A Practical Method to Estimate the Benefits of Improved Road Network Reliability: An Application to Departing Air Passengers☆

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Abstract

This paper develops a practical approach to estimate the benefits of improved reliability of road networks. We present a general methodology to estimate the (changes in) scheduling costs due to (changes in) travel time variability for car travel. We focus on situations where only mean delays are known, which are the typical output of a standard transport model. We show how to generate travel time distributions from these mean delays, which we use to estimate the scheduling costs of the travellers, taking into account their optimal departure time choice. We illustrate the methodology for car access by air passengers to Amsterdam airport and show how improvements of the highway network lead to shorter expected travel times, lower travel time variability, later departure times and reduced access costs. We found that on average the resulting absolute decrease in access costs per trip is small, mainly because most air passengers drive to the airport outside the peak hours. However, the relative reduction in access costs due to improvements in network reliability is substantial. For every 1-Euro reduction in mean travel time costs, there is an additional cost reduction of about 0.75-0.85 Euro due to lower travel time variability and hence lower scheduling costs. This implies that passenger benefits from network improvements are underestimated by ca. 45 percent if reliability benefits are ignored.

Keywords: Value of reliability, Airport access, Dynamic accessibility, Travel time variability

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1. Introduction

The main contribution of this paper is the derivation of a practical method to estimate the reliability benefits of improvements in road networks, using standard output of existing transport models. This is a challenging task, since such transport models typically provide only estimates of mean travel times, not distributions of travel times. Mean travel times can be obtained in the fourth step of the typical transport model, traffic assignment, where the route choice process is simulated (Ortúzar and Willumsen, 2011). Here demand (the OD matrix) is confronted with supply (the road network), resulting in simulated traffic flows. In situations where traffic congestion arises equilibrium assignment techniques are typically used to approximate Wardrop's first principle of route choice (Wardrop, 1952). These techniques rely on speed-flow relationships to describe how travel times on a link increase when the traffic volumes gets closer to capacity. A widely-used form of the speed-flow curve is the so-called BPR function (FHWA). By subtracting free-flow travel times from congested travel times mean delays can be calculated, for individual links but also for OD-paths.

To generate travel time distributions from mean travel times we use the results of Peer et al. (2012) who observed that there is a strong proportional relation between the mean delay and the standard deviation of travel times. This result is confirmed by others, including recent research by Kouwenhoven and Bel (2014). Another assumption we make is the distribution of travel times: we assume a log-normal distribution. Right-skewed distributions are frequently observed in empirical analysis of travel time data (see for example, Emam and Ai-Deek (2006) and Rakha et al. (2010)). Therefore our log-normal distribution might be a reasonable approximation of the true travel time distributions.

The next step in the process is the estimation of the costs of travel variability. During the last two decades transport economics research has paid considerable attention to the choice of departure time when travel times are variable (see Carrion and Levinson (2012) for a recent overview). This explicit consideration of travellers' trip timing is of key importance here, since travellers tend to anticipate travel time variability by leaving earlier from home. Noland and Small (1995) were the first to develop this idea by employing an expected utility model of departure time choice based on the scheduling model of Vickrey (1969) and Small (1982). Noland and Small (1995) assumed that delays follow a uniform or exponential distribution. Their model was later extended by Fosgerau and Karlström (2010) for general travel time distributions. Koster et al. (2011) adapted the linear scheduling model to travellers going to the airport, adding a penalty for missing a flight.

We use a reduced-form function of expected access cost, assuming a log-normal distribution of travel times. This function takes the behavioural responses of car drivers to travel time variability into account. Travellers schedule their trips in such a way that they trade off the costs (or dis-utility) associated with arriving early at their destination against the costs of arriving late. The latter includes the costs of arriving later than preferred, and also the costs of not being able to carry out the desired activity at all.

Although our methodology is general, we illustrate it by applying it to Dutch car travellers going to Amsterdam Schiphol Airport (AMS) to travel by plane from there. In 2013, about 40% of the travellers to AMS travelled by car to the airport (taxi travel excluded). This is a situation where potentially large costs of unreliability are be incurred, particularly when a flight is missed. Because travellers do not want to be late at the airport, they use a safety margin (buffer) to cope with travel time variability. The buffer tends to increase when travel times become more variable. This intuitive behavioural response was already suggested more than 40 years ago by Thomson (1968), Gaver (1968) and Knight (1974). Hall (1983) was probably the first author to apply this principle to the choice of departure time for travellers going to the airport.

