Monitoring and predicting freeway travel time reliability

Using width and skew of the day-to-day travel time distribution

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Abstract: Day-to-day variability of route travel times on for example freeway corridors is generally considered closely related to the reliability of a road network. The more travel times on some route $r$ are dispersed in a particular time-of-day (TOD) and day-of-week (DOW) period, the more unreliable travel times on $r$ are conceived. In literature many different aspects of the day-to-day travel time distribution have been proposed as indicators of reliability. Mean and variance do not provide much insight since these metrics tend to obscure important aspects of the distribution under specific circumstances. We argue that both skew and width of this distribution are relevant indicators for unreliability, and consequently propose two reliability metrics, based on three characteristic percentiles, that is, the 10th, 50th and 90th percentile for a given route and TOD/DOW period. High values of either metric indicate high travel time unreliability. However, the weight of each metric on travel time reliability may be application or context specific.

The practical value of these particular metrics is in the fact that they can be used to construct so-called reliability maps, which visualize not only the unreliability of travel times for a given DOW/TOD period, but also help identify DOW/TOD periods in which it is likely that congestion sets in (or dissolves). This means identifying the uncertainty of start, end and hence length of morning and afternoon peak hours. Combined with a long-term travel time prediction model, the metrics can be used to predict travel time (un)reliability. Finally, the metrics may be used in discrete choice models as explanatory variables for driver uncertainty.

Keywords: Reliability, Reliability metrics, Travel time distribution, Travel time prediction.

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INTRODUCTION

Route travel times are considered key indicators on the reliability of a road network (Lo, 2002, Cassir et al., 2001). In the Oxford Dictionary reliable is defined as "consistently good in quality or performance, and able to be trusted", and reliability as "the quality of being reliable". Although many different definitions for travel time reliability in a transportation network or corridor are proposed (refer to for example (Bell and Cassir, 2000)), in general travel time reliability relates to properties of the (day-to-day) travel time distribution as a function of time of day (TOD), day of the week (DOW), Month of the Year (MOY), and external factors such as weather, incidents and road works. In this paper, we do not specifically address the causes of (un)reliability, but take a more phenomenological approach. Nonetheless, research into what we would call “the fundamental diagram of reliability” has been recently taken up at the Delft University of Technology and will be published in the course of 2005.

Zooming in on the day-to-day travel time distribution, one can state that the wider (longer-tailed) it is on a particular TOD/DOW, the more unreliable travel time on a freeway network or corridor is considered. In terms of (Lomax et al., 2003), variation coefficients, such as variance or standard deviation are hence indicators of travel time unreliability. However, as we will show, the day-to-day travel time distribution is sometimes sharply skewed. This implies that descriptive statistics such as mean and variance (standard deviation) are not very useful in reconstructing the travel time distribution or as indicators of reliability. Rather, we should focus on median and percentile values (Bates et al., 2002, Bates, 2001) which provide us with more robust estimates of how likely a specific travel time is given certain circumstances (e.g. TOD and DOW values), and provide us with easier means to reconstruct the travel time distribution. Later in this paper (see Figure 6) we will return to this claim.

The next question to be answered then is “when do we consider travel time to be unreliable?” In our view, there are many equally valid – but different – answers, depending on application and context. For example, a traveler may conceive reliability totally different than a traffic manager. Two common approaches are (a) to consider the width of the travel time distribution as an indicator for unreliability, and / or (b) to look at the skew of the travel time distribution. The latter is done also (implicitly) with the so-called misery index (e.g. (Lomax et al., 2003)), which calculates the distance between the mean travel time and the mean travel time of the 20 percent most unfortunate travelers. In this paper, we build on the work in (Van Lint et al., 2004) and consider both width and skew as indicators of (un)reliability. We present two respective metrics based on characteristic percentiles of the day-to-day travel time distribution given a particular TOD and DOW, and show how these can be used to identify travel time unreliability. In the second part of this paper, we present two (example) applications of these metrics. The first application pertains to reliability maps, which visualize travel time unreliability in certain DOW/TOD periods combining both metrics. The second pertains to a long-term travel time prediction model, suitable for in-car or web-based route planning applications. In future work we will also demonstrate the value of these metrics as explanatory variables in discrete (route and departure time) choice models.

