Costs of travel time uncertainty and benefits of travel time information: Conceptual model and numerical examples

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Abstract

A negative effect of congestion that tends to be overlooked is travel time uncertainty. Travel time uncertainty causes scheduling costs due to early or late arrival. The negative effects of travel time uncertainty can be reduced by providing travellers with travel time information, which improves their estimate of the expected travel time, thereby reducing scheduling costs. In order to assess the negative effects of uncertainty and the benefits of travel time information, this paper proposes a conceptual model of departure time choice under travel time uncertainty and information. The model is based on expected utility theory, and includes the variation in travel time, the quality of travel time information and travellers’ perception of the travel time. The model is illustrated by an application to the case of the A2 motorway between Beesd and Utrecht in the Netherlands.

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1. Introduction

For several decades now, recurrent congestion has been considered to be one of the most serious issues that urgently needs to be addressed by transport policies. Policies that have been proposed to reduce congestion include expansion of road capacity by extra lanes, stimulating the use of other transport modes and congestion pricing. Cost–benefit analyses are usually carried out to determine ex-ante the costs and benefits of such policies. User benefits are usually expressed as the decrease in travel time brought about by a policy (e.g., Khattak et al., 1996).

Although providing relevant insights into the effects of such policies, this common practice overlooks a second source of user benefits: the reduction of travel time uncertainty. Recurrent congestion implies not only longer travel times, but also a larger day-to-day variation in travel times, and, consequently, a greater uncertainty (Polak, 1987; Noland and Small, 1995; Bates et al., 2001; Noland and Polak, 2002). Travel time...
uncertainty implies that travellers have to keep a larger safety margin if they want to avoid arriving late with a reasonable certainty and that the probability of arriving too early (and having to wait) or arriving too late increases. Consequently, a reduction of recurrent congestion levels does not only generate benefits in terms of travel time savings, but also in terms of reduced uncertainty about daily travel times. In addition, non-recurrent events will have less serious impact in case of lower congestion levels, leading to less variation in travel times.

Another way of reducing uncertainty, without resolving congestion and the associated travel time variation itself, is to supply road users with detailed information about the state of the transport network, which allows them to better anticipate possible delays, avoid early or late arrival, and reduce the required safety margin. A number of technologies, jointly described as ATIS, is now available to provide travellers with such information. ATIS-technologies can provide information in both the pre-trip and en-route stages, and may lead travellers to change their choice of mode, destination, departure time and/or route.

The literature on traveller response to congestion and ATIS (e.g., Hatcher and Mahmassani, 1992; Mahmassani and Jou, 2000; Jou et al., 1997; Mahmassani and Herman, 1990; Chang and Mahmassani, 1988; Hu and Mahmassani, 1997; Mahmassani and Liu, 1999; Khattak et al., 1996) suggests that the most common response to (information about) congestion is to change departure time, although changing routes also occurs frequently. This paper will therefore focus on departure time choice as the dominant response to traffic information. The propensity of travellers to switch departure time increases if more complete information is provided (not only regarding one’s own trip but also regarding system performance) and information is more specific: quantitative instead of qualitative, predictive instead of descriptive.

According to Khattak et al. (1996) and van der Mede and van Berkum (1993), travel information can be classified into a number of classes, depending on the time at which it is provided and the nature and objective of the information (Table 1).

The first category of traffic information is retrospective information, describing the performance of the traffic system (realised travel times) in the past. Retrospective data serve to improve travellers’ perception of the average state of the transportation system and its variability. As a result, travellers are better able to choose the departure time that gives the best outcome under average conditions.

The second category is descriptive information, describing the current characteristics of the transportation system. This information may be qualitative (“unexpected congestion on your usual route”) or quantitative (“the current delay is $X$ minutes”). In contrast to retrospective information, descriptive information allows travellers to adjust their behaviour to the situation on a specific time and place. Decisions about departure time can therefore be taken more effectively. Although descriptive information is useful to travellers, the situation of the traffic system may have changed by the time the trip is actually made. Ideally, traffic information should therefore be given in the form of a prediction (“the delay when departing at time $Y$ will be $X$ minutes”). Khattak et al. (1996) indicate that travellers are more sensitive to predictive information than to other types of information. However, predictions are inherently uncertain. It should be noted that descriptive information can also be interpreted as a prediction, as the state of the traffic system at e.g., 7.00AM is an indication of the situation to be expected at 8.00AM. Thus, both descriptive and predictive information can be described in terms of predictions with a certain amount of uncertainty involved. The effect of traffic information can therefore be regarded as a reduction of the uncertainty, rather than an elimination of uncertainty. The size of the reduction depends on the quality of the information.

Given the omission of the effects of travel time uncertainty in cost–benefit analyses to date, it would be useful to further explore the costs brought about by travel time uncertainty, which can be regarded as benefits if

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<tr>
<th>Type of information</th>
<th>Concerns</th>
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<tr>
<td>Retrospective</td>
<td>Qualitative</td>
<td>Average + variation</td>
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<tr>
<td>Descriptive</td>
<td>- Qualitative</td>
<td>Current situation</td>
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<td></td>
<td>- Quantitative</td>
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<td>Predictive</td>
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<td>Day specific value + uncertainty measure</td>
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the uncertainty is reduced by increasing road capacity, and the specific benefits brought about by ATIS technologies in reducing travel time uncertainty.

In this paper, a conceptual model of how travellers choose departure time under travel time uncertainty and its associated costs is developed. The model is able to distinguish between true travel time distributions and errors in travellers’ perception of travel time. This model is extended to describe the reduction in generalised costs (through reduced uncertainty) that can be brought about by ATIS technologies. In this respect, the accuracy of the travel time information and the perceived accuracy are included in the model. The model is applied to assess user benefits to be gained from traffic information (by individual users) in a number of ATIS scenario’s for the concrete setting of the A2 highway in The Netherlands.

This paper is organised as follows. Section 2 addresses the state of the art in departure time choice modelling, based on expected utility theory (EUT). Some pros and cons of EUT in comparison with other approaches are discussed. Section 3 describes the conceptual model that was developed, accounting for perception errors and the availability and quality of information. Section 4 presents the results of simulations that were run with the model. Finally, Section 5 draws conclusions about the applicability of the approach and addresses avenues for further research.