In our Amsterdam Airport case study we compare the airport access costs of car travellers arising from mean delays and travel time unreliability for two different network specifications: (1) the Dutch road network as it existed in 2010, and (2) an improved version of that network as it is planned for 2020. The 2020 road network will benefit from considerable investments in additional road capacity leading to lower mean delays and better reliability. By analysing the differences in access costs between the two networks we learn how the reliability benefits of the road improvement program add to the more traditional benefits in mean travel time.

The paper proceeds as follows. The next section discusses the departure time choice model, that is used to estimate the access costs. Section 3 discusses how log-normal travel time distributions can be derived from transport models that only provide estimates of the mean delay. Section 4 introduces the Dutch national transport model and discusses the numerical results that were obtained. Section 5 concludes.

2. Behavioural scheduling responses to travel time variability

We first introduce the airport access cost function as introduced by Koster et al. (2011). In their model, travellers face costs of arriving earlier or later then their (exogenously given) preferred arrival time at the airport. For a given delay D, schedule delay early is then defined as $SDE = \max(0, H - D)$, whereas schedule delay late is defined as $SDL = \max(0, D - H)$. This specification of schedule delays is similar to the standard Vickrey (1969) scheduling model. Noland and Small (1995) extend the standard scheduling model to allow for randomness in travel times. Expected schedule delay early and late, denoted by $\mathbb{E}(SDE; H)$ and $\mathbb{E}(SDL; H)$, respectively, are then given by

$$\mathbb{E}(SDE; H) = \int_0^H (H - D) f_{logn}(D) dD, \tag{1}$$

and

$$\mathbb{E}(SDL; H) = \int_H^\infty (D - H) f_{logn}(D) dD, \tag{2}$$

where $f_{logn}(D)$ is the log-normal probability density function of delays, and H is the additional safety margin that the travellers take into account because of delays. Since travellers can also miss their flight an additional penalty term is added which includes the costs associated with missing a flight. The percentage probability of missing a flight, $PMF(H, T_{Airport})$ depends on the safety margin H and the time spent at the airport $T_{Airport}$, which is the final check-in time minus the preferred arrival time. Travelers who prefer to spend more time at the airport have a lower probability of missing the flight. Therefore, $T_{Airport}$ includes the behavioural response to airport service time delay, which is assumed to be unrelated to delays on the road. The percentage probability to miss a flight is given by:

$$PMF(H, T_{Airport}) = 100 \int_{H+T_{airport}}^{\infty} f_{logn}(D)dD = 100(1 - F_{logn}(H + T_{airport})). \tag{3}$$

Following Koster et al. (2011) the expected access costs are then given by:

$$\mathbb{E}(C(H)) = \alpha(T_f + \mathbb{E}(D)) + \beta\mathbb{E}(SDE; H) + \gamma\mathbb{E}(SDL; H) + \theta PMF(H, T_{Airport}), \tag{4}$$

where α is the value of access time, β is the value of schedule delay early, γ is the value of schedule delay late, and θ is the value of the percentage probability to miss a flight. Let $F_{logn}(D)$ be the log-normal cumulative density function of delays, with shape parameter τ and scale parameter κ. In Appendix A we show that the expected access cost function as defined in Equation 4 can be written in closed-form:

$$\begin{aligned}\mathbb{E}(C(H)) = \alpha(T_f + \mu) + (\beta + \gamma)\left(HF_{logn}(H) - \mu F_{logn}\left(\frac{H}{\exp(\kappa^2)}\right)\right) + \gamma(\mu - H) + \\ \theta 100(1 - F_{logn}(H + T_{airport})).\end{aligned} \tag{5}$$

Travellers optimize this expected access cost function and choose their optimal safety margin H^*, resulting in minimal expected access costs $\mathbb{E}(C(H^*))$. There is no closed-form solution available for $\mathbb{E}(C(H^*))$. Therefore we determine H^* and $\mathbb{E}(C(H^*))$ numerically, using a behaviourally plausible step-size for H of 5 minutes.

