Effectiveness of Information Systems in Networks With and Without Congestion

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The use of road transport informatics (RTI) is a recent development that optimizes the use of existing facilities in the transportation system and serves three main goals: alleviation of congestion, diminution of air pollution, and reduction of incidents. RTI instruments deal with traffic information. Examples of RTI systems are pretrip planning, roadside displays, radio data system–traffic message channel, and in-car navigation. To model the effects of providing the road user with information a method is used in which stochastic and deterministic assignments were compared for both networks with and without congestion. To let information also effect destination choice and the spatial distribution of activities, the assignment models were combined with different distribution models. The amount of information that travelers have was translated to a "level of uncertainty" measure. The more informed a traveler is, the lower the level of uncertainty. Since the effects appeared to be network dependent, a number of different networks were examined. Simulations show that the amount of kilometers driven decreases when travelers are provided with better and more information.

The use of road transport informatics (RTI) is a recent development that optimizes the use of existing facilities in the transportation system and serves three main goals: alleviation of congestion, diminution of air pollution, and reduction of incidents. RTI instruments deal with traffic information. Systems such as pretrip planning, roadside displays, radio data system–traffic message channel, and in-car navigation are all part of RTI. From a planners' viewpoint, it is essential to know the possible impact of RTI on the traffic system. One way to predict effects of RTI is to model individual travel behavior and to incorporate information explicitly as a model component. In this way, the effect of information on travel behavior can be simulated. Before this can be done, however, it is necessary to model the current situation, in which the traveler is not perfectly informed and therefore makes nonoptimal choices.

In many existing models it is assumed that people have perfect knowledge of all travel alternatives. This assumption means that the usefulness of providing information to travelers cannot be determined. In the approach presented in this paper, the classic four-stage model is central. The key issue is, however, that the perceived travel times instead of the objective travel times are being used in all stages. Therefore, a measure of uncertainty is introduced. Uncertainty affects not only route choice, but also destination choice and the spatial distribution of activities. A further assumption is that information reduces uncertainty. So by using models in which route choice, distribution, or location of activities, or all three, are influenced by the (perceived) travel times and the outcomes for different levels of uncertainty are compared, it is possible to get an insight in the effects of information.

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RELATED STUDIES

In recent years, many approaches have been presented to provide insight into the possible benefits of information systems in transport.

The feasibility of the Comprehensive Automobile Traffic Control project (*1*) was studied by using a simulation model in which the noninformed users choose their route on the basis of various factors, such as travel time, length of the route, number of lanes, number of turns, and so on, and the informed users choose their route solely on the basis of travel time. It was found that in Tokyo travel time could be reduced by 6 percent and fuel consumption by 5 percent. Tsuji et al. (*2*) investigated the effectiveness of a route guidance system by using a mathematical model. Among other factors, they used travel time reduction as a measure of effectiveness. The outcomes, however, must be related to the heavy assumptions under which the model is valid. The reduction in travel time was found to be 11 percent. van Vuren (*3*) tried to model the effectiveness of route guidance by using a multiuser class equilibrium and stating that the noninformed users behave greedily, as in an deterministic user equilibrium, whereas the informed users behave according to the principle of a system optimum. The results were found to be unrealistic because the uninformed users were better off.

Koutsopoulos and Lotan (*4*) modeled the impact of information on travelers by using a stochastic user equilibrium and stating that information systems reduce the variance in travel time. They found a reduction in travel time of about 5 percent, dependent on the assumed reduction in variance.

Mahmassani and Jayakrishan (*5*) modeled the effectiveness of a real-time information system on a small test network with three parallel highways and a number of switching possibilities. The researchers chose one information supply strategy and focused on the users' reaction by defining them as bounded rational individuals. An important result was that the system performance might actually worsen by myopic local actions of the drivers. Van Berkum and van der Mede (*6*) presented a dynamic approach that simulates rational, uncertain, persistent individuals who base their decisions on experience and have a limited knowledge of alternatives.

