

FORECASTING TRAVEL TIME RELIABILITY IN URBAN ROAD TRANSPORT

Mattias Juhász¹, Tamás Mátrai², Csaba Koren³

^{1,3} Department of Transport Infrastructure, Széchenyi István University, Győr, Hungary

² Department of Transport Technology and Economics, Budapest University of Technology and Economics, Budapest, Hungary

¹e-mail: mjuhasz@sze.hu

²e-mail: tamas.matrai@mail.bme.hu

³e-mail: koren@sze.hu

Abstract: *Assessment of travel time reliability as a fundamental factor in travel behaviour has become a very important aspect in both transport modelling and economic appraisal. Improved reliability could provide a significant economic benefit if it is adequately calculated in cost-benefit analyses for which the theoretical background has already been set. However, methods to forecast travel time reliability as well as travel behaviour models including its effects are rather scarce and there is a need for development in this field. Another important aspect could be the influencing factor of reliability in travel demand management and related policy-making. Therefore, this paper intends to further analyse reliability focusing exclusively on urban road transport based on automatic measurements of journey times and traffic volumes from a dataset of the city of Budapest. The main finding and the novelty of the study is a model which can forecast the standard deviation of travel times based on the volume-capacity ratio and the free-flow travel time. The paper also provides a real-life numerical experiment in which the proposed model has been compared with other, existing ones. It proves that besides existing mean-delay-based models, travel time reliability can be forecasted based on the volume-capacity ratio with an adequate accuracy.*

Key words: *travel time reliability, forecasting, urban road transport, appraisal, congestion.*

1. Introduction

Management and planning of urban transport systems is a complex task which demands a comprehensive approach in supporting decision-making. In order to make ‘well-informed’ decisions (e.g. choose the best alternatives in developing the system), it is indispensable to take into consideration every relevant aspect and effect of the given interventions. For this purpose, there are different policy and project assessment tools. A universal, widely accepted and long-standing tool is cost-benefit analysis (CBA) which is mainly assessing projects from an economic point of view. However, one can argue that the method itself has its own limitations and there are important effects which can be hardly monetized (or just quantified). Previous papers reviewed these limitations and challenges ahead for appraisal methods (Mátrai and Juhász, 2012; Mátrai, 2013). Major transport economists accept that there are new, innovative methods, but most of them believe that with methodological additions and proper quality of implementation CBA

still allows the most prudent form of analyses to be carried out. (Laird et al., 2014; Vörös et al., 2015)

In recent years travel time reliability (TTR) is an increasingly important issue among transport experts (ITF, 2010). One of the leading international organizations – OECD – organized a roundtable in late 2015, where several transport economists provided their view on this issue (Kouwenhoven and Warffemius, 2016; Fosgerau, 2016). Travellers intend to optimize their daily activity chains (Esztergár-Kiss and Rózsa, 2015), which results in shorter travel times and they are also sensitive to the variability (predictability) of travel times as unreliability press users to use safety margins (buffer times) which cause an additional disutility (travel cost) beyond pure travel time. Therefore, TTR is a fundamental factor in understanding and modelling travel behaviour. Furthermore, improved reliability could be a significant economic benefit if it is calculated in CBAs. Several countries have recently decided to include TTR in their CBA guidelines and defined the monetary values (i.e.

value of reliability, VOR). However, methods to predict the impact of interventions on TTR (reliability forecast models) as well as travel behaviour models including TTR effects are also needed. These models are still rather scarce and there is no concord among professionals on which method should be used. (Eliasson, 2006; de Jong and Bliemer, 2015).

Another important aspect could be the influencing factor of reliability in travel demand management and related policy-making. On the one hand, in case of restrictive road projects (e.g. traffic calming projects) a decrease in reliability could mean an undesirable side effect (a loss for the society). On the other hand, in case of a public transport or non-motorized development, modal shift can have a positive effect on overall TTR. Moreover, reliability of travel times could also influence land-use decisions, so it should be a factor in land-use and transport interaction modelling as well (Juhász, 2014). TTR can be also important for analysis of cycling investments, since the mode shift from car to cycling is usually marginal. In absolute terms the number of cars decreases only with a small amount which provides nearly no impact on travel times, but might have a significant one on reliability.