For the preference parameters we use the median of the panel mixed logit estimates of Koster et al. (2011), which are based on a survey among 345 business and 625 non-business travellers. For our empirical analysis we distinguish between business and non-business travellers. The assumptions on preferences are summarized in Table 1.

Table 1: Assumed values for the preference parameters

	business	non-business
α	39.71	28.93
β	32.19	23.45
γ	47.07	34.29
θ	8.51	6.20
$T_{Airport}$	1.19	1.46

Note: values for α, β and γ are in €$/h$, whereas the value for θ is in €/%. The value for $T_{Airport}$ in is hours.

Not surprisingly, business travellers have higher willingness to pay values than non-business travellers, and have a preferred arrival time closer to the final check-in time, meaning that they spend on average less time at the airport.

3. Predicting OD travel time distributions

3.1. Estimating the standard deviation of delays

Many transport models only provide estimates of the mean delay for every OD-pair rather than travel time distributions. In this case, the OD travel time distributions can only be derived using additional assumptions. Empirical work of Peer et al. (2012) suggests that the standard deviation of travel time increases in the mean delay, and that a simple linear relationship between the mean delay and the standard deviation of delay for an OD-pair explains much of the variation in real world data.[1] This is especially true for somewhat longer mean delays (>4 minutes for shorter trips and >8 minutes for longer trips). While they show that the relation is non-linear for shorter mean delays and depends on variables such as link length, the number of lanes, free-flow speed, speed-at-capacity, the relative presence of different forms of congestion as well as the extent drivers are informed about factors that affect travel times, we intend to simplify matters here. We assume that the relation between travel time variability is constant across links. Moreover, we assume that the relationship is affine, meaning that we neglect the existence of a small constant (i.e. the extent of variability when mean delay is 0) in the original estimations. For every OD-pair, the relationship can thus be described in a simple way as follows:

$$\hat{\sigma} = \hat{a}\mu \tag{6}$$

We assume throughout our analysis that $\hat{a}$ is 0.8. The value of 0.8 is close to the slope coefficient 0.764 as estimated in their Model 1, Table 3, p. 85 (we round the value upwards because we ignore the positive constant of their regression). This model of Peer et al. (2012) assumes a linear specification without additional covariates and assumes that drivers are ill-informed about factors that affect travel times. Kouwenhoven and Bel (2014) estimate a similar model for longer road stretches using Dutch data. They find a slope coefficient of 0.660 with again a positive constant that can be interpreted as the variation in free flow travel time. The estimates for μ are obtained from the Dutch National Transport Model which is described in Section 4.1.

3.2. Parametrization of the log-normal distribution

Throughout the paper it is further assumed that delays follow a two parameter log-normal distribution. Let τ and κ be the parameters that describe the log-normal distribution. These parameters can be derived analytically if μ and $\sigma = \hat{a}\mu$ are known using the equations $\exp(\tau + \frac{\kappa^2}{2}) = \mu$, and $\exp(\tau + \frac{\kappa^2}{2})\sqrt{\exp(\kappa^2) - 1} = \hat{\sigma} = \hat{a}\mu$. These two equations can be

[1] They estimate the relationship between mean delay and travel time variability on a set of 145 highway links in the Netherlands.

solved for to obtain the parameters of the log-normal distribution as a function of the mean delay and the standard deviation of delays. The shape parameter of the log-normal is then given by

$$\tau = \log(\mu) - \frac{1}{2}\log\left(1 + \frac{\hat{\sigma}^2}{\mu^2}\right) = \log(\mu) - \frac{1}{2}\log\left(1 + \hat{a}^2\right), \tag{7}$$

and the scale parameter of the log-normal distribution by

$$\kappa = \sqrt{\log\left(1 + \frac{\hat{\sigma}^2}{\mu^2}\right)} = \sqrt{\log\left(1 + \hat{a}^2\right)}. \tag{8}$$

This implies that the log-normal distribution of delays is fully determined by the mean delay μ, which is a standard output of network models, and our assumption on $\hat{a}$, which pins down the standard deviation of delays. This results in different travel time distributions for different values of mean delays.