2. Departure time modelling under uncertainty: the expected utility approach

Given that departure time adjustment appears to be the dominant response to traffic information through ATIS, this section reviews the state of the art in departure time choice modelling under uncertainty. As the scope of this paper is on detailed departure time choice, the discussion is limited to models describing departure time choice on a (nearly) continuous scale.

The literature is comprised of a series of different approaches to continuous scale departure time modelling. Hazard models of activity timing and duration (e.g., Bhat and Steed, 2002; Ettema et al., 1995) and time allocation approaches treating departure time as the outcome of a utility-maximizing process of time allocation to activities and travel (e.g., Wang, 1996; Ettema and Timmermans, 2003) dominate the field. However, these approaches are, in their present form, not capable of representing travel time uncertainty as an explanatory variable.

The only approach addressing travel time uncertainty is the expected utility approach (e.g., Polak, 1987; Noland and Small, 1995; Bates et al., 2001; Noland and Polak, 2002). This approach treats departure time choice as a choice out of a large number of small discrete time intervals (Small, 1982). It is assumed that a traveller can choose between a number of (small) departure time intervals, and that from each departure time \( t \) a utility \( U_t \) is derived. The utility \( U_t \) depends on a set of trip characteristics \( X_{jt} \), which are specific for departure time \( t \):

\[
U_t = \sum_j \beta_j X_{jt}
\]

Trip characteristics typically included in the utility function are travel time and travel cost. However, schedule delay associated with departure at \( t \) may also be included. The schedule delay concept departs from the assumption that a traveller has a preferred arrival time (PAT), at which he wants to arrive. Arriving earlier or later causes a schedule delay. Schedule delays are defined as

\[
\text{SDE} = \max((\text{PAT} - t^a), 0) \quad \text{(2)}
\]

\[
\text{SDL} = \max((t^a - \text{PAT}), 0) \quad \text{(3)}
\]

where

- SDE is an early schedule delay;
- SDL is a late schedule delay;
- \( t^a \) is the actual arrival time.

A constant penalty is included for late arrival. Thus, the utility function can be written as

\[
U_t = \alpha * T_t + \beta * \text{SDE} + \gamma * \text{SDL} + \vartheta * L
\]

where $T_t$ is the travel time when the trip departs at $t$ and $L$ is a dummy variable, which is equal to 1 if $t_a > \text{PAT}$ and 0 otherwise. The probability $p_t$ that an individual departs at $t$ is then described in a logit form as

$$p_t = \frac{\exp(U_t)}{\sum_j \exp(U_{t_j})}$$

(5)

where $j$ is a discrete time interval. It is recognized that the discrete choice model theoretically conflicts with the concept of departure time as expressed on a continuous scale. However, by choosing the size of the time intervals sufficiently small, departure time is modelled on a nearly continuous scale. In addition, the discrete choice framework is consistent with the notion that individuals trade off alternative departure times in terms of their resulting travel and departure times. Also, the model structure allows us, in contrast to alternative approaches, to depict departure time choice as relative to the preferred arrival time as an anchor point. Therefore, we feel the use of a discrete choice model to describe departure time choice to be justified. Models of this type have been tested empirically in the context of commuting, using both RP and SP data. Typical values of $\beta$, $\gamma$ and $\vartheta$ found by Small (1982) using on RP data without travel time uncertainty are $\beta = 0.61 * \alpha$, $\gamma = 2.40 * \alpha$ and $\vartheta = 5.47 * \alpha$. Noland et al. (1998) and Small et al. (1999), using SP data with travel time uncertainty included as an explanatory variable, found more or less comparable values, suggesting reasonable stability in the valuation of schedule delays relative to travel time.

Based on these parameters, schedule delays and late arrival can be expressed in monetary terms as follows:

$$\text{VSDE} = \frac{\beta}{\alpha} \text{VOT}$$

(6)

$$\text{VSDL} = \frac{\gamma}{\alpha} \text{VOT}$$

(7)

$$\text{VL} = \frac{\vartheta}{\alpha} \text{VOT}$$

(8)

where

VSDE value of early schedule delay (in €/min);

VSDL value of late schedule delay (in €/min);

VL value of late arrival (in €).

This basic framework has been extended by Polak (1987) and Noland and Small (1995) to account for the effect of travel time uncertainty on departure time choice. In particular, they assumed that travel time $T$ consists of the free flow travel time $T^f$, the recurrent congestion $T^r$ and the non-recurrent congestion $T^\alpha$. Hence, $T^r$ is (at least to the traveller) a random component following some probability density function with $\min(T^r) = 0$. The expected utility approach now assumes that departure times are chosen based on the expected utility, given the distribution of $T^r$:

$$E[U_t] = \int_0^\infty \left[ \alpha * (T^f + T^r + T^\alpha) + \beta * \text{SDE}(\text{PAT}, t, T^f, T^r) + \gamma * \text{SDE}(\text{PAT}, t, T^f, T^r) + \vartheta \right. \left. \text{L}(\text{PAT}, t, T^f, T^r) \right] f(T^r) d(T^r)$$

(9)

where

$\text{SDE}(...)$ the early schedule delay given PAT and $t_a = t + T^f_t + T^r_t + T^\alpha_t$;

$\text{SDL}(...)$ the early schedule delay given PAT and $t_a = t + T^f_t + T^r_t + T^\alpha_t$;

$\text{L}(...)$ a dummy variable indicating late arrival given PAT and $t_a = t + T^f_t + T^r_t + T^\alpha_t$.

Thus the expected utility approach assumes that an individual traveller assesses all possible outcomes, and bases his/her decision on the consequences of this outcome (the utility) weighted by the likelihood of such an outcome.

Noland and Small (1995) elaborated several cases for the distribution of $f(T^r)$ under the assumption that $f(T^r)$ is identical for all $t$ and that the congestion level increases at a constant rate. Under these assumptions, it is possible to determine the optimal departure time (giving the highest expected utility) for an exponential dis-
tribution of \( f(T' t) \), with the associated probability of late arrival \( (P_L) \) and the associated utility. For various scenarios, they calculated the optimal safety margins and the costs of incident delay. Their approach is idealized in that they assumed that travellers are able to determine their optimal departure time given a probability density function \( f(T' t) \). In reality, departure time choice is likely a probabilistic event. Travellers will choose between various departure times with some probability \( p_t \). It is assumed that a logit model characterizes this probability (Eq. (5)), with unobserved taste variation (e.g., risk averse and risk prone travellers) captured in the error term.