DAY-TO-DAY TRAVEL TIME DISTRIBUTION

Empirical observations

For the analysis below we look at the (estimated) travel times between 6:00 AM and 8:00 PM for one whole year (2002) on the 6.5 kilometer eastbound carriageway of the A20 freeway between Rotterdam Centre and Rotterdam Alexander polder. This densely used freeway stretch is part of the northern beltway around the metropolitan area of Rotterdam in The Netherlands. Travel times were estimated with the PLSB trajectory algorithm (Van Lint and Van der Zijpp, 2003) for every departure minute between 6:00 AM and 8:00 PM, while the TOD period was chosen as 15 minutes. Per 15 minute TOD period the median value (50 percentile) of the available 15 travel times was taken as the travel time for that particular TOD/DOW. This implies that for each TOD/DOW we have approximately 52 (median) travel time values per year. Note that the uncertainty inherent to the PLSB method is not taken into consideration here, since we assume it provides (almost) unbiased estimates of real travel time. For a in-depth analyses on these issues refer to (Van Lint, 2004).

Figure 1 shows the variability of travel times on the A20 for three DOW values, that is, Thursdays, (Figure 1 top), Fridays (Figure 1 middle) and Saturdays (Figure 1 bottom). In the figure 5, 10, 25, 50 (median), 75, 90 and 95 percentiles are shown as a function of time of day (TOD). A 75 percentile value of say 10 minutes for TOD 16:00-16:15 reflects the percentage of days on which during that TOD a median travel time of 10 minutes or less occurred. On Thursdays (which may be classified as a typical weekday travel time pattern), a morning and afternoon peak are clearly identifiable, while on Fridays in more than half the cases no morning peak occurs. On Fridays the afternoon peak starts earlier and lasts longer than on other weekdays. On Saturdays in 75% of the cases no congestion occurred, albeit that there were some serious exceptions. In 5% of the cases travel times were even three times as high as in the normal (no congestion) case of 4 minutes.
As a general rule, one can observe that in free flow conditions (for example Figure 1 bottom: Saturdays between 6:00 and 9:00), the width of the day-to-day travel time distribution is small, that is, the distance between for example the 5th and 95th percentile is small, while in TOD periods in which (almost always) congestion occurs the distribution is wide, implying greater uncertainty (for example Figure 1 top: Thursdays between 17:00 and 18:00). In the TOD periods just before or after the peak periods (for example Figure 1 middle: Fridays between 12:00 and 15:00), a different picture emerges. Although median and even 75 percentile travel times are low (free-flow level), the 90th and 95th percentile values are high, indicating that although in up to 75% of the cases these periods are un-congested, in more than 10% of cases still heavy congestion occurred and hence high travel times. As a result, the day-to-day travel time distribution in these periods is heavily skewed. Arguably, also here travel times are unreliable, since there is a significant chance (>10%) of incurring travel times of several magnitudes higher than the average.

Modeling framework

Based on these empirical observations, we therefore identify four phases, which yield distinctively different shapes of the day-to-day travel time distribution; these are (a) free flow conditions; (b) congestion onset; (c) congested traffic; and (d) congestion dissolve. Schematically, the associated day-to-day travel time distributions for each of these phases are shown in Figure 2.

ad. a) Free flowing traffic
In these conditions, median travel times are low and also the spread of the distribution is small. The distribution of travel times is approximately symmetric and travel time can be considered reliable in these circumstances.

ad. b) Congestion onset
In these conditions median travel times are still low, but the distribution is strongly skewed to the left. This implies that in most cases traffic conditions are still free flow, but there are a number of days on which at this particular TOD already congestion occurred resulting in travel times much higher than median.

ad. c) Congested traffic
In this case median travel times are high, while the day-to-day travel time distribution is wide and right skewed. In these periods congestion can be expected, albeit in different degrees of severity, yielding a wide range of possible travel times. The right skew relates to the fact that in (a few) cases no congestion occurred.

ad. d) Congestion dissolve
Finally in these conditions, median travel times are low, but the distribution is strongly skewed to the left again, reflecting the fact that in most cases congestion dissolved at this TOD, but in a – decreasing – number of cases still heavy congestion occurred.