The approach that is followed in this paper is an extension of the work of Koutsopoulos and Lotan (*4*). The situation of recurrent congestion was also studied in this research. But whereas Koutsopoulos and Lotan restricted the effects of better information to route choice, the impact on destination choice and the location of activities has also been studied here. Another difference is that the amount of uncertainty in their approach was initially too small. Further, they examined one network, whereas different networks are studied here. Because the results are network dependent, it is difficult to compare results, but the results they found on route choice are on the same order of magnitude as the results presented in this paper. The results gained from the present research are not comparable with the results found by Mahmassani and Jayakrishan. They studied the reaction of people on dynamic traffic information that reports the actual traffic conditions. When drivers react myopically, this information becomes invalid. An adjustment process will occur, which in the end will lead to an equilibrium. This equilibrium is focused on in this paper. This further implies that the information given to the drivers is in some sense not real-time information but rather future-time information.

MODELING APPROACH

General

The main hypothesis of this study is that the fact that people are uncertain about travel times on links has more effects than only on route choice. There will also be effects on destination choice as well as on the spatial distribution of activities. People make trips because they want to perform activities that are spatially separated. In the traditional four-stage models, the spatial distribution of activities is fixed. In this study models are used that include the spatial distribution of activities as endogenous. Users choose a route by minimizing some measure of cost. In this study travel time will only be used as cost. Travelers do not possess perfect information about the network they travel on. This means that people do not minimize the objective time but rather the perceived travel time.

Destination choice can also be modeled by using a cost minimization procedure (*8*). Because of the observation made previously, this means that in determining the origin-destination (O-D) flows, the perceived cost or travel time must also be used. A basic assumption here is that route choice is made on the basis of the same perceived travel times as destination choice and the location of activities are made. Traffic information affects the perception of travel times in the network. The perceived travel times will be modeled as stochastic variables whose distribution is influenced by the amount of available information.

The approach that has been followed uses the traditional four-stage model as a basis, although an adjusted form has been developed. The following assumptions are therefore needed:

- All people base their decisions on what they know; and
- People base their route and destination decisions on the same perceived travel time.

In order to make the approach not too complex the following limitations have been adopted:

- The total number of trips is constant under all levels of uncertainty;
- All people have access to the same level of information;
- Information is assumed to be good and true; and
- No distinction has been made between different modes and purposes.

Route Choice

Link travel times on the network are defined as stochastic variables. The variance in travel times—that travel times are unpredictable to a certain extent—may be understood as uncertainty of travelers. Consequently, users will have different perceptions of travel times on the links.

A deterministic user equilibrium (DUE) can be defined as the situation in which no traveler can improve his or her travel time by unilaterally changing route (*9*). This definition assumes that every traveler has an exact knowledge of travel times and flows on all links in the network. A stochastic user equilibrium (SUE) can be defined as the situation in which every traveler *thinks* that he or she cannot improve the travel time by unilaterally changing routes (*9,10*). This definition assumes that travelers have different perceptions of travel times. Comparing a SUE with a DUE enables estimating the effect of providing information to travelers (or reducing their uncertainty) on the traffic system (*4,11*), because this comparison can be translated as comparing travelers with exact knowledge of all travel times in the network with travelers with different perceptions of travel times in the network.

In networks without congestion the DUE assignment becomes a simple all-or-nothing assignment, where the SUE assignment becomes a classic stochastic assignment (*12,13*). The impedance Z_{ap} of a link a in a network for person p is a function of a number of variables X_{ak} such as time, cost, and distance and their relative importance β_k plus some measure of uncertainty. We define

$$Z_{ap} = \sum_k \beta_k \cdot X_{ak} + e_{ap} \qquad (1)$$

where e_{ap} is a noise term. The resulting route choice model depends on the distribution of e_{ap}. It is supposed that e_{ap} is normally distributed with mean 0 (*13*), which yields a probit model for route choice. The introduction of the noise term e_{ap} can be explained by stating that (*a*) behavior cannot completely be explained by all X_{ak}'s, (*b*) individuals have different perceptions of the X_{ak}'s and their relative importance therefore may differ, and (*c*) individuals are uncertain about the exact value of the X_{ak}'s, especially because these values differ in time. Instead of impedance, generalized cost, or generalized time only travel time will be considered as a measure for deterrence in this study.

The travel time on a link a in a network *without congestion* is

$$Z''_a = Z_a + \alpha \cdot R \cdot \sqrt{Z_a} \qquad (2)$$

where

Z_a = mean travel time of link a,
R = draw from a normal [N(0,1)] distribution, and
α = factor determining the variance (from now α will be called *level of uncertainty*).