Nowadays the pervasive development of information technologies and intelligent transport systems (e.g. intelligent sensors) provides the opportunity to further analyse TTR and expand possibilities in forecasting. These investigations should be focused on urban regions for two important reasons: (1) more than 50% of the world population is living in an urban area and according to the general predictions this ratio is expected to further increase (United Nations, 2015); (2) congestion (and unpredictability) as a major transport issue are mainly concentrated in cities (ITF, 2010; Rao A.M. and Rao K.R., 2012). As well-established and widely accepted guidelines are missing on how to forecast TTR, there is a need for further analysis. This study focuses exclusively on urban road transport as it is presumed that the reliability issue is mostly significant in this setting, however it is likely to be relevant in other circumstances (such as for long-distance or public transport trips) as well (Eliasson, 2006; Sławińska, 2015; Horbachov et al., 2015). The database of road operators can be a platform to measure reliability as road authorities often collect data of traffic volumes

and individual vehicle trips for different purposes (e.g. to provide information for road users on estimated travel times to a certain destination). From these dataset, the reliability of a given route can be characterized, if the traffic situation (e.g. saturation level) is also known.

Based on the aforementioned aspects and focusing on urban road transport, the objective of this paper is to:

- provide a brief review on TTR approaches;
- explore the relation between TTR and relevant traffic parameters based on the case study of Budapest, in which automatic travel time measurement of a traffic information system has been used;
- propose a methodology to forecast TTR and draft further research.

2. Review of TTR approaches in transport appraisal

The topic of TTR has been investigated by numerous studies. The history of the research is summarised by Taylor (2013). In this section a brief review is provided from the most relevant papers to describe the background of the topic and this research.

Travel times of road trips are usually not stable over time. Variations occur as a consequence of fluctuations in travel demand and road capacity. A part of these fluctuations is known to road users (e.g. regular, cyclical variations), while another part is not (irregular or random variations). This paper focuses on unexpected variations which can cause that road users arrive earlier or later than expected. The unreliability forces travellers to add buffer times to their trips in order to avoid being late. This is then an additional disutility (cost) to mean travel time. But in some cases standard buffers ('head starts') could be insufficient and lateness could also cause another disutility, while arriving too early can also have its unpleasantness. So unreliability could mean a cost for users as they might face additional travel times, lateness, waiting times and even they may need to reschedule their activities. All of these might be accompanied by bad feelings such as anxiety. (Dale et al., 1996 ; Bates et al., 2001; Peer et al., 2010; Taylor, 2013)

TTR is the level of unpredictable, day-to-day variation of travel times, which represents the temporal uncertainty experienced by road users during their trips and it is related to transport

network conditions in a complex way. In this interpretation, reliability is basically equivalent to the predictability of travel times and associated with the statistical concept of variability (Kouwenhoven and Warffemius, 2016). A high level of reliability means a low level of variability (uncertainty), which indicates that travel times are mostly predictable. However, reliability can also be approached from the aspect of expectations. In that regard, users are expecting (!) a certain level of service upon which they organize their activities and reliability is proportional to the ability of the transport system to fulfil this requirement. Travel time variability can be caused by special events (e.g. accidents) as well but in this paper the focus is purely on day-to-day variations which mainly arise in congested situations as several studies found that the main explanatory factor of travel time variability is mean travel time (i.e. the sum of free flow travel time and mean delay). In a severe congestion, this variation might be very significant, but if it is very severe, variability can also become a decreasing function of travel time as in a very congested situation travel times are mostly homogeneous (Eliasson, 2006; Mátrai 2012). By improving TTR, additional 'buffer' times, waiting times and the probability of lateness could be decreased. For certain projects, not including TTR in economic calculations, a significant benefit or loss may be disregarded. That is why the economic impacts of TTR changes are more and more about to appear in CBAs. Travel time-related benefits are traditionally measured as the improvement of journey times. With incorporating reliability, those time benefits need to be split into (conventional) travel time savings and savings on TTR. Different studies proved that reliability could have a very significant effect in CBAs. Previous papers (e.g. Mátrai and Juhász 2012) pointed out that including reliability benefits in a public transport investment could add to 8-15% to the economic benefits, while others such as Eliasson (2006) or Kouwenhoven and Warffemius (2016) found that in road investments it could also add 10-60% to the benefits. In order to calculate the economic impact of TTR in a given project the following steps are needed based on the papers of Kouwenhoven and Warffemius (2016) and Fosgerau (2016):

1) determination of a monetary value of reliability (VOR – the cost to travellers per unit of travel time variability),

- 2) measurement and prediction of the level of TTR (the quantity of travel time variability),
- 3) incorporating the reaction of users to reliability in travel behavioural models (e.g. in route choice models by including the cost of variability into the generalised travel cost function).