Note that over a particular weekday the change in shape of the day-to-day travel time distribution is smooth from phase to phase. For example, in TOD periods between phases b) and c) we gradually see the distribution transform from strongly left-skewed to symmetric to right-skewed, while from phase c) to d) the opposite occurs. We now propose two simple metrics for skew and width of the travel time distribution based on percentiles that allow us to differentiate between these four phases; identify transitions between phases and subsequently classify between reliable and unreliable TOD/DOW periods.

RELIABILITY METRICS: SKEW AND WIDTH OF THE DAY-TO-DAY TRAVEL TIME DISTRIBUTION

As argued in (Bates, 2001) the 90th percentile is a robust statistic representing the upper bound of travel times occurring. We will therefore use it together with the 10th percentile in the reliability metrics we propose below. As stated above, heavily left-skewed distributions indicate either a period where congestion may set in or a period where congestion usually is practically dissolved. In terms of reliability, skew therefore closely relates to the Misery Index (MI) reported in for example (Lomax et al., 2003). The MI looks at the difference between the mean of the 20% highest travel times and the mean of all travel times occurring on a particular road and time period, relative to the mean of all travel times. We propose for skew a more robust metric based on percentiles, that is, the ratio of the distance between the difference of the 90th and 50th percentile and the distance between the 50th and 10th percentile (Van Lint et al., 2004):
\[
\lambda_{skew} = \frac{T^{90} - T^{50}}{T^{50} - T^{10}}
\]

In which TXX denotes the XX percentile value. Since \( \lambda_{skew} \) is a ratio it can be interpreted and applied regardless of the absolute magnitude of travel times. In terms of reliability this is very relevant: a deviation of 5 minutes on a trip of two hours would not be interpreted as an indication of unreliability, while a five-minute delay on a trip, which on average takes five minutes, certainly would. In general, for very small \( \lambda_{skew} \) the distribution is highly right-skewed, while for very large \( \lambda_{skew} \) the distribution is strongly left-skewed. We argue therefore that large \( \lambda_{skew} \) should be interpreted as unreliable, since it implies that at least in 10% of the cases travel times (costs for travelers!) occurred that are significantly larger than median. If \( \lambda_{skew} \) equals one the distribution is symmetric and we need to look at the width of the distribution in order to say something about reliability. The wider the distribution is (relative to the median), the larger the range of travel times that may occur and hence the lower travel time reliability. Following the same argument as with skew, we propose the following relative metric

\[
\lambda_{var} = \frac{T^{90} - T^{10}}{T^{50}}
\]

which is the ratio of the range of travel times in which 80% of the observations around the median fall into, and the median travel time. Large values indicate the width of the travel time distribution is large relative to its median value, and hence travel time reliability may be classified as low. Note that although both metrics are relative, differences in route length may still lead to slightly different results between routes. In the next section we will address this issue in formulating the so-called unreliability index. But first some preliminary analyses of both reliability metrics are presented.

Figure 3 shows for three particular weekdays in 2001 (Thursdays (top), Fridays (middle) and Saturdays (bottom)) the evolution of both \( \lambda_{skew} \) (right graphs) and \( \lambda_{var} \) (left graphs) over a day (values on the horizontal axis represent 15 minute periods) on the 6km A20 freeway stretch. Clearly, in TOD periods in which congestion occurs the day-to-day travel time distribution is wide and right-skewed, yielding large \( \lambda_{var} \) values and small \( \lambda_{skew} \) values. The peaks in \( \lambda_{skew} \) mark – in most cases – the “transitional” periods, that is, the periods in which it is likely congestion sets in or dissolves. In TOD periods where the median travel time equals the free flow travel time, but heavy congestion occasionally occurred – for example on Saturday afternoons (Figure 3 (bottom graphs)) – \( \lambda_{skew} \) is also large while \( \lambda_{var} \) is larger than in free flow conditions but smaller than in heavily congested periods.

