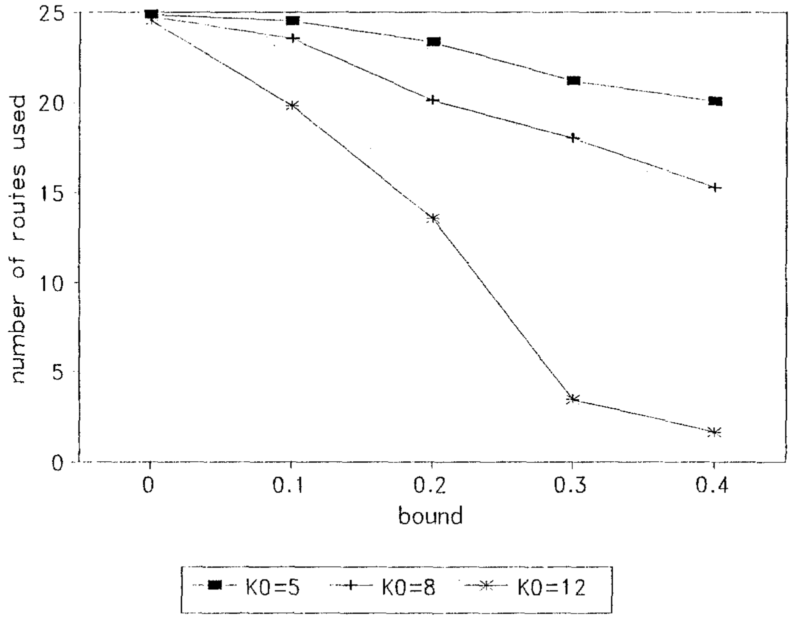

Fig. 6. Number of routes used for models with different bounds and three levels of congestion.

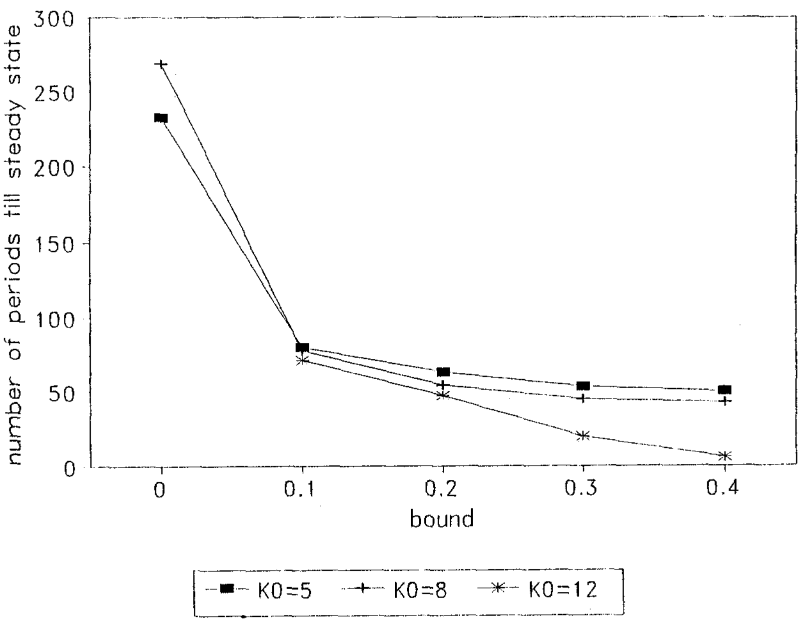

Fig. 7. Number of periods till steady state is reached for models with different bounds and three levels of congestion.