In order to go through the aforementioned steps, first and foremost a unit of measurement needs to be defined for TTR. Approaching the topic from this operational (measurement) aspect, there are two main groups of definitions for reliability. The first one is the 'mean-dispersion' model which defines a measure of dispersion of travel time distribution (standard deviation, variance range, percentiles etc.). In this model the standard utility function contains the travel cost, the travel time and the dispersion of travel time. Value of time (VOT) can be defined as the marginal rate of substitution between travel time and travel cost, while VOR is the rate of substitution between reliability and travel cost. The latter represents the monetary value travellers place on improving the predictability of travel times (i.e. reducing the travel time variability). The second group is the 'scheduling delay' model, in which the scheduling consequences of TTR are measured by the expectations of arriving or departing earlier or later than the preferred time. (Dale et al., 1996; Eliasson, 2006; Fosgerau and Hjort, 2008; Fosgerau et al., 2008; TRB, 2011; de Jong and Bliemer, 2015).

Having reviewed the literature on TTR approaches, it seems that at this stage (!) standard deviation of travel time is the most appropriate way to quantify the variability of travel times within the mean-dispersion model. It seems the era of scheduling models is still to come as there are only a limited number of practical researches on this field. Furthermore, the data on the preferred arrival time of the users is very limited which is a prerequisite of using the scheduling model. Then the mean-dispersion model can be applied and the only question is how to measure the dispersion within. Numerous studies pointed out that travel times are not normally distributed and there is an evidence of skewness to the upper tail (Taylor 2013; Susilawati et al. 2013; de Jong and Bliemer 2015). Due to this fact some papers like Eliasson (2006) or de Jong and Bliemer (2015) suggested to not use the standard deviation as a measure of dispersion because it is affected by this skewness, as it is basically (and

more appropriately) used for symmetrically distributed variables. Therefore, these papers suggested to use the difference of specific quantile values or difference between quantiles and the mean travel time. However, Fosgerau (2016) showed that the standard deviation is proportional to the other measures of dispersion such as differences of specific quantiles. Moreover, he also stated that theoretically standard deviation is more appropriate for commuters with inflexible working times which are more general among travellers in an urban peak hour. Standard deviation has several advantages: (1) it is easy to estimate, (2) it is easy to include in a transport model and in a CBA, and (3) it is the most common TTR measurement in practice. However, there are further arguments against as there are difficulties in calculations over routes as it is not an additive formula (only variances of links can be summarized). Another mode of visualisation of travel time reliabilities and changes is the rubber sheet method used on travel time maps (Ficzere et al., 2014; Kouwenhoven and Warffemius, 2016). Based on the consideration of Fosgerau and due to the limited data on preferences required for scheduling models, in this research the standard deviation is used as a proxy for TTR.

The conceptual models of the valuation of travel time variability (basic model, step model, slope model) are summarised by Fosgerau (2016), while a study from de Jong and Bliemer (2015) provides a comprehensive review on deriving VOR and on TTR forecast models. VOR is mostly expressed as the product of VOT and a reliability ratio. Based on this review, reliability ratios are mostly in the range of 0.4 and 1.1 for passenger transport, while it is usually a bit lower (between 0.1 and 0.4) for freight transport. In terms of TTR forecast models the study mentions seven national methods from which five is summarized here by Table 1, in which ‘D’ is the

distance; ‘MD’ is the mean delay, ‘s’ and ‘s₀’ is the maximum and minimum of standard deviation of travel times respectively; ‘std’ is the standard deviation of travel times; ‘t’ is the (mean) travel time; ‘t₀’ is the free-flow travel time, ‘v’ is the speed; ‘F/C’ is the traffic volume (flow) – capacity ratio, while ‘a’, ‘b’, ‘c’ and ‘d’ are constant parameters.

Most of these models calculate the standard deviation of travel times based on the estimated mean delay (ratio of mean travel time and free-flow travel time) as an indicator of congestion. All of these models are quite useful to measure TTR impacts (standard deviation), but the problem is that TTR cannot be incorporated to a standard assignment model in a way that it is depending on the mean travel time as it is calculated within the process. So the main issue is the interdependence between these values. Furthermore, it is important to note that some interventions could have different impacts on mean travel time and TTR, which also suggests to forecast the standard deviation independently of the mean delay. The model from New Zealand is an exception as it calculates the standard deviation based on the extreme values and the F/C ratio. This model avoids the issue of TTR and mean delay interdependence (the ‘endogeneity’ issue), but it is also impossible to incorporate TTR to assignment models this way as the model uses the extreme values of standard deviation, which cannot be properly estimated beforehand for future years.