The value of α is dependent on the chosen dimension (*14*). Given an O-D matrix, α can be determined by comparing true with model flows. When the dimension is minutes, it has been estimated that $0.5 < \alpha < 1$ for a regional network with relatively few alternative routes (*15*). Furthermore, Bovy (*14*) developed an efficient methodology for estimating α from observed flows.

In reality the uncertainty will, among other things, be a function of the frequency with which a person travels between a certain O-D pair. The lower the frequency, the higher the uncertainty. In this study, the uncertainty is assumed to be equal for all travelers.

The travel time of a link in a network with congestion is

$$Z''_a = Z'_a + \alpha \cdot R \cdot \sqrt{Z'_a} \tag{3}$$

with

$$Z'_a = Z_a\left[1 + \tau\left(\frac{q_a}{c_a}\right)^4\right] \tag{4}$$

where

Z_a = the mean travel time of link a,
q_a = the flow on link a,
c_a = the capacity of link a,
R = a draw from a normal [N(0,1)] distribution,
α = the level of uncertainty, and
τ = a parameter dependent on the definition of capacity.

Destination Choice and the Location of Activities

Because the distribution process is a utility maximization process (or disutility minimization), information will also have impact on destination choice resulting in a distribution of flows and the location of activities. In this study, the following interaction model with elastic constraints is used (*16*):

$$\min \sum_j \left(\sum_i T_{ij} - m_j^{-h} \cdot A_j\right)^2 + \sum_i \left(\sum_j T_{ij} - l_i^{-g} \cdot D_i\right)^2 \tag{5}$$

Subject to

$$T_{ij} = \theta l_i m_j Q_i X_j \exp[-0.4 \ln^2(Z_{ij} - d_{ij} + 1)] \tag{6}$$

where

T_{ij} = number of trips between i and j,
l_i, m_j = equilibrium factors,
Q_i, X_j = polarities,
Z_{ij} = objective travel time between i and j,
A_j, d_i = arrivals and departures, and
d_{ij} = difference between objective and perceived travel time between zones i and j.

In solving the model, the terms $1/(1 + g)$ and $1/(1 + h)$ become important. These terms will be called elasticities. Thus when g and h are both 0 the elasticities become 1 and the model turns into the classic gravity model with fixed constraints. To coordinate spatial planning, transportation development, and spatial development, the model with elastic constraints was developed. The value of the equilibrium factors in Equation 6 is a function of the extra effort needed to comply with the constraints. In poorly accessible areas, the value is high and, inversely, in easily accessible areas the value is low. When the number of arrivals and departures is seen as dependent, though not exclusively, on the accessibility, the objectives in Equation 5 must become elastic.

Combining the Assignment and the Distribution Model

To determine the effects of information on route choice, route and/or destination choice, and/or the location of activities, the following models must be compared:

- In the case of *no* congestion, a distribution model with and without elastic constraints will be compared with the same model but combined with a stochastic Burrel assignment.
- In the case of congestion, first the DUE assignment will be combined with the distribution model without (*10,17*) and with elastic constraints (*18*). Second, the same combination will be made, but with the SUE assignment.

To combine a SUE assignment with a distribution model, including the assumption that both models deal with the same perceived travel times, it is necessary to determine how the perceived travel times must be used in the distribution stage. In the proposed distribution model there is one value for travel time between each O-D pair. In reality this travel time is different for every individual (perceived travel time). Starting with Z_{ijrp}, the perceived travel time between i and j along route r of person p, person p chooses that route with the smallest perceived travel time. Therefore, it holds that

$$Z_{ij,p} = \min_r Z_{ijrp} \tag{7}$$

Suppose the population B is divided in two groups, B1 and B2. Persons belonging to B1 find route *1* the best, and persons belonging to B2 do not, so

$$Z_{ij1p} \leq Z_{ijrp} \ \forall\, p \in \text{B1 and } r \neq 1 \tag{8}$$

For persons belonging to B2 it holds that

$$Z_{ij1p} \geq Z_{ij,p} \ \forall\, p \in \text{B2} \tag{9}$$

So

$$Z_{ij,p} \leq Z_{ij1p} \ \forall\, p \in (\text{B1} \cup \text{B2}) \tag{10}$$

Suppose there are N persons in B, then

$$Z_{ij} = \frac{1}{N}\sum_p Z_{ij,p} \text{ and } Z_{ij1} = \frac{1}{N}\sum_p Z_{ij1p} \tag{10.1}$$