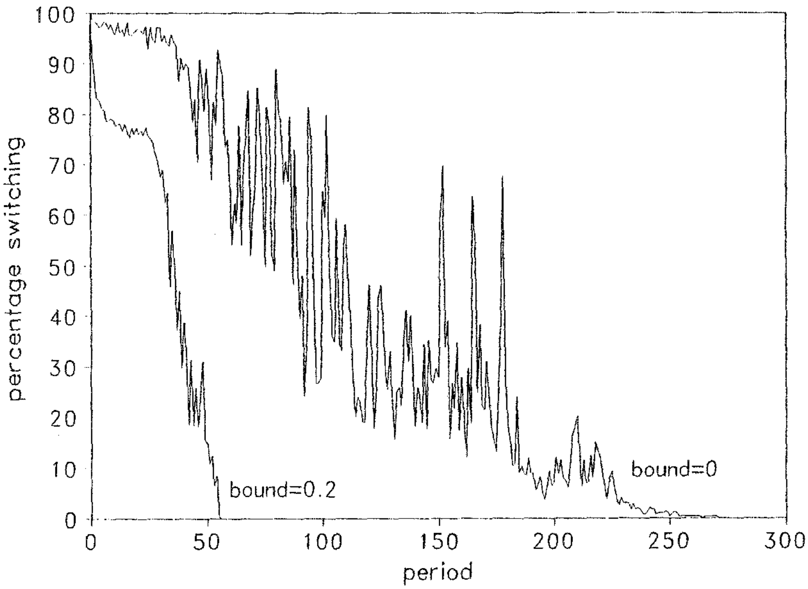

Fig. 8. Evolution of drivers' switching propensity under model with different bounds and congestion level K0 = 8.

switching routes from day-to-day) is obviously larger the smaller the bound. In addition, it can be seen that the curve gets smoother the larger the bound.

Combining the results in Figs. 6, 7 and 8, Fig. 5 could be explained by arguing that drivers use the different route alternatives more efficiently in a model with bound. Furthermore, they can better rely on their own expected travel time, since the switching propensity of the other drivers is smaller. However, if the bound gets too large, the overall network performance deteriorates due to too many missed good route opportunities. The optimal value for the bound seems to lie, dependent upon the level of congestion, between 0.2 and 0.3.

These results are in agreement with the insights gained by the work of Mahmassani and co-authors. They argued that in general better system wide performance is attained when path switching behaviour is dampened by an indifference band (the bound in our model). Potential negative effects of extreme behaviour could occur if drivers' behaviour is modelled with a *myopic* switching rule, i.e. drivers will always select the best path in terms of travel time (Mahmassani & Chen 1991). In our model this corresponds to a value of the bound equal to zero.

5.3. *After-trip information*

In this section, the implications of after-trip information provision are investigated. Throughout the section it is assumed that drivers provided with after-trip information behave as explained in Section 3.1.2, while drivers without information follow Section 3.1.1. Furthermore, it is assumed that drivers make decisions according to boundedly rational model [13], with the bound being equal to 0.2. All combinations of three levels of congestion and five levels of market penetration (0, 2, 5, 20, 50%) were investigated. The results of the experiments are compared with the no information case.

Figures 9, 10 and 11 show the results for drivers with and without information for different levels of congestion. It should be noted that the y-axis is not scaled equally across these figures. Different scales were needed to preserve the information in each figure. The following points can be made:

- Drivers with information benefit compared to the base case as long as the level of market penetration is under 20 per cent. In addition, they are best off if the level of congestion is not too severe, i.e. if KO = 8.
- As the level of market penetration exceeds 20 per cent, drivers without information perform better than drivers with information.[16] In a different context, the same phenomenon can be recognized in some of the experiments of Mahmassani & Chen (1991) and Mahmassani & Jayakrishnan (1991).[17] This could be explained by referring to the phenomenon of over-

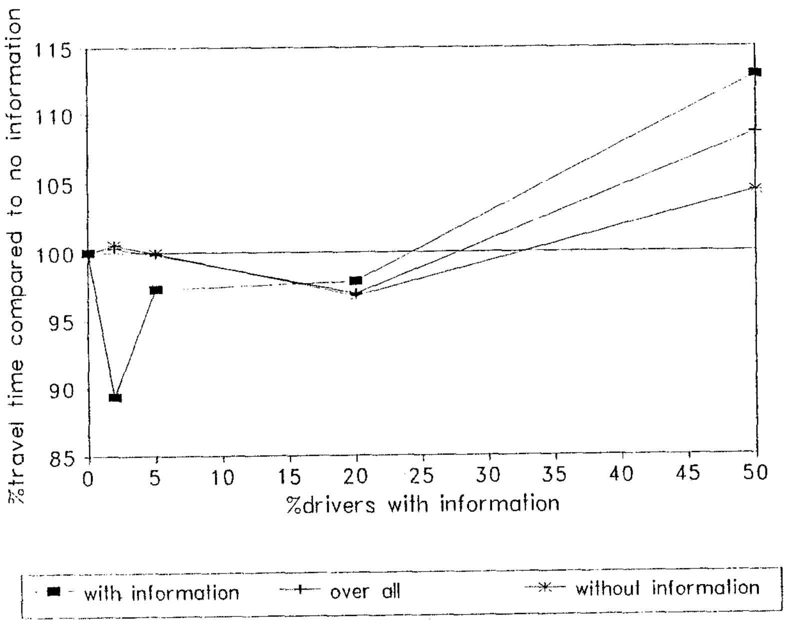

Fig. 9. Travel times compared to no information case. KO = 5.