4. Case study of Amsterdam Schiphol Airport

4.1. Implementation using a large scale transport model

For our analysis we use the Dutch National Transport Model System (NMS, e.g. Gunn (1994)) to predict mean delays for trips with the destination Amsterdam Schiphol Airport (AMS). The NMS is a large, comprehensive transport model system that is based on discrete choice models for trip frequency, destination choice, mode choice, and time-of-day choice. It is highly disaggregated and simulates demand for six different modes of transport, while distinguishing ten different travel purposes. The resulting origin-destination flows are assigned to the road network using Qblok, an equilibrium type car assignment model that takes account input flow restrictions due to congestion effects upstream (Bakker et al., 1994). Furthermore, it uses speed-flow curve information calibrated on data of the Dutch motorway network. As usual, link travel times are equal to their free flow travel time plus an estimated amount of delay, where mean delay depends on the volume/capacity ratio.

The NMS is the 'standard' tool, developed and used since 1985 in the Netherlands, for assessing the effects of transport policies. The model distinguishes 1379 origin and destination zones, so it allows for a highly detailed spatial analysis of the accessibility of Amsterdam Schiphol Airport airport from all regions in The Netherlands. The model distinguishes three time periods: the morning peak (MP) which lasts from 7:00-9:00, the evening peak (EP) which starts at 16:00 and ends at 18:00, and the remaining hours of the day (ROD), for an average working day. Therefore the model provides separate estimates for the mean travel time delay for each of these three periods.

We apply our model to two different situations. First, the base year car traffic OD matrix of 2010 is assigned to the road network that was available in year 2010. Second, the same car traffic OD matrix of 2010 is assigned to an improved road network for the year 2020. The 2020 network contains all the infrastructure improvements that have been planned and anticipated for that year. This enables us to establish the effects of road network improvements on mean travel times, and hence the expected access costs.

For our analysis we assume that the overall number of air travellers arriving by car to the airport does not change between 2010 and 2020, hence assuming that demand is inelastic. Improvements in access costs will therefore not lead to additional car trips to Amsterdam Schiphol Airport.

The number of passengers arriving by car at Schiphol in 2010 as included in the model have been derived from large-scale air passenger counts and surveys conducted at the airport, the so-called 'continuous Schiphol-survey'. This survey has been carried out for many years. About 60.000 departing air passengers per year are interviewed resulting in data about their travel and personal characteristics. A complex stratified sample and expansion procedure is applied to ensure that all air destinations and nationalities of passengers are included.

Our analysis only concerns an average working day. According to the survey results about 8.32 million air passengers travelled on working days by car to Schiphol Airport in 2010. For 320 working days[2] in a year this is about 26000 travellers per day. Table 2 shows a breakdown of these travellers by type of travel purpose and by time of the day. Most passengers are found to travel to the airport outside the peak.

Table 2: Daily number of car travellers going to Schiphol Airport based on NMS 2010

	MP	ROD	EP	Total
Business	2172	9095	2154	13421
Non-business	1825	9348	1241	12414
Total	3997	18443	3396	25836