Using Equation 10 it holds that

$$Z_{ij} \leq Z_{ij1} \tag{10.2}$$

The same result can be derived for every route r, so

$$Z_{ij} \leq Z_{ijr} \qquad \forall\, r \tag{11}$$

Thus the perceived travel time between any O-D pair used in the distribution stage is always less than or equal to the perceived travel time of any of the chosen routes between the OD pair.

The difference between the best route and the travel time between an O-D pair is dependent on the network. When, for instance, one route is by far the best so that every traveler between that OD pair will choose that route, the equal sign in Equation 11 holds for this particular route. When there is a spreading over the routes for all r the less than sign will hold. When the level of uncertainty α becomes larger, the spreading in routes becomes larger and Z_{ij} will decrease, or in other words the difference between model travel time and the mean perceived travel time of the objectively seen best route (which is by definition the objective travel time of the best route) becomes larger. So in the distribution stage the following travel time is used:

$$Z_{ij} - d_{ij}$$

Where Z_{ij} is the mean perceived travel time of the objectively seen best route between zone i and j; d_{ij} is an increasing function of α (obviously when $\alpha = 0$, also $d_{ij} = 0$).

Models and Algorithms

To study the effects of more or better information on route choice the "A model" is used, which is a stochastic equilibrium assignment with a given, fixed O-D matrix. To study the effects on destination choice and on the resulting O-D flows too, the "A + D model" is used. In this model, a stochastic equilibrium assignment and distribution with fixed constraints are combined. In the O-D matrix, the numbers of departures and arrivals are fixed for each zone. The cell volumes solve Equation 5 subject to Equation 6 with $g = h = 0$.

To study the effects of activities on the locations, the "$A + D + L$ model" is used. In this model, a stochastic equilibrium assignment and distribution with elastic constraints are combined. In the O-D matrix, the numbers of departures and arrivals are variable for each zone, but the total number of trips is fixed. The cell volumes solve Equation 5 subject to Equation 6 with g and h not necessarily equal 0.

In Figures 1 through 4, the separate algorithms for the congestion situation are depicted. Basically, the methodology as proposed by Evans (*17*) is followed. The steps that have to be executed more than once because the draw must take place m times have been depicted with a thick line. In the case of no congestion, the step where new travel times are computed becomes trivial.

A generalized description of the used algorithm is

1. Read network;
2. Draw link travel times for every link;
3. Determine travel times from shortest routes between every O-D pair;
4. Repeat No. 2 and No. 3 m times;
5. IF model = A THEN
   read O-D matrix
   ELSE determine mean travel times with the travel times per draw determined in No. 3. Determine O-D matrix with elastic constraints (A + D + L) or with fixed constraints (A + D) using a Gauss-Seidel interation procedure to solve Equation 5 subject to Equation 6;