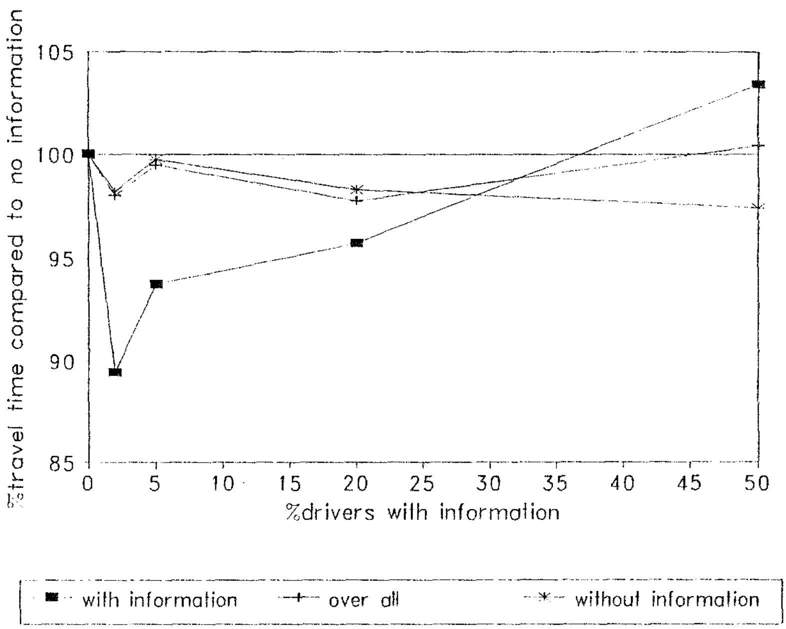

Fig. 10. Travel times compared to no information case. K0 = 8.

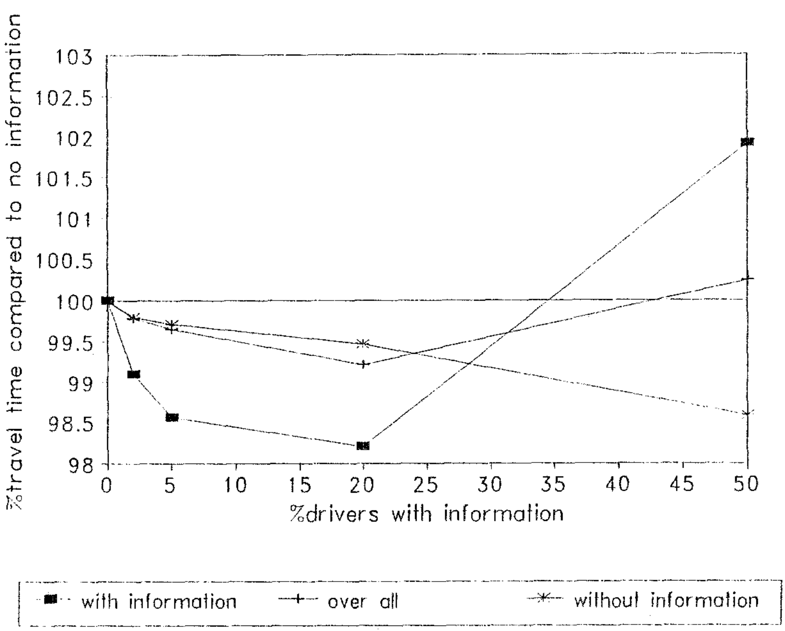

Fig. 11. Travel times compared to no information case. K0 = 12.

reaction and the informativeness of the information. The information given to the drivers is based upon densities realised during the previous day. If too many drivers respond to this historic information, it will not reflect the current situation in the network. Thus too many drivers responding to *old* information decreases the informativeness and accuracy of the information and causes overreaction. A similar result was obtained by Koutsopoulos & Xu (1993). In these situations, Mahmassani & Jayakrishnan (1991) argued that coordinated information is necessary.