3. Forecasting reliability in urban road networks

Based on the aforementioned aspects of existing methods, this study aimed at developing a model to forecast the standard deviation of travel times based purely on the F/C ratio and the free-flow travel time. This approach is basically parallel to developing volume-delay functions (VDFs) which describe the

Table 1. Summary of existing TTR forecast models based on de Jong and Bliemer (2015)

#	Name of model (nation)	Expression
1	Arup 2003 (UK)	$std = 0.148 MD^{0.781} D^{-0.285} t$
2	NZTA 2010 (New Zealand)	$std = s_0 + (s - s_0) / (1 + \exp[a (F/C - 1)])$
3	Kouwenhoven et al. 2005 and Kouwenhoven, Warffemius 2016 (The Netherlands)	$std = a + b MD + c \ln (MD+1) + d D$
4	Eliasson 2006 (Sweden)	$std = t \exp(a + b (MD-1) + c (MD-1)^3)$
5	Geistefeldt et al. 2014 (Germany)	$std = a MD^b$

mean-delay based on the saturation level and the free-flow travel time of a link. In this way it would be easy to calculate an index of TTR (standard deviation) within a standard macroscopic transport model and also to incorporate reliability into the choices of travellers. In this paper it was also intended to develop this new method and compare the results with those of the existing models.

3.1. The concept

On a macro transport modelling level, the widely-used VDFs are describing the expected values of travel time (or mean delays). These functions provide fairly good estimations and a better way of estimation is still to be discovered. However, existing urban transport models usually does not calculate the standard deviations of these expected travel times (so that TTR). Therefore, and based on the review of existing TTR forecast models, the essential concept was to develop a similar function to VDFs to determine the relationship of traffic volume and TTR. With such a function TTR could be forecasted for 'do-nothing' (reference) and 'do-something' (project) cases during a transport modelling procedure. As reliability is generally affected by the level of congestion, i.e. the F/C ratio, a universal parameter of traffic state has been chosen as an explanatory variable for two reasons: (1) it is easy to calculate it in a transport model; (2) it can purely represent the level of congestion without using other estimated and interdependent values such as mean delay. To this end and based on Taylor (2013) a longitudinal data collection was needed in which trip times and saturation levels for given (preferably longer) urban routes were simultaneously measured. In case of the latter, counting the traffic volumes is enough as road capacities are known from design standards. Ultimately, assignment models and economic assessments can use the estimated values of standard deviations.

3.2. Data

In case of the city of Budapest (Hungary) it became possible to carry out the aforementioned experiment due to the so-called 'Easyway' project in which a traffic information system was implemented. A previous paper (Juhász et al., 2016) analysed the speed-flow relationship on urban roads which used the same data, therefore the description of it is based on that paper. On the inner section of M1-M7

motorway and main road No. 6 automatic number plate recognition cameras and variable message signs were installed in 2012 in order to inform the inbound traffic on the real-time average access time of the Danube bridges. Fortunately, the affected area is mostly covered with traffic-counting detectors which made it possible to measure traffic volumes on the road network. Figure 1 shows the measurement area.

A dataset from April 2014 was selected in order to carry out this research. The total number of measurements for the whole month is 525,000 (i.e. those trips for which it was possible to register both the travel time and the related traffic volumes). The automatic travel time measurement procedure classified the data into 6 and 15-minute time intervals for peak (from 4 a.m. to 5 p.m.) and off-peak periods respectively. Traffic volumes were registered by detectors in time intervals of 4, 8 and 10 minutes for peak (from 4 a.m. to 10 a.m. and from 12 a.m. to 6 p.m.), intermediate (from 10 a.m. to 12 a.m.) and off-peak (from 6 p.m. to 4 a.m.) periods respectively.

As travel time values were automatically rounded to minutes, whole routes were analysed because these rounded values are not characterising shorter road sections adequately. That was a severe limitation this research needed to face. Therefore, it was also needed to calculate route-level F/C values based on sectional ones. However, analysing whole routes has the advantage, that the results are easily comparable with drivers' expectations, as they think on the route level rather than on short section level.