Expected utility theory has recently been criticized for its lack of behavioural realism (e.g., Avineri and Prashker, 2003; Bonsall, 2003). It has been argued that expected utility theory does not give a valid representation of the way in which individuals deal with risky decisions under uncertainty. In particular, experimental research in this area (Tversky and Kahneman, 1992) has shown that large and small probabilities as well as gains and losses are valued differently, which is neglected by expected utility theory.

Prospect theory (Tversky and Kahneman, 1992) accounts for the aforementioned differences in valuation and has been suggested as an alternative to expected utility theory. However it is not readily evident how prospect theory can be generalised to departure time choice. One problem is that prospect theory typically describes choice alternatives in terms of a small number of outcomes with particular probabilities, and not in terms of continuous probability density functions, which typically apply to travel time distributions.

Moreover, expected utility theory can be modified to meet some of the criticisms. With respect to risk sensitivity, Polak (1987) indicated that modified utility functions can be used to represent concepts of risk aversion and risk seeking in expected utility theory. Senbil and Kitamura (2004) for example integrated the valuation of choice outcomes in terms of gains and losses into utility theory.

Given the above considerations and acknowledging that these issues deserve more attention, we decided to use expected utility theory as a starting point for a model describing the generalised costs and benefits of travel time uncertainty and information in the context of the present research project. While recognizing some of the criticisms discussed above, we note that the approach captures some mechanisms that are likely to take place in real life decision-making. It is logical that individuals, when choosing their departure time, trade off the probability of a delay (or early arrival) against the consequences of the delay (or early arrival). Although in practice people will use approximate rules and heuristics to trade off probabilities and consequences of arrival times, the expected utility approach provides a useful framework for looking at travel time uncertainty at a more analytical level, and investigating the effect of uncertainty in terms of travel time distributions.

3. Conceptual model

3.1. General approach

Building upon the earlier work mentioned before, we extend the approach by introducing additional variables that are relevant to the understanding of decision-making under travel time uncertainty and the response to information provision:

- **The true travel time.** This is the travel time as it can be measured on the road for a particular departure time \( t \) on a particular day. Measured over a large number of days, it is possible to define a true distribution of travel times, with a particular true mean and true variance.

- **The perceived travel time.** This is the perception a traveller may have of the true distribution of travel times. The perception may differ from reality with respect to both the perceived mean and the perceived variance of the distribution.

- **The predicted travel time.** This is the travel time predicted for a particular departure time \( t \) on a particular day. We define travel time information as predictive information, as it always leads to an expectation of the travel time one is likely to experience that day. We define a relationship between predicted travel time and true travel time. In particular, it is assumed that the prediction differs from true travel time by a term \( m \), described by a mean and variance.

- **The perceived travel time prediction.** This is the assessment by the traveller of the predicted travel time. For instance, a traveller may have, through experience, knowledge of the confidence level of the predicted travel
time. The prediction may contain a random error characterized by a variance or may be systematically biased to the upper or lower side by a term \( m \).

Based on the general theory, outlined in Section 2, we will first discuss the approach to calculate user benefits gained from a reduction in travel time variability. Then, we will discuss the methodology to calculate the benefits of travel time information as the difference in generalised costs between the outcomes of the decisions made under false/incomplete and correct/complete information. We distinguish between two cases: misperception of the true travel time distribution and lack of information about the traffic condition on a particular day.

In case of misperception of the true travel time distribution, travellers may have a false perception of the mean and/or the variance of the travel time distribution. For instance, an overestimation of the variance of the travel time distribution will result in maintaining a too large safety margin, and higher early schedule delays. Providing information about the general travel conditions may then lead to a proper assessment of the probabilities and consequences of travel times. In case of a lack of information about the traffic conditions on a particular day, the departure time decision has to be based upon knowledge of the average travel conditions, described by a travel time distribution. This implies the use of safety margins, and, consequently, considerable schedule delays. If information would be available about the traffic condition on a particular day, it would not be necessary to keep a safety margin, as one can base the departure time decision on the true travel time for that day. Thus, arriving early or arriving late and the associated scheduling costs can be avoided.

These two cases are elaborated in Sections 3.3 and 3.4. In Sections 3.2–3.4 we will use, without loss of generality, the term \( T \) to describe the total travel time consisting of \( T_f, T_x \) and \( T \). When we discuss the distribution of \( T \), this distribution equals the distribution of \( T_r \) plus a constant term \( (T_f + T_x) \).

3.2. Benefits of decreasing uncertainty

As described in Section 2, the expected utility of departing at \( t \) is given by

\[
EU^t_f = \int_{T_{\min}}^{T_{\max}} \left[ x \ast T_t + \beta \ast SDE(t, T, PAT) + \gamma \ast (t, T, PAT) + \vartheta \ast L(t, T, PAT) \right] f(T_t) d(T_t)
\]  

(10)

where \( f(T_t) \) is the current distribution of travel times when departing at \( t \). Other than in existing departure time models, we assume that the travel time distribution \( f(T_t) \) may be different for different departure times. It is noted that Eq. (10) implies that each amount of travel time is weighted equally, irrespective of the type of travel (free flow, recurrent congestion, non-recurrent congestion). However, the methodology can be extended in a straightforward way to distinguish between free flow and congested travel time, each with different valuation. Also, the above formulation assumes homogeneity in travel time and delay valuations, thereby neglecting taste variation (e.g., depending on the confidence that travellers have in the transportation system performance). Without materially changing the approach, this can be accounted for by including socio-demographic (or other segmentation) parameters into the model. The probability that a traveller chooses \( t \) over another departure time \( v \) is then

\[
p^t_v = \frac{\exp(EU_t)}{\sum_r \exp(EU_r)}
\]  

(11)

To calculate the total generalised costs \( C \) for a population (or segment) we define

\[
C_f = \sum_t p_t \ast \int_{T_{\min}}^{T_{\max}} \left[ VOT \ast T_t + \frac{\beta}{\lambda} \ast VOT \ast SDE(t, T, PAT) + \frac{\gamma}{\lambda} \ast VOT \ast SDL(t, T, PAT) \right. \\
\left. + \frac{\vartheta}{\lambda} \ast VOT \ast L(t, T, PAT) \right] f(T_t) d(T_t)
\]  

(12)