After-trip information is most beneficial to everyone if the level of market penetration is below 20 per cent. This contradicts the results in Mahmassani & Tong (1986). In experiments concerning real commuters they found that after-trip information improved the system performance, even at a market penetration level of 100 per cent. However, recent research by Emmerink et al. (1993b) and Van Vuren & Watling (1991) suggests that the optimal level of market penetration is highly dependent upon the kind of information provided.

The figures presented so far are related to the steady state average travel time. However, if after-trip information is provided it is also interesting to investigate the process leading to the steady state for both the drivers with and without information. Figure 12, shows a typical pattern if the level of market penetration is low. It can be seen that drivers with information out-

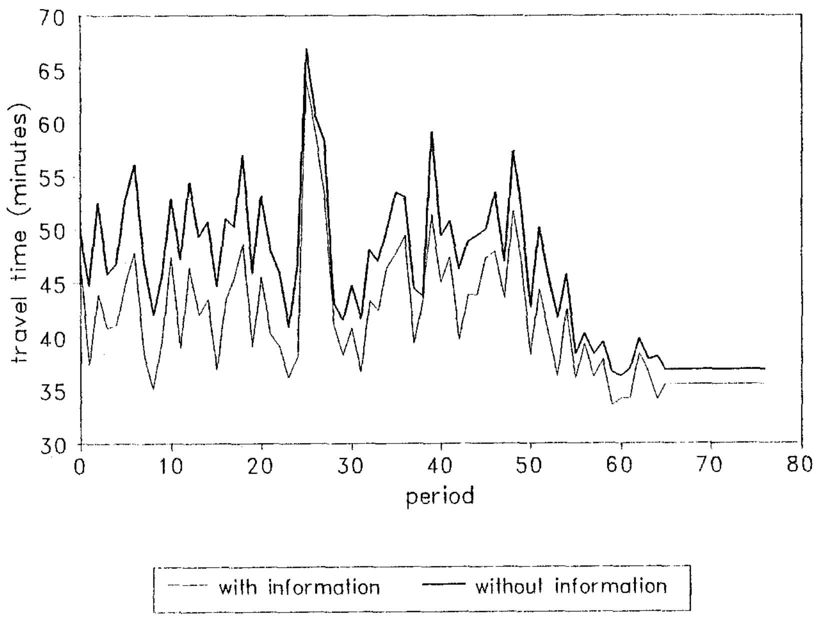

Fig. 12. Average daily travel times for drivers with and without information. K0 = 5, level of market penetration is 5%.

perform the ones without every period. It seems that if drivers with information benefit in the steady state situation, they have been better off during the process leading to the steady state as well.

During some simulation experiments a steady state was not reached after 400 days. In these cases a cyclical pattern arose. These findings underline theoretical work by Horowitz (1984). He argued that even in a two-link network under an information mechanism as given by equations [2] and [3] the situation in the network could oscillate perpetually.

Finally, it was observed that drivers with information try a considerable smaller number of routes than drivers without information. Summarising the results in this section, drivers with information experience shorter travel times if the level of market penetration is under 20 per cent. They achieve this using a significantly smaller number of routes. If the level of market penetration exceeds 20 per cent, overreaction takes place and the network performance deteriorates.

5.4. *Real-time en route information*

This section analyses the effects of real-time en route information provision. It is assumed that all the drivers update their travel time predictions following Section 3.1.1. However, drivers equipped with an information device make their pre-trip route choices according to model [13], and their en route decisions following model [16]. In this model the parameter τ is set at 1 minute, and the bound is specified as in [18].

$$\text{bound} = (\#\text{ of links remaining}) * 0.05\ [\ ] \qquad [18]$$

Figure 1, shows that each route consists of 7 links. Therefore, the bound in [18] decays from 0.30 (6 links remaining) to 0.05 (1 link remaining). Unequipped drivers make their decisions following model [13], in which the bound is set equal to 0.2.

The pattern in Fig. 13 prevailed in all the simulations experiments. Figure 13 shows that a high level of market penetration has a strongly decreasing effect on the variance in travel time, but an increasing effect on the number of days to steady state. Furthermore the steady state travel time under information provision does not differ largely from the situation without information provision. The gains of information are reached in the process leading to a steady state, the gains in steady state travel time itself are marginal. This is a result one could expect in a network with only recurrent congestion.