3.3. The methodology

As transport modelling usually tries to represent a common, average setting of the transport system, its conclusions are mostly limited to generalized statements. While it would certainly worth to analyse the data of diverse time periods such as seasons or specific days, however, this study needs to follow the underlying generalization of transport modelling. Due to this consideration the dataset was filtered and days from Friday to Monday have been excluded.

As a first step the statistical solidity was checked for each measurement (for both the travel times and the traffic volumes). Due to failures or obviously wrong measurements some traffic counting locations were excluded from the analysis.

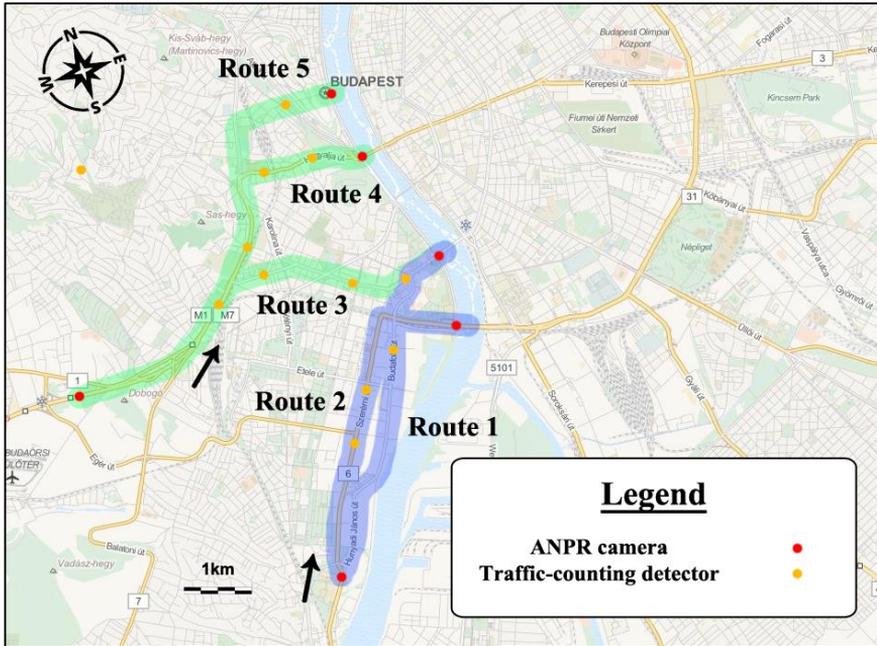


Fig. 1. The map of the measurement area (based on Juhász et al. 2016)

Extreme events were also excluded from the dataset based on Kouwenhoven and Warffemius (2016) in order to focus purely on day-to-day variations and to maintain consistency with underlying methods, as speed-flow curves and VOR stated preference surveys also exclude these extremes. Following the suggestions of the study, a boundary of exclusion was set to three times the raw standard deviation of travel times. As a consequence of filtering the extreme events (1,750 observations in total) a 3% decrease in the mean travel time and 15.4% in the standard deviation have been observed.

This study presents its results based on the data of route no. 4 as it had the most reliable dataset. The results were fairly similar on the other routes, but some lack of data and slight errors affected them. In case of route no. 4 around 80,000 measurements were available throughout the workdays that were involved in the analysis. The data coverage is shown by Figure 2. One can note that at least 100 measurements can be found in each saturation group of 5% and also in each ‘hour of the day’ group (the latter indicates the hour in which the measured car passed the starting point of the route) - Juhász et al. (2016).

Route no. 4 is a major – transit – route which is about 6.1 km long, starts at the end of a motorway and ends in the city centre. The selected route consists of different major road types. It means that minor and residential roads are not included but this should not be a problem as TTR is basically relevant on major urban roads. Speed limits are varying throughout the route (100-70-50 km/h as someone approach the city centre). In terms of intersections, there are six locations with traffic lights in a 24/7 mode and four pedestrian crossings without any signalization. Traffic volume is around 38,000 vehicles per day per direction on an average, from which around 20% is transit traffic. The morning peak is stronger, therefore the inbound direction was analysed in this work (see Figure 2) - Juhász et al. (2016)

In this study – contrary to other ones – the travel time dataset was not divided into specific (e.g. 15-minute) time intervals. Instead, F/C groups were created to calculate mean travel times and standard deviation as a relationship was sought between F/C values and standard deviation of travel times.