Finally, Figure 4 shows the relation between \( \lambda_{skew} \) and \( \lambda_{var} \). The figure clearly shows the transition of the day-to-day travel time distribution between the phases identified above. Note that the phases denoted in red (congestion dissolve, congestion, etc) are to some extent overlapping. Cluster analyses could provide more solid statistical evidence for the phase categorization proposed. Nonetheless, Figure 4 shows that during congestion onset the distribution is more heavily skewed than during congestion dissolve. Arguably, this implies that travel times just before or during congestion onset are more unreliable than during congestion dissolve. It also appears there is hysteretic behavior (denoted with black arrows in Figure 4) analogous to the hysteretic behavior of traffic in terms of the fundamental diagram (see e.g. (Zhang and Lin, 2002)). Here, we express that behavior in terms of skew and width of the day-to-day travel time distribution, rather than traffic flow and density. Finally note that to a degree, the skew in the transient conditions may also be influenced by the (arbitrary) choice of the TOD period size (in our case 15 minutes). Different binning of the data may lead to a slightly different pattern, we argue - tentatively, the general pattern stays the same. Only if sample size is set very large (>45 minutes), one may expect to see the peaks in skew gradually disappear. We recommend these hypotheses be further supported by empirical research and/or surveys in the future.

The preliminary conclusion is that three characteristic percentiles provide us with two key indicators for freeway travel time reliability, which together distinguish between the four phases identified above and enable us to label certain TOD/DOW periods as reliable or unreliable. Based on Figure 4 we argue that for this particular freeway stretch

- For \( \lambda_{skew} \approx 1 \) and \( \lambda_{var} \leq 0.1 \) travel time is reliable, that is, traffic is mostly free flow (we can expect free flow travel times in most cases)
- For \( \lambda_{skew} < 1 \) and \( \lambda_{var} > 0.1 \) traffic is mostly congested, that is, we can expect high travel times in most cases. The larger \( \lambda_{var} \) the more unreliable travel times may be classified
- For \( \lambda_{skew} > 1 \) and \( \lambda_{var} \geq 0.1 \) congestion may set in (or dissolve), that is, we can expect both free flow and high travel times. The larger \( \lambda_{skew} \) the more unreliable travel times may be classified.
APPLICATIONS

In the scientific realm, the most obvious application of these metrics is in discrete choice modeling (e.g. route, departure time choice). For example, in (Katsikopoulos et al., 2002) and (Bogers and van Zuylen, 2004) it is shown that people prefer routes with higher mean travel time and small variability over a route with lower mean travel time but higher travel time variability. Moreover, this risk-averseness is proportional to travel time variance. In this paper, we show two other practical applications of our representation of the travel time distribution and the reliability metrics proposed above. The first pertains to constructing an unreliability index, the second to long-term prediction of travel time and travel time reliability.

Reliability maps

With the rules of thumb postulated above, we can draw a so-called reliability map for a particular (freeway) stretch or route. Traffic managers (politicians) can visualize and analyze travel time reliability of routes on their networks using such a map. For this particular freeway stretch, in case of congestion ($\lambda_{\text{skew}} << 1$ and $\lambda_{\text{var}} > 0.1$) unreliability is proportional to $\lambda_{\text{var}}$, while in “transient” periods (congestion onset and dissolve) unreliability is proportional to $\lambda_{\text{skew}}$. However, for other freeway stretches these values may be different; for example, $\lambda_{\text{var}}$ values around 1 are not likely\(^1\) on very long road stretches. In order to get rid of this “location-specifity” we divide by the route length (in km), implying we interpret travel time per unit length. Finally, the degree of reliability should be regarded with respect some reference or threshold-value\(^0\), which represents the degree of unreliability acceptable for a traffic manager. We propose the following indicator for unreliability:

$$ UI_{\text{var}}(\text{TOD, DOW}) = \frac{\lambda_{\text{var}}(\text{TOD, DOW})}{\theta L_r} $$

where

$$ \lambda_{\text{var}} = \max\left(\lambda_{\text{var}}, 0.1\right) $$
$$ \lambda_{\text{skew}} = \max\left(\lambda_{\text{skew}}, 1\right) $$

in which $\alpha \in [0, 1]$ is a parameter determining the weight of $\lambda_{\text{skew}}$ on unreliability and $L_r$ denotes the length of the route under consideration. In this paper we set $\alpha = 0.5$ and $\theta = 1$. Figure 5 and Figure 6 show so-called reliability maps for the A20 freeway stretch mentioned earlier. Figure 5 shows a contour map of $\lambda_{\text{var}}$ (top) and $\lambda_{\text{skew}}$ (bottom) for each DOW and 15 minute TOD period based on data from the years 2001 and 2002. The top graph of Figure 6 shows a contour map based on the reliability index presented above (eqn (3)), while the bottom-graph shows a contour map of an alternative reliability index based on mean and standard deviation of travel time

$$ UI_{\text{alternative}}(\text{TOD, DOW}) = \frac{\text{std}[\text{TT}(\text{TOD, DOW})]}{\text{mean}[\text{TT}(\text{TOD, DOW})]} $$