The results of the simulation experiments are summarised in Figs. 14, 15, and 16.[18] The numbers plotted are averages over ten simulated runs. The following conclusions can be drawn:

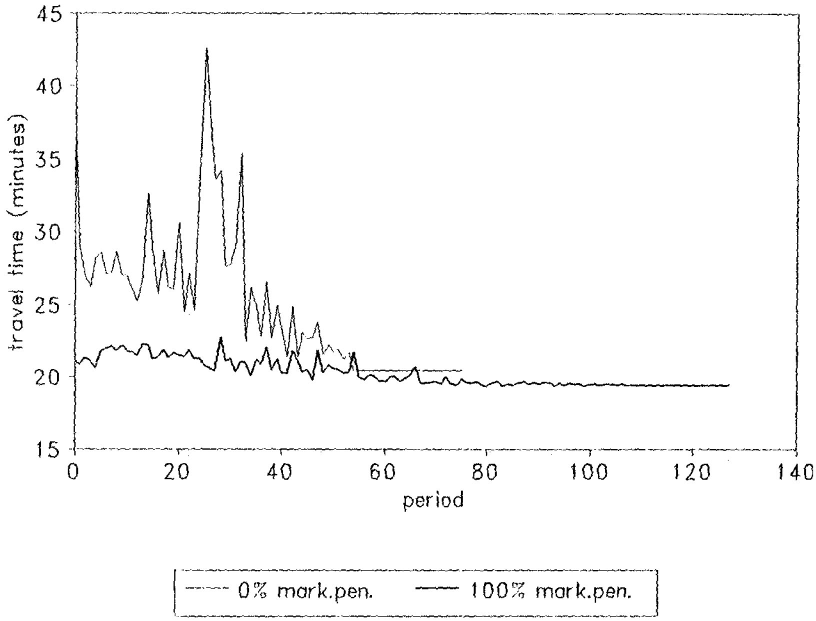

Fig. 13. Daily travel time pattern for no and full market penetration. K0 = 8.

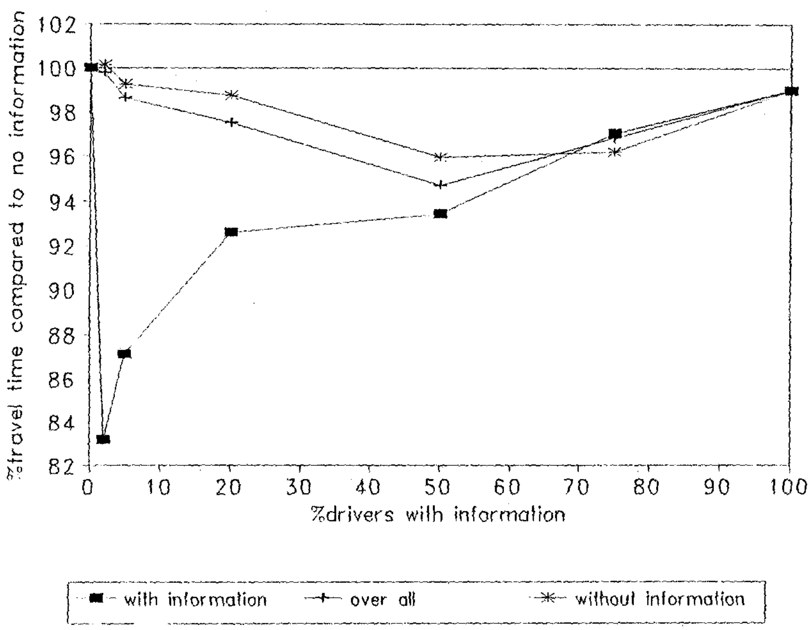

Fig. 14. Travel times compared to no information case. K0 = 5.