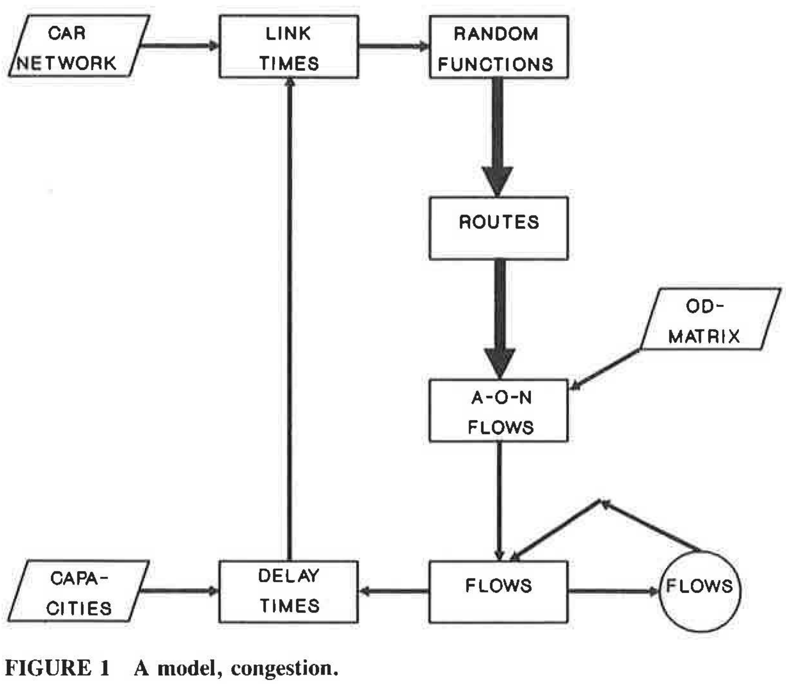

FIGURE 1 A model, congestion.

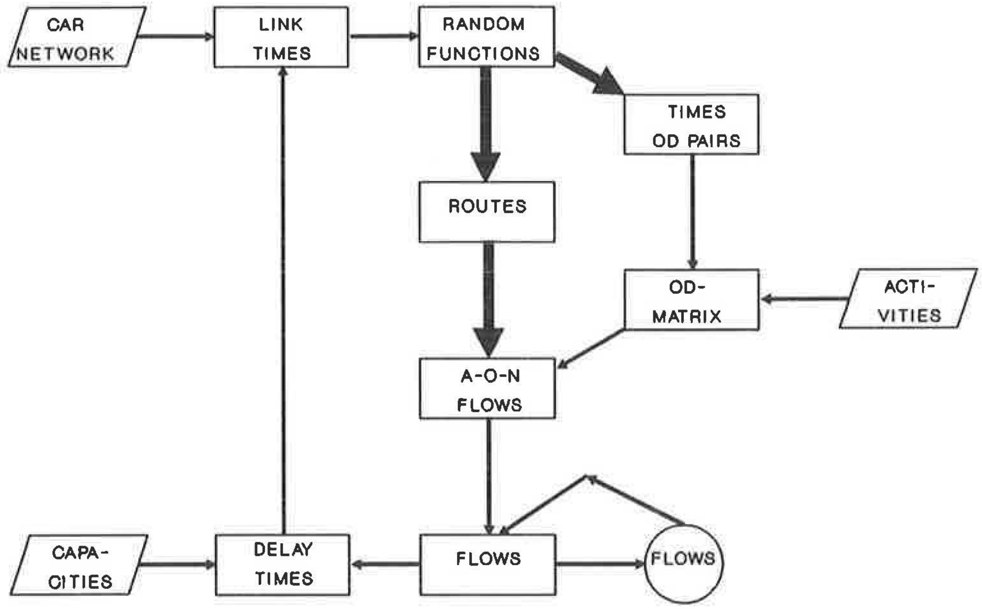

FIGURE 2 A + D model, congestion.

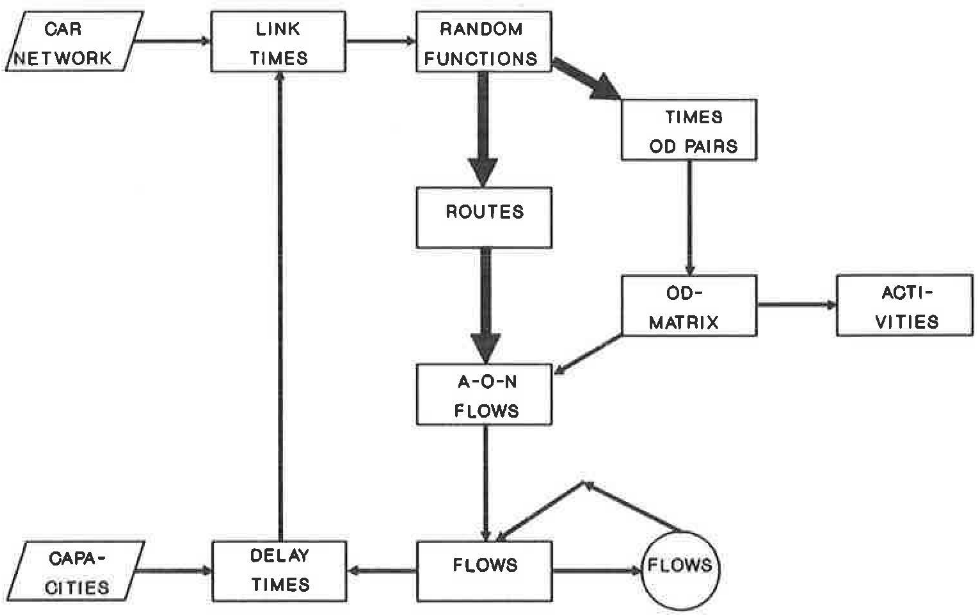

FIGURE 3 A + D + L model, congestion.