4.2. Numerical results

4.2.1. Introduction

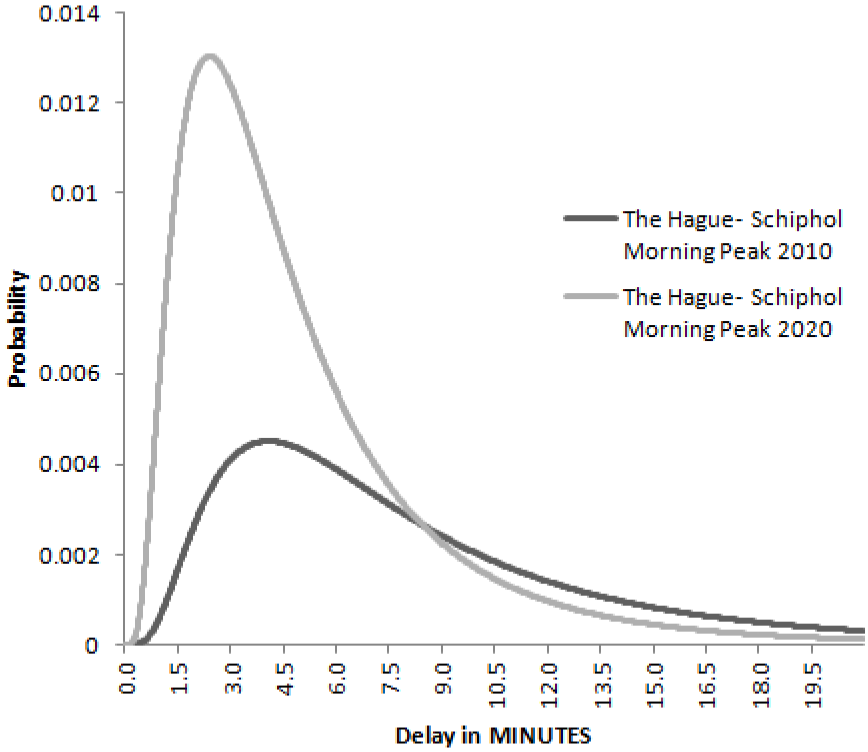
This subsection discusses the numerical results. We compare the Dutch road network of 2010 with the road network of 2020. For 2020, substantial infrastructure investments will be made to alleviate congestion at the key bottlenecks in the network. These investments do affect the travel time distribution of every OD-pair and therefore result in travel time and travel time reliability gains for departing air travellers who travel by car. We first provide a numerical example for one OD-pair in order to show how the model works (Section 4.2.2). The analysis is then repeated for all 1379 links in the analysis, and the aggregate results will be presented in Section 4.2.3.

4.2.2. Example for one OD-pair

To illustrate how the model works, we select one OD-pair, where O is an area in the city of The Hague, and D is Schiphol Airport. From the Dutch National Transport Model we

[2] This is calculated by assuming that Saturdays count for 70% as working day and Sundays for 50%. For 52 weeks in a year we then get: $52 \times (5 + 0.7 + 0.5) = 322$, which is rounded to 320 working days.

Figure 1: Travel time distributions for the 2010 and 2020 road network for one OD-pair (The Hague-AMS)