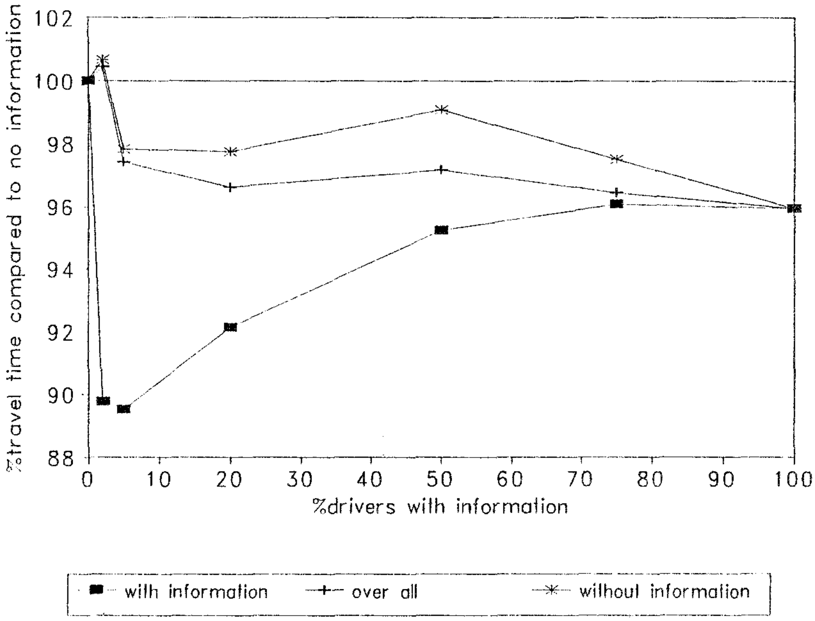

Fig. 15. Travel times compared to no information case. K0 = 8.

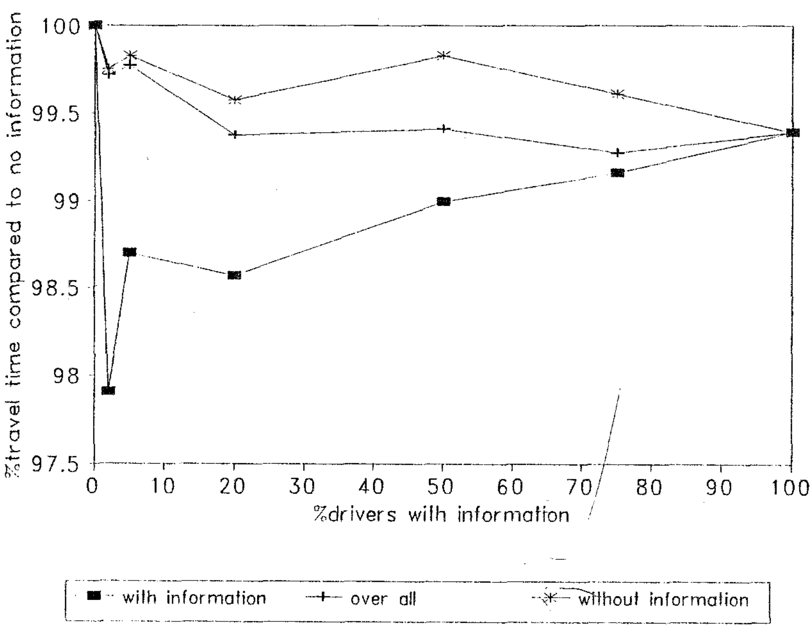

Fig. 16. Travel times compared to no information case. K0 = 12.

- If KO = 12, the gains of providing real-time en route information are very small, due to the fact that the network is practically uncongested.
- For KO = 5 and KO = 8, there are considerable gains for the drivers with information, up to a level of market penetration of 75 per cent. If KO = 8, a level of market penetration equal to 100 per cent still provides substantial gains for the drivers.
- There are savings between 3 and 5 per cent in overall travel time for a level of market penetration between 10 and 75 per cent.
- Drivers without information benefit as well. Their travel time savings are between 1 and 4 per cent.[19]
- The difference between the *with* and *without* information curve converges as the level of market penetration increases and is already relatively small at a 75 percentage level.