This equation states that the costs experienced by an average user depend on the probability of choosing a departure time interval \( t \), and the distribution of travel times for this interval \( t \). Now, we assume that travel
time variability decreases, leading to a changed distribution of travel times: \( g(T_t) \). The expected utility, choice probabilities and generalised costs are then

\[
EU_t^g = \int_{T_{\min}}^{T_{\max}} [\alpha * T_t + \beta * SDE(t, T_t, PAT) + \gamma * SDL(t, T_t, PAT) + \vartheta * L(t, T_t, PAT)] g(T_t) d(T_t)
\]

\[
P_t^g = \frac{\exp(EU_t^g)}{\sum_t \exp(EU_t^g)}
\]

\[
C^g = \sum_t p_t^g \int_{T_{\min}}^{T_{\max}} \left[ \text{VOT} * T_t + \frac{\beta}{\alpha} * \text{VOT} * \text{SDE}(t, T_t, \text{PAT}) + \frac{\gamma}{\alpha} * \text{VOT} * \text{SDL}(t, T_t, \text{PAT}) \\
+ \frac{\vartheta}{\alpha} * \text{VOT} * L(t, T_t, \text{PAT}) \right] g(T_t) d(T_t)
\]

The difference in generalised costs is then expressed as

\[
A = \sum_t \int_{T_{\min}}^{T_{\max}} \left[ \text{VOT} * T_t + \frac{\beta}{\alpha} * \text{VOT} * \text{SDE}(t, T_t, \text{PAT}) + \frac{\gamma}{\alpha} * \text{VOT} * \text{SDL}(t, T_t, \text{PAT}) \\
+ \frac{\vartheta}{\alpha} * \text{VOT} * L(t, T_t, \text{PAT}) \right] * \left[ f(T_t) * p_t^f - g(T_t) * p_t^g \right] d(T_t)
\]

Hence, the difference in generalised costs arises both from a difference in the travel time distribution and from a difference in the chosen departure times. Note that this approach is based on the ‘true’ travel time distributions, and does not account for perception errors.

### 3.3. The cost of misperception of average travel conditions

As noted by Bates et al. (2001), the traveller may encounter higher generalised costs if he bases his departure time decision on a misperception of the travel time distribution. Let \( f^*(T_t) \) be the true distribution of travel times for departure at time \( t \), defined by mean \( \mu_t^* \) and standard deviation \( \sigma_t^* \). Let \( \tilde{f}(T_t) \) be the perceived travel time distribution, defined by mean \( \tilde{\mu}_t \) and standard deviation \( \tilde{\sigma}_t \). Thus \( \tilde{f}(T_t) \) may differ from \( f^*(T_t) \). If an individual has the correct perception of the travel time distribution, his generalised costs are calculated as follows. First, the expected utility of departure at \( t \) is calculated as

\[
EU_t^* = \int_{T_{\min}}^{T_{\max}} [\alpha * T_t + \beta * SDE(t, T_t, \text{PAT}) + \gamma * (t, T_t, \text{PAT}) + \vartheta * L(t, T_t, \text{PAT})] f^*(T_t) d(T_t)
\]

According to this equation, individuals integrate the possible outcomes of a departure time (travel time and schedule delays), weighted by the probability of such an outcome. The expected utility is defined for each alternative departure time \( t \), based on different travel time distributions. The probability of departing at \( t \) is then

\[
P_t^* = \frac{\exp(EU_t^*)}{\sum_t \exp(EU_t^*)}
\]

To calculate the total generalised costs \( C^* \) for a population (or segment) we define:

\[
C^* = \sum_t p_t^* \int_{T_{\min}}^{T_{\max}} \left[ \text{VOT} * T_t + \frac{\beta}{\alpha} * \text{VOT} * \text{SDE}(t, T_t, \text{PAT}) + \frac{\gamma}{\alpha} * \text{VOT} * \text{SDL}(t, T_t, \text{PAT}) \\
+ \frac{\vartheta}{\alpha} * \text{VOT} * L(t, T_t, \text{PAT}) \right] f^*(T_t) d(T_t)
\]

The costs of travel under misperceived travel time are calculated similarly, but a distinction is made between the perceived probability density function \( \tilde{f}(T_t) \), which determines the expected utilities \( \tilde{EU}_t \), and the true
probability density function \( f'(T) \), which determines the actual costs encountered by a traveller. The expected utility is then defined as

\[
E \bar{U}_t = \int_{T_{\min}}^{T_{\max}} \left[ a * T_t + b * SDE(t, T_t, PAT) + c * SDL(t, T_t, PAT) + d * L(t, T_t, PAT) \right] f'(T_t) d(T_t)
\]

The probability of departing at time \( t \) is

\[
\tilde{p}_t = \frac{\exp(E \bar{U}_t)}{\sum_t \exp(E \bar{U}_t)}
\]

Finally, the generalised costs \( \tilde{C} \) actually experienced are

\[
\tilde{C} = \sum_t \tilde{p}_t \int_{T_{\min}}^{T_{\max}} \left[ VOT * T_t + \frac{\beta}{\alpha} * VOT * SDE(t, T_t, PAT) + \frac{\gamma}{\alpha} * VOT * SDL(t, T_t, PAT) \right] f'(T_t) d(T_t)
\]

It is easily seen that differences in the costs arise only from differences in the probability density function \( f(T_t) \), leading to a difference between the choice probabilities \( p^* \) and \( \tilde{p} \). The potential benefit \( B \) to be obtained through providing travellers with the correct information is then

\[
B = \tilde{C} - C^* = \sum_t \int_{T_{\min}}^{T_{\max}} \left[ VOT * T_t + \frac{\beta}{\alpha} * VOT * SDE(t, T_t, PAT) + \frac{\gamma}{\alpha} * VOT * SDL(t, T_t, PAT) \right] \left[ \tilde{p}_t - p^*_t \right] f'(T_t) d(T_t)
\]

Thus, the benefit of providing information depends upon the difference between the true and the perceived distribution of travel times, and the effect that the misperception has on the choice of departure time. A possible way of improving the perception of the travel time distribution is by providing travellers with historical data regarding system performance.