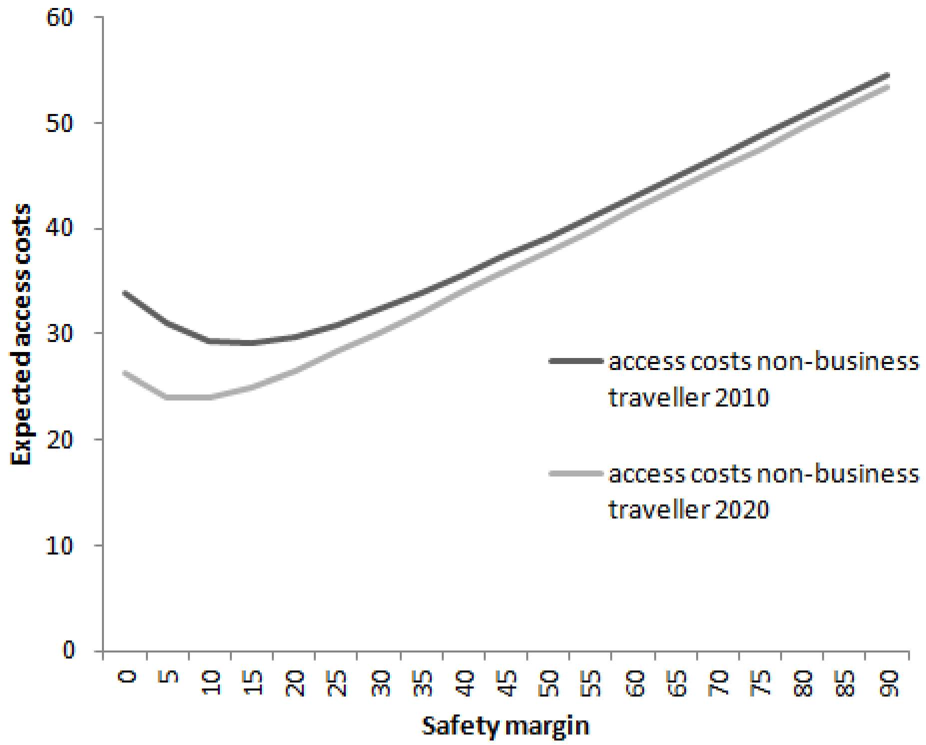


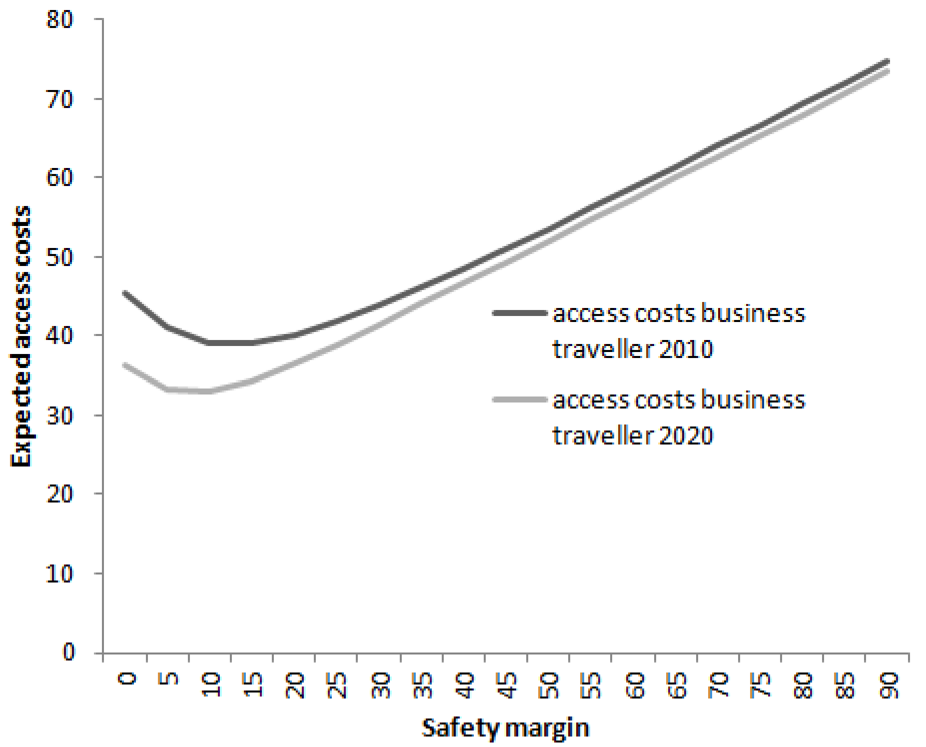
have data on the mean delay for 2010 and 2020 for this OD-pair. Using the prediction model of Section 3, we obtain travel time distributions for 2010 and for 2020 for the morning peak, the evening peak and the rest of the day. Figure 4.2.2 depicts these travel time distributions for the morning peak. This figure clearly shows the change in the travel delay distribution due to the investments in the road network. Comparing the 2010 and the 2020 distribution shows that the probability of large delays decreases whereas the probability of smaller delays increases for the 2020 network. This is the direct consequence of the assumption that travel time variability is positively related to the mean delay.

Because the delay distribution changes, the behavioural response of the travellers changes as well. Since the mean delays and the delay variability are lower in 2020 it is likely that the traveller will depart later from home in 2020, resulting in a lower optimal safety margin H. This becomes evident if we plot the expected access cost function (Equation 5), as a function of the safety margin H with a step-size of 5 minutes. We use the willingness to pay values as given in Table 1. Because the values of schedule delay are higher for business travellers, their cost curve is steeper than the cost curve of non-business travellers.

For 2010, the optimal safety margin of both types of travellers is 15 minutes, whereas for 2020 the optimal safety margin is equal to 10 minutes, again for business and non-business

Figure 2: Expected access costs for a non-business and a business traveller





travelers. As expected, the decrease in mean travel delay and travel time unreliability due to road network investments leads to a lower optimal safety margin in 2020. Second, the optimal expected access costs decrease because of the improvement in the mean delay and the delay variability. For a given safety margin, the expected access costs for 2020 are always lower than the expected access costs for 2010: for 2010, the optimal expected access costs are €39.01 and 29.14 for business and non-business travel, respectively, whereas for 2020 we find expected optimal access costs of €32.93 and 23.92. This implies that there is an improvement of €6.08 in expected access costs for business travellers and of €5.22 for non-business travellers. For business travel 40 percent of this gain can be attributed to improvements in reliability, whereas for non-business travel this is 49 percent. These numbers indicate that the absolute benefits of road network improvements are limited, especially if one compares them to the air fares that travellers pay. However, the relative contribution of reliability benefits in the total benefits can be substantial.