One of the major issues of this research was the difference between observed and modelled saturation ratios.

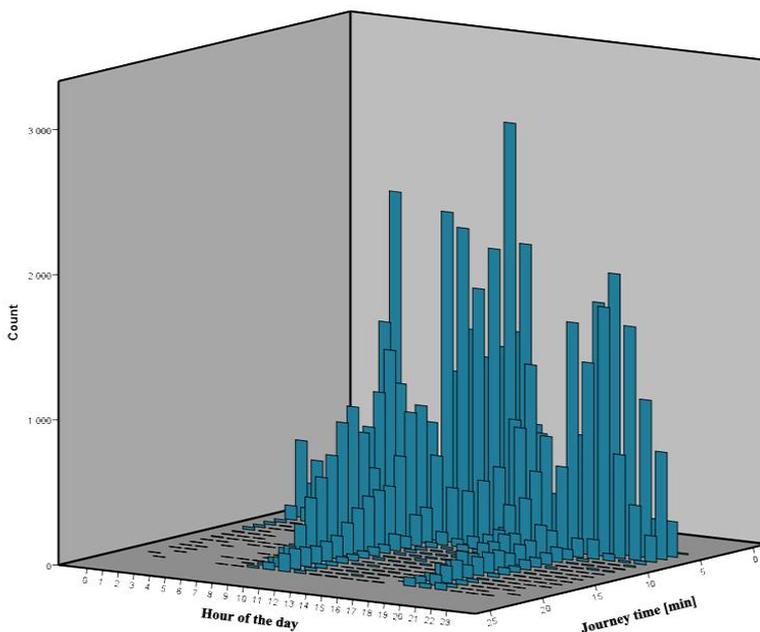


Fig. 2. The number of measurements according to the time of the day and journey times for route no. 4

Observed ones are calculated based on the actual traffic volume, but modelled values are in connection with travel demand, which means the number of users that are intended to use the road. The whole problem can be well-illustrated by the difference between two diagrams: the speed-flow diagram (the so-called fundamental diagram on the basis of Greenshields (1935) and Stamos et al. (2015)) and the standard VDF applied in transport modelling (see Ortúzar and Willumsen, 2011). In order to give an example, take a measured F/C value of 0.7 which can mean 0.7 in modelling if there is no congestion (labelled as ‘normal state’ and illustrated by point A in Figure 3) and a value above 1 if there is congestion (labelled as ‘congested state’ which is illustrated by point B). One can note that these traffic states are referred by different names in the literature: ‘ordinary congestion’ and ‘hyper-congestion’ are also in use respectively.

The task was to: (1) distinguish normal (not congested) states from congested states on the speed-flow curve; (2) find the proper F/C value in a modelling sense which can adequately represent a given congested state (point B’ in the figure). In order to accomplish, first and foremost the validity

of the speed-flow relationship for urban routes should be clarified. It was done in another part of this research and the results can be found in another paper (see Juhász et al., 2016). The applied method and relevant consequences are summarised in the following paragraphs.

‘Normal’ and ‘congested’ traffic states were distinguished with a method that analyse the dataset in a time sequence (going through each time step of the measurement). The classification method was defined based on the theoretical shape of the speed-flow curve (assuming that it is valid for this case based on Woollett et al. (2015) and Vasvári (2015)). The theory suggests that a traffic state should be ‘normal’ if the F/C ratio and the mean travel time are changing in the same direction compared to the previous time step. And all other states should be labelled as ‘congested’ ones. Note that speed values of the fundamental diagram can be easily converted into journey times as the length of the route is given. However, within the literature congestion or congested states are often defined based on absolute or relative increases in travel times (e.g. in Eliasson, 2006).