### 3.4. Benefits of traffic information

This section focuses on the difference between decisions made with knowledge of the average conditions and knowledge about the travel conditions at a specific day \( d \). In the previous section we showed that the generalised costs of travel under knowledge of the average travel conditions equals:

\[
C^* = \sum_t p^*_t \int_{T_{\min}}^{T_{\max}} \left[ VOT * T_t + \frac{\beta}{\alpha} * VOT * SDE(t, T_t, PAT) + \frac{\gamma}{\alpha} * VOT * SDL(t, T_t, PAT) \right] f'(T_t) d(T_t)
\]

Now suppose that, on a given day \( d \), the true travel time, when departing at time \( t \), is \( T^*_{td} \). Thus, this is a travel time that could be measured on the road, but that is not known exactly before the trip starts. We also define a predicted travel time \( T^p_{td} \), giving the prediction of the travel time when departing at time \( t \) on a given day \( d \). Logically, it is not possible to give an exact prediction of travel time \( T^*_{td} \). \( T^p_{td} \) is at best an estimate of \( T^*_{td} \), with a certain confidence interval. In equation:

\[
T^p_{td} = T^*_{td} + \tilde{e}_{td}^p
\]

with \( \tilde{e}_{td}^p \sim \mathcal{N}(\mu_{td}^p, \sigma_{td}^p) \). \( \sigma_{td}^p \) is the standard deviation of the prediction and defines the confidence interval. For \( \sigma_{td}^p \neq 0 \), there is an under- or overprediction of travel time. In addition, we define a variable \( \bar{T}^p_{td} \), indicating the traveller’s perception of the predicted travel time. The relationship between \( T^p_{td} \) and \( \bar{T}^p_{td} \) is given by

\[
\bar{T}^p_{td} = T^p_{td} + \tilde{e}_{td}^p
\]
with $\tilde{\varepsilon}_{td} \approx N(\tilde{\mu}_{td}, \tilde{\sigma}_{td})$. Thus, the traveller may perceive both inaccuracy in the prediction by the standard deviation $\tilde{\sigma}_{td}$ as well as structural over- or underprediction through $\tilde{\mu}_{td}$. It should be noted that the variables $T_{td}^p$ and $\tilde{T}_{td}^p$ are of a fundamentally different nature. The error term $\tilde{\varepsilon}_{td}$ represents the technical and methodological limitations in the ex ante prediction of travel times, whereas $\tilde{\varepsilon}_{td}$ represents the traveller’s estimate of these limitations. In fact, if the traveller knows that travel time predictions are uncertain, he will not reckon with only one prediction, but construct an expected utility based on his estimate of the confidence interval of the travel time prediction. Thus, given a predicted travel time $T_{td}^p$, travellers’ perception can be regarded as a distributed variable $f(\tilde{T}_{td}^p)$, defined by $\tilde{\mu}_{td}$ and $\tilde{\sigma}_{td}$.

To determine the travel costs of a traveller receiving travel time information we define:

$$E\bar{U}_{td} = \int_{-\infty}^{\infty} \left[ x^* \tilde{T}_{td}^p + \beta^* \text{SDE}(t, \tilde{T}_{td}^p, \text{PAT}) + \gamma^* \text{SDL}(t, \tilde{T}_{td}^p, \text{PAT}) + \delta^* L(t, \tilde{T}_{td}^p, \text{PAT}) \right] f(\tilde{T}_{td}^p) d(\tilde{T}_{td}^p)$$

and

$$\bar{p}_{td} = \exp(E\bar{U}_{td}) \sum_t \exp(E\bar{U}_{td})$$

Given that the perceived travel time prediction is a distributed variable, the choice probability $\bar{p}_{td}$ can be regarded as a distributed variable $f(\tilde{p}_{td})$, given a true travel times $T_{td}$.

The average generalised cost encountered by a traveller now depends on both the choice probability $\bar{p}_{td}$, derived from the perception of the predicted travel time, and the true travel time $T_{td}^*$. To calculate this, we integrate for each departure time over the distribution of true travel times as well as over the distribution of choice probabilities, given travel times. For each travel time $T_{td}^*$, the choice probability $\bar{p}_{td}$ depends on the distribution of the predicted travel time and travellers’ perception of the prediction. In equation:

$$C^p = \int_{T_{td}^*=T_{td}^*}^{T_{max}} \int_{p_{td}=0}^{1} \sum_t \bar{p}_{td} * \left[ \text{VOT} * T_{td}^* \frac{\beta}{\lambda} * \text{VOT} * \text{SDE}(t, T_{td}^*, \text{PAT}) + \frac{\gamma}{\lambda} * \text{VOT} * \text{SDL}(t, T_{td}^*, \text{PAT}) + \frac{\delta}{\lambda} * L(t, T_{td}^*, \text{PAT}) \right] * f^*(T_{td}^*) * d(T_{td}^*) * f(\tilde{p}_{td}) * d(\tilde{p}_{td})$$

Thus, other than in the case without travel time information, the costs arise from the confrontation between the true realised travel time on a particular day and the chosen departure time, which depends on the perception of the travel time prediction. Given the dynamic nature of travel time prediction (as a function of the day-to-day variation in travel time), the choice probabilities are here defined as day specific.

Given the definitions of the generalised cost, the benefits of travel time information can now be defined as

$$B^t = C^* - C^p$$

From the above formulation, it follows logically that the benefits from traffic information arise from the fact that the probabilities $\bar{p}_{td}$ match the actual travel times $T_{td}^*$ better than the probability $p_{td}^*$, which is based on the average traffic conditions.

4. Numerical examples

To assess the effect of travel time information on generalised travel costs, a series of numerical examples are presented in this section. These examples concern (i) the effect of changes in the uncertainty levels of travel time; (ii) the effect of misperception of the average travel conditions; and (iii) the effect of day-specific traffic information.

4.1. Case

The examples presented concern the A2 motorway between Beesd and Utrecht in the Netherlands. This trajectory has a length of 28 km. Speeds and traffic volumes are constantly measured at a series of points along the trajectory. Using the trajectory-methodology, travel speeds on the trajectory can be calculated for each
departure time. The departure time is defined as the point in time when one enters the trajectory. Using data for a considerably long period, a distribution of travel speeds has been calculated for each “departure time”. These data provides a unique base for the assessment of the potential effect of travel time uncertainty. The travel speed distribution is displayed in Fig. 1. We used the calculated travel speed distributions as a base for travel time distributions to be used in the numerical examples. First, the free flow travel time was determined from the travel speed during congestion free periods. Then, for each 5-min interval, we determined the average delay, due to congestion. In line with the literature (e.g., Noland and Small, 1995), we have assumed that delay due to congestion follows an exponential distribution, with probability density function:

$$f(T_i) = \frac{1}{b} e^{-\frac{T_i}{b}}$$

(31)

where $b$ equals both the mean and standard deviation. Then, we tested whether the 15th and 85th percentile of the exponential distribution reflected the same percentiles of the speed distribution well. This appeared to be the case, supporting the use of the exponential distribution as an approximation in this case.