4.2.3. Results for the Dutch road network

Next, we present the aggregate results for all OD-pairs. The analysis of the previous section is repeated to obtain monetary estimates for the improvements in mean delays and travel time reliability due to road network investments between 2010 and 2020. Tables 3 and 4 show the results for business and non-business travel respectively. These results are obtained by repeating the analysis presented in the previous section for all 1379 OD-pairs in our dataset. The results demonstrate that the largest cost improvements are realized during the morning peak. This is because congestion is most severe during this time of the day, and therefore the corresponding marginal reduction in costs is substantial. Surprisingly, the average travel time cost savings are largest for non-business travellers for the morning peak. It can be shown that this is due to the fact that non-business travel relatively more often on links with larger improvements in mean delays.

The average absolute improvement in access costs per trip is not large in absolute terms (€1.95 for business and €1.67 for non-business travellers), especially when compared to the spendings on airline tickets. This means that the accessibility of Schiphol does not improve substantially due to the planned road network investments for 2020. The reason for these results is straightforward: as Table 2 shows, most travellers travel outside the morning peak to Amsterdam Schiphol Airport. The potential and willingness of policy makers to improve mean travel times and reliability during periods with little recurrent congestion is limited. Our results are thus distinct from the (more common) models that derive the benefits of network reliability for commuters: then most of the travellers will travel in the morning peak resulting in higher benefits.

However, the relative contribution of travel time variability improvements in total cost improvements is substantial. For each Euro improvement in mean delay costs we find a 0.86 Euro improvement in the costs of travel time variability for business travellers and a 0.77

Table 3: Cost improvements in €per trip for business travellers for optimally chosen buffers

	Business				
	MP	ROD	EP	Average business	%
Travel time cost savings per trip	3.77	0.35	1.25	1.05	54%
Travel time variability cost savings per trip	3.96	0.25	0.59	0.90	46%
Total cost savings per trip	7.73	0.60	1.84	1.95	100%

Table 4: Cost improvements in €per trip for non-business travellers for optimally chosen buffers

	Non-business				
	MP	ROD	EP	Average Non-business	%
Travel time cost savings per trip	4.18	0.39	1.11	0.94	57%
Travel time variability cost savings per trip	3.95	0.20	0.49	0.73	43%
Total cost savings per trip	8.13	0.60	1.60	1.67	100%

Euro improvement in access costs for non-business travellers. This implies that passengers' benefits of improvements in the road network are underestimated by about 45 percent if reliability benefits are ignored.

5. Conclusions

We developed a practical method to estimate the benefits of improvements in road network reliability. It allows for the estimation of reliability benefits without requiring the use of a full blown dynamic network model, while still capturing the essential behavioural response of drivers to travel time variability. The model is based on a standard scheduling model for departure time choice, and uses as inputs the travel time estimates of static transport models and an estimated coefficient that describes the (by assumption affine) relation between mean delays and travel time variability. Moreover, we assume that delays are log-normally distributed and travel demand is inelastic. Because we assumed that overall demand is inelastic, our estimate of the total benefits may be an underestimate because we ignored the additional consumer surplus stemming from new air travellers entering the road network because of lower generalised costs.

We applied the model to passengers going to the airport in order to catch a flight, hence a situation where (access travel time) reliability is strongly relevant. We find that the average absolute improvements in access travel costs are fairly small, mainly because most passengers travel to the airport outside the peak. However, the relative contribution of reliability benefits is large: we showed that passengers' benefits are underestimated by around 45 percent if reliability benefits are ignored. We expect that a similar practical approach can be followed for the analysis of travel time variability for other trip purposes such as commuting or leisure trips, although for commuting our assumption of inelastic demand may be less plausible.

Our estimate of the costs of travel time unreliability may be an underestimate if the travellers do not have full knowledge of the travel time distribution. When moving from rational expectations to more behaviourally plausible models of expectation formation, decisions will be sub-optimal and expected costs due to variable access times are higher than our estimates (see for example Koster and Verhoef (2012) for a model that allows for probability weighting).