As variance (standard deviation) grows large relative to mean travel time, this metric also gets large. In all graphs dark areas depict DOW/TOD periods in which travel times are – based on the indicator chosen - considered unreliable. The four graphs clearly summarize the findings above:

1. If width ($\lambda_{\text{var}}$) is considered the principle indicator for travel time unreliability, then those DOW/TOD periods during which in most cases congestion occurred (morning and afternoon peaks) are considered the most unreliable - Figure 5 (top).
2. If skew ($\lambda_{\text{skew}}$) is considered the principle indicator for travel time unreliability, then those DOW/TOD periods during congestion might set in / dissolve (periods just before / after the peak hours) are considered the most unreliable - Figure 5 (bottom).
3. If we consider both metrics and combine them with eqn (3), then travel times are considered unreliable in both congestion and “transient” periods, the magnitude depending on the weight posed on each metric - Figure 6 (top).

\(^1\) If $\lambda_{\text{var}}=1$, the difference between the 90th and 10th percentile equals median travel time.
4. Clearly, the reliability index based on our metrics (and thus percentiles) offers a much more detailed picture than the alternative based on mean and standard deviation - Figure 6 (bottom). Consequently using the new metrics allows for a much more detailed analysis of travel time reliability.

In sum, which metric is considered most important in terms of unreliability depends on how we define unreliability, which may be application or context specific. In the unreliability index we propose (eqn (3)) a parameter $\alpha$ which enables weighing the skew and width parameter. Also a threshold parameter $\theta$ is provided to further tune the unreliability index to application specific needs. As a result, which DOW/TOD periods are considered unreliable also depends on application and context. We argue, however, that a wide distribution with high median and strong right-skew (large $\lambda_{\text{var}}$, small $\lambda_{\text{skew}}$) could be considered more reliable than a highly left-skewed distribution (large $\lambda_{\text{skew}}$), since in the first case traffic is almost always congested and a traveler is likely to encounter large delays, while in the second case the odds point to free flow travel time with a – still considerable - 10% chance of encountering relatively very long delays. This preference would imply choosing $\alpha$ larger than 1.

**Long term travel time prediction model**

The analyses and results so far are descriptive by nature, summarizing a large database of realized travel times in terms of a day-to-day travel time distribution. Nothing prevents us, however, from approximating the distribution found with a (parameterized) probabilistic model, which is able to reproduce the day-to-day distribution of travel times conditioned on DOW and TOD, and potentially, other factors such as weather and season, which influence spread and skew. Since there is not much theoretical underpinning of the underlying relationships, this model has a phenomenological nature. The advantage of such a model is that it can serve as a long-term travel time prediction model, usable for example in (in-car or internet-based) route planning software. Since this model is nothing but a compact parameterized version of the day-to-day distribution conditioned for all TOD and DOW, its "predictions" are based on the past only. Nonetheless, in a long term planning application, this still is a very useful approach.

**Model derivation**

Schematically, such a model is outlined in Figure 7. Since we found that we can summarize the day-to-day distribution with three characteristic percentiles, a pragmatic choice for this model is the following

\[ y = G(TOD, DOW, \ldots, \Omega) \]  

(5)

in which $G$ is some non-linear parameterized mapping, $\Omega$ the vector of parameters to be estimated, and

\[ y = \begin{bmatrix} T_{50} - T_{10} \\ T_{50} \\ T_{90} - T_{50} \end{bmatrix} \]  

(6)

denotes the model output. The reason for this particular choice of $y$ is that this ensures $T_{10} \leq T_{50} \leq T_{90}$, given we choose a function $G$ which yields positive output for all inputs. Note that the three percentiles can be easily obtained with this output vector. As a preliminary choice we propose a simple two-layered feed-forward artificial neural network (ANN), which uses as inputs TOD and DOW only. The neural network model has an output layer of containing three neurons with so-called logistic transfer functions - see eqn (7) - producing the output vector $y$ shown in eqn (6). For the hidden layer (containing $H$ neurons) we choose a hyperbolic tangent transfer function - see eqn (7). The number of inputs $U$ to that layer equals two (TOD and DOW).