To determine generalised costs, the following assumptions were made. The parameters $a$, $b$, $c$ and $d$ were derived from Small (1982), using the values $a = -0.106$, $b = -0.065$, $c = 0.254$ and $d = 0.58$. Other studies (Noland et al., 1998; Small et al., 1999) have found similar parameter values, suggesting these parameters will produce representative results. It is noted that Small’s estimates concern commuter travel. For the VOT, we used the value calculated in the 1997 Dutch VOT Survey, corrected for inflation. This results in a VOT of €6.00/h. Finally, to apply Small’s base model, schedule delays were calculated assuming a preferred arrival time of 8.30 AM.

The case study is subject to the following restrictions. First, we assume that the distribution of travel times as described above is constant. In case of information provision on a large scale, departure time decisions of many travellers would change affecting the overall pattern of travel time distributions. Hence, if we discuss the effect of travel time information, we assume that information is given to a small group of travellers, so that the distribution across departure times is not fundamentally changed. Second, the model describes only the effect of pre-trip information. Thus, information about accidents happening after departing are not accounted for in the simulation. The calculated user benefits are based on the assumption that no serious accidents take place after departure. Third, the case concerns the A2 motorway between Beesd and Utrecht, but not the parts of the trip before and after this trajectory. Thus, the user benefits can only be brought about if travel time var-

![Fig. 1. Distribution of travel times on A2 motorway Beesd–Utrecht.](image-url)
iability of the other trip parts is small. Finally, it is assumed that $T_{d/t} = T_{d/t}$ is constant for all $t$ on a given day $d$. That is to say, delay on a given day is the same fraction of the average delay for all departure times.

4.2. Costs and benefits of changes in travel time uncertainty

Based on the previously described travel time distribution of the A2 motorway, we used Eq. (15) to calculate the average generalised costs of one person travelling on the trajectory. Departure time choice is modelled as a function of the expected utility as specified in Eq. (14). Hence, the departure time choice is based on the distribution of possible travel times for each departure time, assuming that travellers base their decision on the expected average situation.

Generalised costs were calculated for a number of alternative scenarios, in which the average travel time was kept constant, but the fraction consisting of incident delay was varied. Thus, if $T^f$, $T^r$ and $T^r$ are the free travel time, recurrent congestion and incidental congestion in the base scenario (as observed from the A2 data), and $T_0^f$, $T_0^r$ and $T_0^r$ are travel time components in an alternative scenario, the following relationship holds:

$$T^f + T^r + T^r = T_0^f + T_0^r + T_0^r$$

(32)

Without loss of generality we will in the remainder denote $T^f + T^r$ as $T^r$, being the non-variable part of the travel time. $T^r$ is assumed to follow an exponential distribution with mean $\bar{T}^r$. The results of the calculations are displayed in Table 2.

The results suggest that for the current situation on the A2 ($\bar{T}^r = 1.10$) the travel time accounts for about 60% of the total generalised cost. An important additional cost factor is the early schedule delay (SDE) which can be seen as the waiting time due to the safety margin kept by travellers and unexpected early arrivals. Late arrivals (SDL and late penalty) bring about lower costs, as they are largely avoided.

If the variable travel time part $T^r$ decreases, the costs also decrease. This gain is brought about by a decrease in the schedule delay costs. The reverse happens with increasing the variable part of travel time: travel time cost decreases (because travellers choose less congested departure times), but schedule delay cost increases sharply.

4.3. Information on average travel conditions

Based on the travel time information described before and using Eqs. (17)–(19), we calculated the total generalised costs of a trip made in the morning peak (6.00–10.00). Following Section 2, it is assumed that departure time choice is made according to the average traffic conditions as defined by mean and standard deviation. Choice probabilities were calculated based on the true distribution of travel times $f(T^r)$, but also based on misperceived distributions $f(T^r)$ resulting in $p_i \neq p_i^*$.

The total generalised costs were calculated using Eqs. (20)–(22) for different scenarios, where the perceived distribution of delay differed from the true distribution. In particular, the mean of the perceived travel time delay distribution may be smaller or larger than reality. Because we assume an exponential distribution of the delay term $T^r$, the standard deviation is over- or underestimated accordingly. It was assumed that an over- or underestimation of the travel time is made consistently for all departure times. That is to say, the mean of

<table>
<thead>
<tr>
<th>Average travel time variability (in % of $\bar{T}^r$)</th>
<th>Total cost</th>
<th>Travel time</th>
<th>SDE</th>
<th>SDL</th>
<th>Late penalty</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{T}^r = 0.25 \times \bar{T}^r$</td>
<td>4.37</td>
<td>3.15</td>
<td>0.95</td>
<td>0.19</td>
<td>0.08</td>
</tr>
<tr>
<td>$\bar{T}^r = 0.5 \times \bar{T}^r$</td>
<td>4.63</td>
<td>3.14</td>
<td>1.09</td>
<td>0.31</td>
<td>0.09</td>
</tr>
<tr>
<td>$\bar{T}^r = 1 \times \bar{T}^r$</td>
<td>5.24</td>
<td>3.12</td>
<td>1.43</td>
<td>0.60</td>
<td>0.09</td>
</tr>
<tr>
<td>$\bar{T}^r = 2 \times \bar{T}^r$</td>
<td>6.52</td>
<td>3.06</td>
<td>2.19</td>
<td>1.17</td>
<td>0.09</td>
</tr>
<tr>
<td>$\bar{T}^r = 4 \times \bar{T}^r$</td>
<td>8.78</td>
<td>2.82</td>
<td>4.17</td>
<td>1.72</td>
<td>0.07</td>
</tr>
</tbody>
</table>
the distribution is over- or underestimated by the same percentage for all departure times. The results are displayed in Table 3.