The difference between the *with* and *without* information curve has an interesting interpretation. It reflects the benefits to the population of drivers equipped with the information providing system. And can therefore, in combination with the costs of the system, be seen as an indicator of the market potential of these new technologies. We could call the difference between these two curves the *information benefits to equipped drivers*. In Figs. 14, 15 and 16 it can be seen that the *information benefits to equipped drivers* are high at low market penetration levels, but relatively small at a market penetration level of 75 per cent. Figures 17 and 18 show two possible shapes of the relative size of the information benefits to equipped drivers against the level of market penetration for en route information.[20]

In Fig. 17, between O and A, the curve has a positive slope, implying that drivers currently equipped with an information system will benefit if an

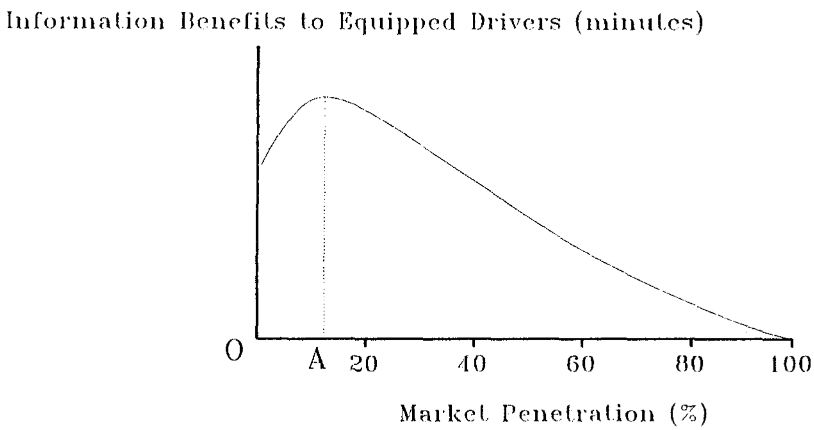

Fig. 17. En route information benefits to equipped drivers as a function of the level of market penetration. Case 1.

additional driver buys an information system. Between A and 100 per cent, the slope is negative. In Fig. 18, the slope is negative for all levels of market penetration. Hence, a marginal equipped driver adversely affects the equipped drivers, but since the information benefits are still positive, it is beneficial for the marginal driver himself to buy the equipment. However, if the information benefits are small, the costs of buying the equipment can outweigh the savings in travel time. Therefore, these curves shed some light on the market potential of motorist information systems.[21]

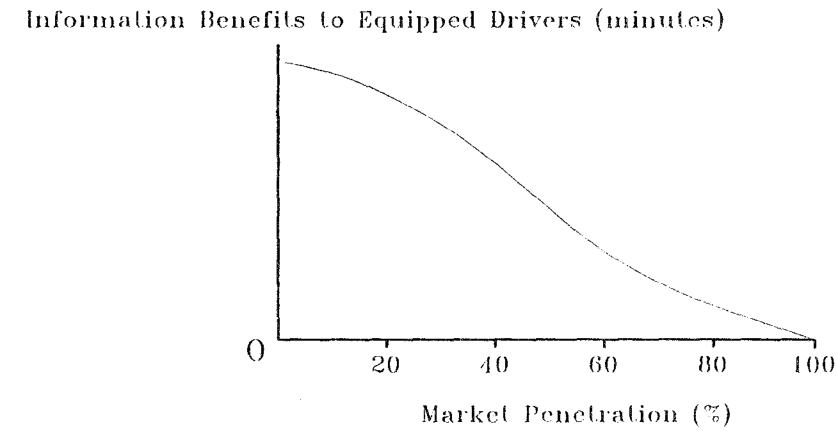

Fig. 18. En route information benefits to equipped drivers as a function of the level of market penetration. Case 2.

6. Concluding comments

The simulation model presented in this paper integrates the route choice dynamics within a day with the day-to-day dynamics. The computer program allows us to investigate the implications of these two levels of decision-making on the travel time patterns.

Four different types of information have been described (own-experience, after-trip, pre-trip, en route), and information mechanisms based upon combinations of these have been specified using boundedly rational models.

Before concluding the results, we would like to stress moreover that these were obtained in a hypothetical setting and could be network dependent. Nevertheless, we believe that they provide useful insights into the potential effects of information provision in a network with recurrent congestion under different information schemes.

The results of the simulation experiments concerning the boundedly rational model (in an environment with information based upon own-experience) are in agreement with the work by Mahmassani and colleagues, summarised in Mahmassani & Herman (1990) and Mahmassani & Chen (1991). A model with a bound between 0.2 and 0.3 performs best (in terms of total network travel time) in the recurrent congested environment.