Mathematically, this ANN model can be written as

\[ y_k = \frac{1}{1 + e^{-z_k}}, k = \{1, 2, 3\} \]

\[ z_k = \sum_{h=0}^H b_{kh} \tanh \left( w_{kh} + \sum_{j=1}^U w_{kj} u_j \right) \]  

(7)

in which $y_k$ denotes one of the three model outputs, $u_j$ denotes one of the $U$ inputs, and $b$ and $w$ the vectors of adjustable parameters of the output and hidden layer respectively. Note both hidden and output layer have a bias

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2 A comprehensive introduction in the field of ANN’s can be found in Bishop, C. M. (1995) *Neural Networks for Pattern Recognition*, Oxford University Press, United Kingdom.
weight. We use the Levenbergh-Marquardt / Bayesian Regularization (LMBR) algorithm described in (Foresee and Hagan, 1997) to train this model. As shown in (MacKay, 1995) and (Van Lint, 2004) the Bayesian statistics behind this algorithm provide a superior and mathematically sound way to prevent ANN over-fitting and, as a bonus, an analytical and unified way of calculating confidence intervals around the predictions. We can therefore set \( H \) initially to the arbitrary size of 15. All input and output data are linearly scaled to the interval \([0.1,0.9]\) for better and more stable learning (Hagan and Menhaj, 1994).

**Results**

We have trained the ANN on the TOD/DOW percentiles for the whole year of 2002 from the same road stretch as before (the A20). Below we test these results against TOD/DOW percentiles calculated for the whole year of 2001. Figure 8 shows the results of the ANN model of eqn (7) for the same three days as were shown in Figure 1, that is, on Thursdays, Fridays and Saturdays. In the figure, it is clear the ANN provides a smooth approximation of these three characteristic percentile time series. We may conclude the model has certainly learned the key differences between these travel time profiles on different days.

- On Thursdays, in more than 50% of the cases both a morning and afternoon peak occurs, the first between 8:00 and 9:00 AM, the latter between 15:00 and 18:15 PM
- The Friday afternoon peak starts earlier and lasts longer than on other weekdays
- On Saturdays, most of the time no congestion occurs, during the whole afternoon minor congestion may occur in less than half of the occasions.

As a more quantitative indication of the performance we finally note that on the test data (2001), the following overall performance was obtained. In the ensuing \( N \) denotes the total number of TOD/DOW values\(^3\). In terms of mean relative error (MRE) we then find

\[
MRE = \frac{100}{N} \sum_{v=1}^{3} \sum_{i=1}^{N} \frac{y_k(TOD, DOW) - T_i(TOD, DOW)}{T_i(TOD, DOW)} = -0.1\%
\]

and in terms of standard deviation of the relative error (SRE)

\[
SRE = \frac{100}{N-1} \sum_{v=1}^{3} \sum_{i=1}^{N} \left( \frac{y_k(TOD, DOW) - T_i(TOD, DOW)}{T_i(TOD, DOW)} - \frac{MRE}{100} \right)^2 = 29\%
\]

In both cases \( T (TOD, DOW) \) is a vector \((T10, T50, T90)\). On the average, the model is almost unbiased, albeit there is a considerable residual error in its predictions, which is largely due to the smooth approximation the model makes.

**Implications and Improvements**

In its current form the model could for example be used to answer questions such as “What is the maximum travel time in a particular DOW/TOD period one would encounter in 90% of the cases, and consequently, at what time should one leave to be in time in 90% of the cases?” To be able to give more specific answers, or condition the answer on more factors, this model could easily be extended, with more inputs (e.g. month of the year, weather), or outputs (other percentile values). The prerequisite is that enough historical data are available to specify the travel time distribution conditioned on each input factor. In such a more elaborate model – specifically in case of many conditional relationships - one could choose a probabilistic approach for model (5) for example with Bayesian belief networks.

Secondly, we could apply the two reliability metrics - \( \lambda^{aw} \) and \( \lambda^{skew} \) - on the model outcomes, effectively providing us with a model for predicting travel time reliability. Given a particular DOW/TOD (and perhaps conditioned on more factors) the model would provide an indication whether or not travel time is considered unreliable.