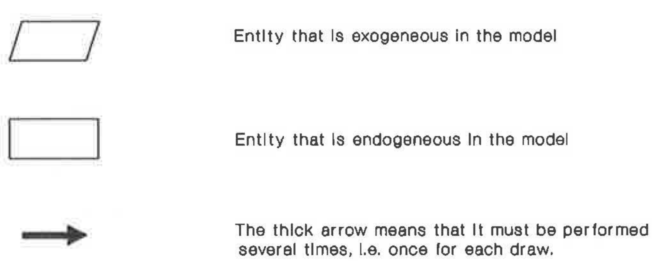

FIGURE 4 Explanation for Figures 1 to 3.

6. Subdivide the O-D matrix in m equal parts and load them to the routes determined in No. 3, yielding loads q_a^+ for link a;

7. load link a in iteration i the network with $q_a^i = [q_a^{i-1} \cdot (i - 1) + q_a^+]/i$;

8. In case of congested networks: determine new travel times; and

9. Go to No. 2 until stop criterion is reached.

EXPERIMENTS

The experiments were performed using the research facilities of the Teacher Friendly Transportation Programs V90.2 (*19*). In the stochastic assignments m, the number of draws was 4 and the number of iterations was 8. Because for every tree of shortest paths, new travel times were drawn, the total number of draws is 32 times the number of zones. Convergence was no problem in all test networks. The number of iterations was far less than expected in a combined distribution-assignment procedure (*10,20*).

Networks

Earlier it was observed that the spreading of chosen routes determines to some extent the value of d_{ij}. The amount of spread is not only dependent on the size of the variance as used in the stochastic assignments, but also on the presence of (relevant) alternative routes. Obviously in a situation in which there are hardly any alternative routes, the spread will be small. Therefore it is important to investigate different networks. In this study four regional networks with a diameter of about 40 km (called REGIO, RING, SLOW, and CBD) and one urban network with a diameter of about 15 km (TOWN) were examined. For the regional networks only, the situation without congestion is considered. For the urban network both the situation with and without congestion are considered.

In Figures 5 to 7 some of the networks with their spreading of activities and flows are shown. In Figure 8 the notation of the activities is shown. The networks RING, SLOW, and FAST are the same size (number of links, number of nodes, distances) as CBD.

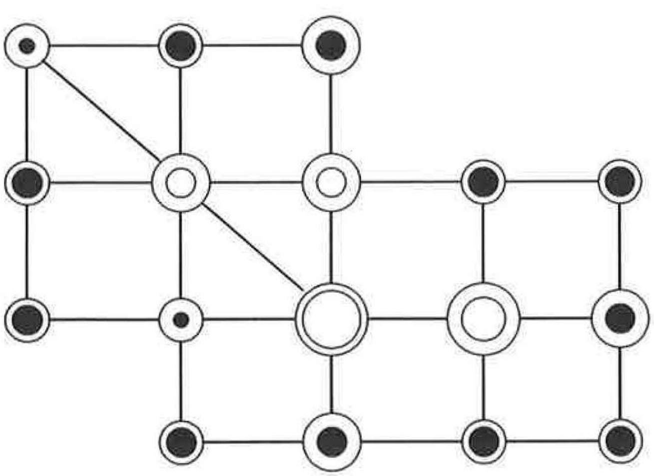

FIGURE 5 Network CBD.