The table indicates that both under- and overestimation of the congestion level leads to increased generalised costs. However, overestimation seems to be more costly than underestimation. In fact, an underestimation of the average congestion level by 10% appears to be slightly beneficial in the setting of this case. The costs of underestimation are caused by increased late schedule delay and lateness penalty, whereas the costs of overestimation are caused by increased early schedule delay.

4.4. The effect of day-specific travel time information

The methodology described in Section 3.3 was used to calculate generalised costs in a series of scenarios. As Eq. (29) is far too complex to compute analytically, we used the following simulation approach.

1. Draw the true travel time $T_{id} = T_i + T_{id}$ from the exponential distribution of $T_i$. The travel times of different departure times correlate perfectly. That is to say: $T_{id} = C T_i$, with the same $C$ for all departure times.

2. Given the true travel time $T_{id}$, departure times are simulated for three cases:
   a. **Perfect information.** In this case we assume that $T_{id} = T_{id}$. Thus, a perfect prediction is made, which is known to the traveller. In this case, choice probabilities are calculated using Small’s base model with $T_{id}$ as the travel time. According to these probabilities, the departure time is drawn. Travel time uncertainty is ruled out by the perfect information. It is evident that this is a strongly idealised situation, which serves as a point of reference in this study.
   b. **Imperfect information.** The travel time prediction contains an error margin, and travellers have their own perception of this unreliability. This is simulated as follows.
      i. A value of the predicted travel time is drawn, from a random distribution with mean $T_{id}$ and standard deviation $e_{id}$. Again, we assumed that the over- or underprediction of the delay time is constant for each departure time. That is, $T_{id} = C T_i$ for each departure time.
      ii. Expected utilities are calculated according to Eq. (27) based on the perceived error term $e_{id}$. To this end, a numerical integration procedure was used.
      iii. Based on the expected utilities, choice probabilities are calculated and the departure time is drawn.
   c. **No information.** In this case the choice probabilities as described in Section 3.2, using Eqs. (13) and (14). Thus, utility of a departure time depends on the expected utility over all possible travel time weighted by their probability. According to the choice probabilities, a departure time is drawn.

3. Given the departure times and the true travel times $T_{id}$, the various cost components and the overall generalised costs are determined for each information case.

This procedure is repeated 1000 times. The average costs for different information schemes are calculated as the average over all simulations.

The simulation procedure was carried out for a series of scenarios, varying the error in the travel time prediction ($e_{id}$) and travellers’ perception of the prediction error ($e_{id}^p$). The results are displayed in Table 4.

The results suggest that the provision of perfect travel time information can reduce the generalised costs of a trip by about 1€. This cost reduction is not caused by travel time savings, which are negligible, but by
Table 4
Generalised travel costs (in € per trip) under different information regimes

<table>
<thead>
<tr>
<th></th>
<th>Cost travel</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total cost</td>
<td>Time</td>
<td>Cost SDE</td>
<td>Cost SDL</td>
<td>Cost late</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.10</td>
<td>2.90</td>
<td>0.59</td>
<td>0.39</td>
<td>0.23</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.1 \times T_{id}$, $\sigma_{id} = 0.1 \times T_{id}$</td>
<td>4.05</td>
<td>2.88</td>
<td>0.94</td>
<td>0.17</td>
<td>0.07</td>
</tr>
<tr>
<td>No information</td>
<td>5.08</td>
<td>2.92</td>
<td>1.55</td>
<td>0.53</td>
<td>0.08</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.28</td>
<td>3.08</td>
<td>0.62</td>
<td>0.37</td>
<td>0.22</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.25 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>4.24</td>
<td>3.02</td>
<td>1.02</td>
<td>0.14</td>
<td>0.06</td>
</tr>
<tr>
<td>No information</td>
<td>5.32</td>
<td>3.12</td>
<td>1.40</td>
<td>0.71</td>
<td>0.10</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.15</td>
<td>2.94</td>
<td>0.66</td>
<td>0.35</td>
<td>0.21</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.5 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>4.20</td>
<td>2.92</td>
<td>0.87</td>
<td>0.21</td>
<td>0.09</td>
</tr>
<tr>
<td>No information</td>
<td>4.99</td>
<td>2.95</td>
<td>1.48</td>
<td>0.48</td>
<td>0.08</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.30</td>
<td>3.10</td>
<td>0.64</td>
<td>0.35</td>
<td>0.21</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.25 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>4.37</td>
<td>3.05</td>
<td>1.03</td>
<td>0.21</td>
<td>0.08</td>
</tr>
<tr>
<td>No information</td>
<td>5.25</td>
<td>3.14</td>
<td>1.38</td>
<td>0.63</td>
<td>0.10</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.32</td>
<td>3.15</td>
<td>0.64</td>
<td>0.32</td>
<td>0.20</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.5 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>4.64</td>
<td>3.02</td>
<td>1.08</td>
<td>0.37</td>
<td>0.09</td>
</tr>
<tr>
<td>No information</td>
<td>5.34</td>
<td>0.63</td>
<td>1.47</td>
<td>0.63</td>
<td>0.09</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.11</td>
<td>2.99</td>
<td>0.59</td>
<td>0.31</td>
<td>0.21</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.25 \times T_{id}$, $\sigma_{id} = 0.5 \times T_{id}$</td>
<td>4.34</td>
<td>2.92</td>
<td>1.21</td>
<td>0.13</td>
<td>0.07</td>
</tr>
<tr>
<td>No information</td>
<td>5.21</td>
<td>3.02</td>
<td>1.50</td>
<td>0.59</td>
<td>0.09</td>
</tr>
<tr>
<td>Perfect information</td>
<td>4.34</td>
<td>3.13</td>
<td>0.59</td>
<td>0.39</td>
<td>0.23</td>
</tr>
<tr>
<td>$\sigma_{id} = 0.5 \times T_{id}$, $\sigma_{id} = 0.5 \times T_{id}$</td>
<td>4.69</td>
<td>3.02</td>
<td>1.27</td>
<td>0.30</td>
<td>0.09</td>
</tr>
<tr>
<td>No information</td>
<td>5.29</td>
<td>3.15</td>
<td>1.39</td>
<td>0.66</td>
<td>0.10</td>
</tr>
</tbody>
</table>

reduced scheduling costs. The largest gain is brought about by a reduction in early schedule delay, implying that travellers profit from not having to keep a large safety margin. Smaller profits are derived from the decreased probability of late arrival (late schedule delay and late penalty). An important conclusion is that the potential benefits of travel time information are not insignificant: in the ideal situation, a reduction of some 20% can be achieved. This is related to the fact that 20–40% of the generalised costs are scheduling costs.