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\(^3\) We used daily profiles from 6:00AM-8:00PM, with 15 minute time periods, yielding \( N = 56*7=392 \) (TOD/DOW combinations)
CONCLUSIONS & RECOMMENDATIONS

Following the generally accepted notion that median and percentile values are more robust statistics than mean and variance for quantifying travel time reliability, we derived two characteristic reliability metrics based on the median, 10th and 90th percentile of the day-to-day travel time distribution.

- $\lambda_{\text{var}}$ provides the relative width of the travel time distribution (with respect to the median) in a certain DOW/TOD period. Large values indicate larger uncertainty and hence unreliability.
- $\lambda_{\text{skew}}$ depicts the skew of the distribution. In DOW/TOD periods where congestion sets in or dissolves, this metric is large ($>>1$), while in severely congested conditions the metric is very small ($<<1$). In free flow conditions $\lambda_{\text{skew}}$ is approximately one. Large values depict high uncertainty and hence unreliability.

Based on both metrics, a clear distinction can be made between different phases of traffic flow operations (free, congested or transient). The metrics can be used to identify not only the unreliability of travel times for a given DOW/TOD period, but also identify DOW/TOD periods in which it is likely that congestion sets in (or dissolves). Practically, this means identifying the uncertainty of start, end and hence length of morning and afternoon peak hours. Which of the metrics is considered more relevant depends on application and context. In terms of applicability, the metrics could for example be used

- in discrete choice models (e.g. route and departure time) which incorporate unreliability as an explanatory variable. We are convinced both metrics have more explanatory value than for instance the standard deviation of the travel time distribution alone.
- in so-called reliability maps, which visualize travel time unreliability on a particular road conditioned on time-of-day and day-of-week (and possibly other factors) - we demonstrated that depending on the weight given to each metric a different unreliability map evolves and also that the proposed metrics give a much more detailed view on travel time reliability than a relative measure based on standard deviation and mean travel time.
- on the outcomes of a long-term travel time prediction model, which predicts characteristic percentile values of the day-to-day travel time distribution

The validity, robustness and most of all usefulness of the reliability metrics should be further investigated in various application domains, ranging from discrete choice modeling (route and departure time), to real time Advance Travel Information Systems (ATIS) such as web-based or in-car route navigation tools. Furthermore, the artificial neural network model we developed here, is still simple, capturing time-of-day and day-of-week trends only. The model could and should be augmented with for example seasonal trends (e.g. month of the year or quarter), and could also include for example external factors such as weather and large-scale road works. For this a large-scale database containing several years of (estimated) travel times and associated external factors on a number of different freeway routes is needed.
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FIGURES

Figure 1: Variability of travel times in 2002 for 15 minute time-of-the-day (TOD) periods between 6AM and 8PM on the northern Rotterdam beltway A20 on Thursdays, Fridays and Saturdays
Figure 2: shape of the day-to-day travel time distribution from free to congested conditions

Figure 3: Example of behaviour of width and skew metrics. The horizontal axis in all graphs depict time of day in 5 minute periods from 6 AM to 21 PM; the left vertical axis in all graphs depict travel time in minutes, while the right vertical axis in the three graphs on the right and left side depict $\lambda_{\text{var}}$ and $\lambda_{\text{skew}}$ respectively.
Figure 4: The relation between $\lambda_{skew}$ and $\lambda_{var}$. The hysteretic behaviour in terms of congestion onset and dissolve is marked with the black arrows. Note that the vertical scale is logarithmic.
Figure 5: Reliability maps for the A20 eastbound (I); top shows $\lambda^{\text{var}}$ for all DOW/TOD periods between 6AM and 8PM, bottom shows $\lambda^{\text{skew}}$. In both graphs, dark areas depict high values.
\[ UR_l = \frac{1}{L_r} \lambda^{\varphi(a)} \cdot (a=0.5) \]

Figure 6: Reliability maps for the A20 eastbound (II); top shows the unreliability index (UL), bottom shows the ratio of standard deviation and mean travel time for all DOW/TOD periods between 6AM and 8PM. In both graphs, dark areas depict high values.

Figure 7: schematic representation of long term travel time (distribution) prediction model
Figure 8: example performance of long term ANN travel time prediction model