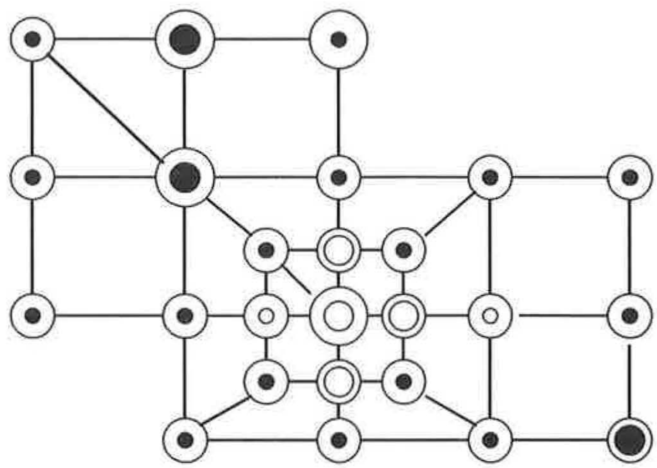

FIGURE 6 Network REGIO.

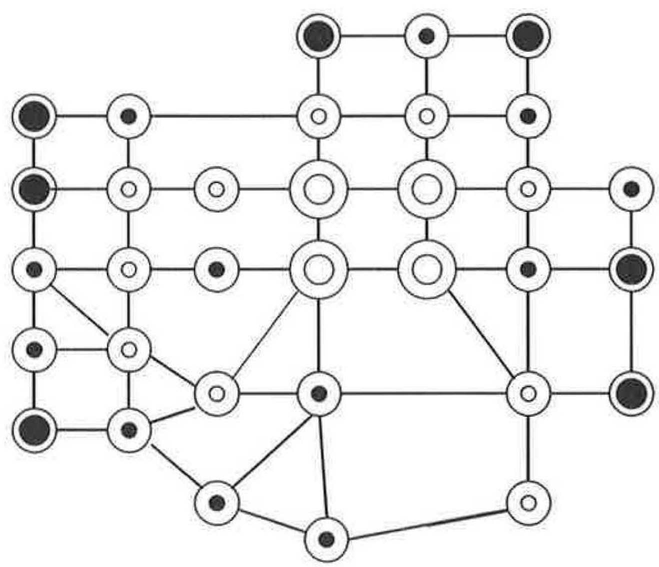

FIGURE 7 Network TOWN.

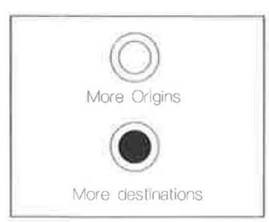

FIGURE 8 Notation of activities.

In Figure 8 the radius of the outer circle is proportional to

$$\left[\max\left(\sum_i T_{ij}, \sum_j T_{ij}\right)\right]^{1/2} \tag{12}$$

The radius of the inner circle is proportional to

$$\left[abs\left(\sum_i T_{ij} - \sum_j T_{ij}\right)\right]^{1/2} \tag{13}$$

The inner circle is open when

$$\sum_{i} T_{ij} < \sum_{j} T_{ij} \tag{14}$$

The description of the networks is as follows:

- CBD—network with speedways (100 km/h) pointed to a central zone; other roads are 40 km/h;
- FAST—network with only speedways (100 km/h);
- REGIO—network like "CBD", but more dense near the center;
- RING—network with speedways in a ring around a central area;
- SLOW—network with only secondary roads of 40 km/h; and
- TOWN—urban network; there are no trips to or from the surrounding areas.

Level of Uncertainty, α

The simulations have been performed for all networks with levels of uncertainty $\alpha = 0$, $\alpha = 0.5$, and $\alpha = 1$. For the network TOWN $\alpha = 0.3$ and $\alpha = 0.8$ were also taken into account.

Results

The results of the simulations for the urban network with and without congestion are given in Tables 1 and 2. Results for the regional networks without congestion are given in Tables 3, 4, and 5. For all networks, the amount of carkilometers (vehicle miles) increases when the level of uncertainty increases. Because provision of information can be translated in a smaller level of uncertainty, it can be stated that providing road users with information reduces the amount of carkilometers. The results show that the gains differ per network. A network means not only the set of links and nodes, but also the initial tripends. This observation implies that it is hard to compare the results of other studies with one another and with these results, because different networks are used in all studies.