The experiments with information provision were restricted to after-trip information and real-time en route information. The results suggested that after-trip information is beneficial to all drivers if the level of market penetration does not exceed 20 per cent. In this case, the drivers with information benefit most; in some cases travel time savings of up to 10 per cent were achieved under low levels of market penetration. If real-time en route information is provided, there are benefits to all drivers for most levels of market penetration. Depending upon the level of congestion, the benefits can be as large as 15 per cent to equipped drivers under low levels of market penetration. With high levels of market penetration the average network travel time savings are between 3 and 5 per cent compared to the situation without information. It should be emphasised that the percentages mentioned are related to steady state travel times. In addition, the process leading to a steady state shows, in particular with real-time en route information, a considerable smaller day-to-day travel time variance. Real-time en route information seems to stabilise the traffic flows, and in our opinion these are the most relevant gains of information provision in a network with recurrent congestion.

Comparing the results obtained with after-trip and real-time en route information it emerges that with the latter high levels of market penetration can be achieved without the occurrence of significant overreaction. It can be concluded that high quality (actual, accurate and informative) information allows a relatively high level of market penetration, possibly close to 100 per cent, while information of low quality (uninformative and inaccurate) causes overreaction taking place already at low levels of market penetration. However, given the shape of the information benefits to equipped drivers curve, it is unrealistic to expect a 100 per cent level of market penetration when these technologies were commercially marketed.

Acknowledgements

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Notes

1. In the US these technologies are known as Intelligent Vehicle-Highway Systems (IVHS).
2. A list of other technologies, currently under investigation or already in use, can be found in the OECD report *Intelligent Vehicle Highway Systems: Review of Field Trials*, OECD (1992).
3. The psychological mechanisms leading to the driver's decision are beyond the scope of this paper.
4. Experiments in a network with non-recurrent congestion are carried out in Emmerink (1993a).
5. As with type C, predictive information is not provided.
6. The results of a survey of drivers equipped with a route guidance system as part of the LISB trial can be found in Bonsall and Joint (1991).
7. A habit component could easily be added to these models (Emmerink 1993a).
8. Schedule delay is defined as the absolute value of the preferred arrival time minus the actual arrival time. The importance of schedule delay for departure time decisions has been pointed out by Hendrickson & Kocur (1981).
9. Although model [13] does not contain an explicit habit component it can be given a habitual interpretation One could argue that if the last travel experience does not exceed the bounds, the driver is not willing to change alternative because of both satisficing and habit considerations. Furthermore, the longer ago the last change in alternative has been made, the more likely it is that a driver will stick to the same alternative in the future, due to the specification of the updating mechanism of ET. It is likely that the ET component will slowly converge to the experienced travel time thereby making the decision a satisfactory one. Only a large disturbance in the network, due to route changes by many other drivers could cause the driver to change route.
10. The term steady state will be explained below.
11. Given the model specification in this paper, a steady state is equivalent with a situation in which the ExperiencedTravelTime is equal to ET for all drivers.
12. Readers interested in the statistical treatment of the results are referred to Emmerink (1993a).
13. However, we acknowledge that a stochastically assigned α-parameter (randomly differing among the drivers) is more realistic.
14. Throughout this paper, the performance indicator *number of routes used* refers to the number of different routes used by a driver during a simulation run averaged over all drivers.
15. In Fig. 7 one point is missing. In this case a steady state was not reached after 400 days.
16. One might argue that it is counter intuitive for drivers with information to be worse off compared to the situation without information. The argument supporting this case could, for instance, be based upon the fact that if the drivers would be worse off by using the information, they would ignore it. However, in our model it is assumed that drivers supplied with information will always use it, as described in Section 3.1.2. Because of these unrealistic results, no experiments with a level of market penetration higher than 50 per cent have been conducted.
17. Compare in their paper Fig. 2 (p. 299) and Fig. 4 (p. 300) for the model without bound and a high level of market penetration.
18. To preserve informativeness, the y-axis's of these Figures are scaled differently.
19. In one case (K0 = 5, market penetration = 75%) drivers without information outperform the ones with information. The same phenomenon prevailed in some simulation experiments in Section 5.3.
20. The curve is discontinuous in market penetration level zero. At a market penetration level of 100 per cent it is assumed that the information benefits to equipped drivers are zero. However, this is only the case if we assume the *user equilibrium* at this level of market penetration (Emmerink et al. 1993b).

21. See Emmerink, Axhausen, Nijkamp & Rietveld (1994) for a detailed analysis of the economic consequences of the shape of these curves.

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