We assume throughout the analysis that flights depart on time. If flights are delayed, the probability of missing a flight may be overestimated in our analysis. Furthermore, our assumption that delays on the road and in the air are independent from each other may not always hold in reality. For instance, adverse weather conditions may cause delays for both car and air travel. We leave this interplay of access delays and flight delays as a topic for further study.

Future research may also focus on obtaining more detailed estimates of the benefits of improvements in network reliability. We expect that our model could be made more precise by a more sophisticated modelling of the estimation of the standard deviation of delays, for example by allowing for non-linear relationships between the mean and the standard deviation of delays and incorporation of road characteristics. Second, more sophisticated travel time distributions could be used to allow for more flexibility in the shape of the travel time distribution. These improvements could be easily accommodated within the structure of our model and would lead to more precise estimates of the travel time distribution and the corresponding travel costs.

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Appendix A. Derivation of closed-form expected access costs

In this appendix we develop a closed-form solution for the expected access costs assuming that delays follow a log-normal distribution. The expected access cost function is given by:

$$\mathbb{E}(C(H)) = \alpha(T_f + \mathbb{E}(D)) + \beta\mathbb{E}(SDE; H) + \gamma\mathbb{E}(SDL; H) + \theta PMF(H, T_{Airport}), \quad \text{(A.1)}$$

where T_f is the free flow travel time, and H is the travellers' additional safety margin. A traveller faces a time-of-day independent cumulative probability distribution of travel delays,

$F_{logn}(D)$, and a corresponding probability density function $f_{logn}(D)$. The expected schedule delay early is given by Equation A.2, where we integrate over all possible early arrivals. Because delays are assumed to be positive (hence, travel times can by definition not be shorter than the free-flow travel time), the integral starts at $D = 0$. And it ends at $D = H$, because then a traveller arrives exactly on time, and the schedule delay early will be 0.

$$\mathbb{E}(SDE; H) = \int_0^H (H - D) f_{logn}(D) dD. \tag{A.2}$$

Substituting $f_{logn}(D) = \frac{1}{D\kappa\sqrt{2\pi}} \exp(-\frac{(\log(D)-\tau)^2}{2\kappa^2})$ gives:

$$\mathbb{E}(SDE; H) = HF_{logn}(H) - \mu F_{logn}\left(\frac{H}{\exp(\kappa^2)}\right), \tag{A.3}$$

where the parameters of the log-normal distribution are given by Equations 7 and 8. Similarly, the expected schedule delay late can be derived by integrating over all late arrivals:

$$\mathbb{E}(SDL; H) = \int_H^\infty (D - H) f_{logn}(D) dD. \tag{A.4}$$

Substituting $f_{logn}(D)$ gives:

$$\mathbb{E}(SDL; H) = HF_{logn}(H) - \mu F_{logn}\left(\frac{H}{\exp(\kappa^2)}\right) + (\mu - H). \tag{A.5}$$

Bates et al. (2001) show that for any travel time distribution it must be true that $\mathbb{E}(SDL; H) - \mathbb{E}(SDE; H) = (\mu - H)$, which is confirmed by Equations A.5 and A.3. Finally, the probability of missing a flight $PMF(H, T_{Airport})$ for a given departure time and a given scheduled flight time depends on the time at the airport $T_{airport}$. This is the final check-in time of the traveller minus the preferred arrival time. The percentage probability to miss a flight $PMF(H, T_{Airport})$ can be written as:

$$PMF(H, T_{Airport}) = 100 \int_{H+T_{airport}}^\infty f_{logn}(D) dD = 100(1 - F_{logn}(H + T_{airport})). \tag{A.6}$$

If we combine A.3, A.5 and A.6 we can rewrite A.1 as:

$$\begin{aligned}\mathbb{E}(C(H)) = \alpha(T_f + \mu) + (\beta + \gamma)\left(HF_{logn}(H) - \mu F_{logn}\left(\frac{H}{\exp(\kappa^2)}\right)\right) + \gamma(\mu - H) + \\ \theta 100(1 - F_{logn}(H + T_{airport})).\end{aligned} \tag{A.7}$$

This expected access cost function can easily be programmed in Excel. The optimal safety margin is determined numerically by inserting values of H in A.7. For this we use a step-size of 5 minutes.