The results for the networks as listed in Tables 3, 4, and 5 are more or less comparable. These results were calculated with models that did not deal with congestion. The results for the TOWN network show a larger increase in carkilometers when α increases (See Table 2). This can be explained by the fact that the TOWN network obviously contains more alternative routes than all the other networks. The spread in route choice will be bigger for this network since there simply exist more alternatives. Because the network outcomes in Tables 3 to 5 reflect few alternative routes, the effect on route choice is small compared with the effect on destination choice (compare the outcomes in Tables 3 and 4). The extra effect on the location of activities is also small compared with the effect on destination choice (compare the outcomes in Tables 4 and 5). When looking at the network TOWN, the effects on route choice are the largest. Change in destination choice and in the location of activities are marginal compared with this effect. Because this network is more realistic than the other ones, this observation may be generally true. By comparing Tables 1 and 2, it follows that the effect of the provision of information is larger in the network with congestion than without congestion.

TABLE 1 CARKILOMETERS FOR TOWN NETWORK, WITHOUT CONGESTION, UNDER DIFFERENT LEVELS OF UNCERTAINTY (KM FOR $\alpha = 0$ ARE 100)

α	A	A+D	A+D+L
1.0	117	128	130
0.7	112	119	121
0.5	104	107	108
0.3	101	102	103
0.0	100	100	100

TABLE 2 CARKILOMETERS FOR TOWN NETWORK, WITH CONGESTION, UNDER DIFFERENT LEVELS OF UNCERTAINTY (KM FOR $\alpha = 0$ ARE 100)

α	A	A+D	A+D+L
1.0	124	129	136
0.7	118	121	126
0.5	106	109	110
0.3	102	103	103
0.0	100	100	100

TABLE 3 CARKILOMETERS DRIVEN FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A-MODEL (KM FOR $\alpha = 0$ ARE 100)

α	CBD	RING	SLOW	FAST	REGIO
1.0	102	103	101	105	103
0.5	100	103	101	101	101
0.0	100	100	100	100	100

TABLE 4 CARKILOMETERS DRIVEN FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A+D-MODEL (KM FOR $\alpha = 0$ ARE 100)

α	CBD	RING	SLOW	FAST	REGIO
1.0	108	109	112	120	111
0.5	102	103	105	107	103
0.0	100	100	100	100	100

TABLE 5 CARKILOMETERS DRIVEN FOR DIFFERENT NETWORKS, UNDER DIFFERENT LEVELS OF UNCERTAINTY WITH THE A+D+L-MODEL (KM FOR $\alpha = 0$ ARE 100)

α	CBD	RING	SLOW	FAST	REGIO
1.0	113	113	113	123	115
0.5	103	103	105	107	104
0.0	100	100	100	100	100

CONCLUSION

Trips and activities are a result of decisions people make. These decisions concern route and destination choice as well as activity choice. The actual choices depend on the perceived travel times, rather than on the objective travel times. As a result, travelers think they choose the best route, but this route is not necessarily the best from an objective point of view. Also destinations are chosen because they appear to be close. This causes extra, unnecessary carkilometers.

The approach presented in this paper has a number of assumptions and limitations about information:

- Information is seen as an abstract entity; it is not possible to evaluate a specific information system or different types of information.
- Because of the equilibrium approach the presented method is able to predict the long-term effects of the provision of information in a situation of recurrent congestion.

The results of this study should be looked at in light of these assumptions as well as in light of the limitations this approach has.

It was proven that the perception of two or more independent routes is always less than or equal to the perception of each of two or more routes together. The travel time of the chosen route is systemically being underestimated. Providing information reduces the difference between perceived travel time and objective travel time. This has an impact on the choice of route, destination, and activity. As a result, the amount of carkilometers decreases. The different test cases show that the form of the network, with respect to the presence of alternative routes, is of importance. Further, the simulations show that in a situation with congestion, the decrease of carkilometers is larger than in the situation with no congestion. Currently it is not possible to quantify the effects of information precisely because the present and future values of α are not exactly known, uncertainty will only partially be influenced by information, and only a part of the travelers will use the information. On the other hand, through route guidance, delays on intersections may be minimized (*21*) and the influence that information about incidents could have is neglected. With the above considerations in mind it seems valid to state that information systems may decrease the amount of carkilometers in urban networks by 15 to 20 percent and in regional networks by 5 to 10 percent.

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