However, the quality of the information determines the benefits of travel time information. If the prediction error is ±20%, the profit diminishes by 0.05€ as compared to the case where perfect information is supplied. For prediction errors of ±50% and ±100%, the profit decreases with 0.07€ and 0.35€ respectively. Thus, the effect of the quality of the travel time prediction is rather small, as long as a reasonable quality (±50%) is maintained. Improving the quality of the prediction beyond the minimum level yields only marginal profits.

To illustrate the effect of over- or underestimation of the quality of information, the loss of profit through imperfect information as compared to the perfect information case is displayed for a number of scenarios (Table 5).

Table 5
Effect of under and overestimation of quality of information

<table>
<thead>
<tr>
<th></th>
<th>Loss relative to perfect information</th>
<th>Effect of underestimation of quality of information</th>
<th>Effect of overestimation of quality of information</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{id} = 0.1 \times T_{id}$, $\sigma_{id} = 0.1 \times T_{id}$</td>
<td>0.05€</td>
<td>+0.01€</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{id} = 0.1 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>0.04€</td>
<td>-0.16€</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{id} = 0.25 \times T_{id}$, $\sigma_{id} = 0.25 \times T_{id}$</td>
<td>0.07€</td>
<td>+0.02€</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{id} = 0.25 \times T_{id}$, $\sigma_{id} = 0.50 \times T_{id}$</td>
<td>0.23€</td>
<td>+0.03€</td>
<td></td>
</tr>
</tbody>
</table>
The effects of over- or underestimation of the quality of the prediction appear to be limited. The only situation in which a misperception of the quality leads to increased generalised costs is when the perceived quality is considerably lower than the actual quality of the prediction. In particular, in this case one will keep a safety margin that is unnecessary large.

Overall, one can conclude that day-specific travel time information leads to a considerable reduction in the generalised trip costs, due to a reduction in the scheduling costs. In the present case, the reduction through travel time information could amount to up to 1€ as compared to the situation without travel time information. However, it should be noted that part of the variation in travel times will be due to factors that are known to experienced travellers without receiving travel time information, such as weather conditions, day of the week, etc. Consequently, the benefits resulting from travel time information will be less than the 1€ found here. The exact magnitude of the benefit depends on the knowledge and deductive capacity of travellers, which should be subject to further research. In addition, one can conclude that the presence of travel time information is more important than the quality of the travel time information as long as some minimum quality is maintained. Even rather approximate information allows travellers to reduce their scheduling costs considerably. Improving the quality of the information beyond the minimum level yields only marginal additional benefits. Finally, misperception of the quality of the information leads to a decrease in the benefits of travel time information, only if the quality is seriously underestimated.

5. Conclusions

In this paper we have developed a model that is able to assess the benefits of travel time information, resulting from changes in departure time. The model is based on expected utility theory, but is extended to account for perception errors with respect to the mean and variance of the travel time distribution and the confidence level of the travel time information. The generalised travel costs, composed of travel time, schedule delays and late arrival, can be calculated and expressed in monetary terms. The model can be applied in a straightforward way to assess the effects of changes in travel time uncertainty, misperception of the structural variability and day-specific travel time information.

An application of the model to the A2 motorway between Beesd and Utrecht in The Netherlands leads the following tentative conclusions regarding the effects of travel time uncertainty and travel time information. First, it is concluded that the costs associated with travel time uncertainty and which materialise in the form of scheduling costs, are not insignificant. For the case study, it was found that scheduling costs account for 30–40% of the generalised costs. This implies that the benefits of infrastructural improvements should not only be measured in terms of travel time savings, but also in terms of reduced scheduling costs. In highly congested settings, this may lead to a better assessment of economic benefits.

A second conclusion from the case study is that a misperception of the structural variation in travel times has a moderate effect. In this respect, especially overestimation of the variability results in higher generalised costs, because it leads to unnecessary large safety margins and high early schedule delay. It should be noted though that to date there is little knowledge as to the perception of travellers of travel time variability. Therefore, it is difficult to assess the benefits arising from informing travellers about the variability of travel time.

Third, it is found that supplying travellers with day specific travel time information leads to a significant reduction in scheduling costs, amounting up to about 1€ per trip. The quality of the information (in particular the confidence level of the prediction) and the (mis)perception of the quality have only a minor effect of the benefits of the information, provided that a minimum quality level is maintained. The largest uncertainty regarding the benefits of information concerns the existing knowledge of travellers about regularities in the travel conditions, related to such factors as weather conditions and day of the week. The better travellers’ insight in these relationships, the smaller the benefit of travel time information. The potential benefit of 1€ found in this study would therefore apply to travellers without any prior knowledge of the network. Experienced travellers would receive lower benefits, but it is impossible at this stage to assess how much lower.

In this study the model is applied to a single segment that is assumed to be uniform in terms of OD-relation, preferred arrival time, VOT and time and schedule delay parameters (associated with trip purpose). In a policy context, it will probably be useful to apply the model for multiple segments that differ on the above aspects.
To conclude, we feel that further research in this area should address the following topics. First, it is noted that the benefits of travel time information depend on the current knowledge level of travellers and their ability to predict travel times based on external factors. Further research should lead to a better insight in the mechanisms guiding the acquisition of such knowledge and the resulting knowledge level. Reinforcement learning theory, applied to transportation contexts by Arentze and Timmermans (2003) and Ettema et al. (2004), may be a potentially valuable approach in this respect. A second direction would be to alleviate the rational framework applied in this study and include travellers’ attitude towards risk into the model. This can be achieved by modifying the utility functions, as indicated by Polak (1987). Another interesting option would be to consider the fact that individuals’ valuation of travel time and schedule delay is related to their perception of travel time uncertainty and their confidence in travel time information. However, this would require a serious calibration of the model to derive the shape of the utility functions of travellers with different attitudes towards risk and uncertainty. Finally, this study has assumed that travellers respond to travel time information only by changing departure time, whereas in reality also changes in route, mode and/or destination may occur. It would be worthwhile to extend the model to account for such additional responses. Of these other responses, route choice appears to be the most frequent and should be the first candidate to be included.

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