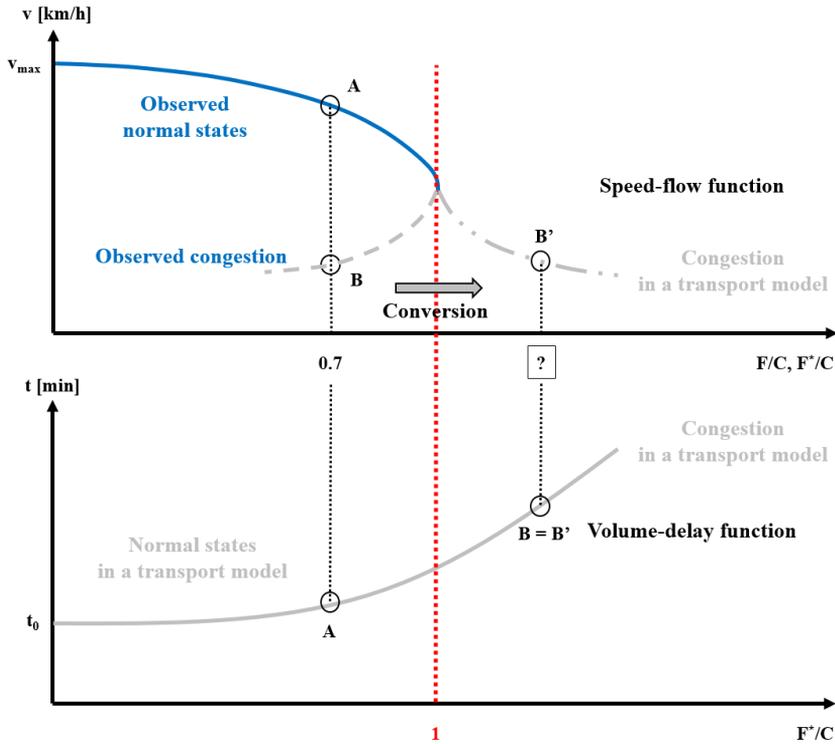


Fig. 3. The connection of the speed-flow relationship and the volume-delay function

In this work congested travel times cannot be analysed in a framework in which the state of congestion is defined on the magnitude of travel time which is a dependent variable. Therefore, this research defines ‘normal’ and ‘congested’ states based purely on the sign of the change. In this way the classifying model is not overdetermined compared to the previously mentioned methods.

As it was needed to analyse longer routes it was a difficult issue how to calculate the route-level F/C ratio in a given time interval. Each traffic counting stations characterise a shorter route section and if congestion starts to evolve in a section it needs time to spread to other sections. It is similar to the well-known wave propagation phenomenon from traffic flow theory (see Daganzo, 2007). Along the route three sections have been distinguished and characterised by traffic counting detector(s). Road capacity values were calculated based on the location of detectors. Having tried different methods to characterise the saturation level of the route,

eventually the maximum of sectional F/C ratios were used. There were two reasons for that: (1) differences between sections were limited to 15-20%, and (2) results were more reasonable (e.g. Bureau of Public Roads - BPR function fit better) compared to taking the minimum or the average of F/C ratios. An underlying reason is the fact that the analysed sections are quite long ones with a length from 1.2 to 3 kilometres and they are strongly interdependent as it was observed that a heavily congested section can significantly influence the travel time on the whole route. It should be noted that the location of the maximum sectional F/C ratio is dynamically changing, which is quite natural.

Based on the distinguished traffic states it was eventually found that the fundamental diagram can also be used in an urban environment. However, there are some uncertainty concerning the transition states around the boundary of normal and congested states. After distinguishing measured F/C values based on whether those representing ‘normal’ or

‘congested’ traffic states, it was needed to transform congested ones. A conversion method was needed as observed F/C values that cannot be higher than 1 can describe congestion (e.g. a 0.7 F/C value can mean a slightly congested state), but in transport modelling congested states are measured with values above 1. Due to the validity of the speed-flow relationship, the transformation has been done using a “mirror” function which consists a contraction as well. The empirical background of the function comes from the difference between observed and modelled traffic states illustrated by Figure 3. A function that describes the conversion between observed and modelled saturation for the congested states was defined based on the VDF estimations of Juhász et al. (2016). It is presented by Equation (1):

$$F / C_{mod} = 1 + \frac{1 - F / C_{obs}}{c}, \tag{1}$$

where the modelled and observed saturation levels are represented by ‘F/C_{mod}’ and ‘F/C_{obs}’, and there is a correction (or contraction) parameter labelled by ‘c’. Its value was calibrated around 1.2 during the VDF experiments.

4. Results and discussion

The process of the aforementioned saturation level correction resulted in a dataset consisting of a mean travel time and a standard deviation value for each

F/C group. Based on the data a BPR function (a standard type of VDF, see Equation 2) was calibrated based on both ‘normal’ (not congested) and ‘congested’ states:

$$t = t_0 \cdot \left(1 + a \cdot \left(\frac{F}{C} \right)^b \right). \tag{2}$$

Within function (2) ‘t’ is the mean travel time, while ‘t₀’ is the free-flow travel time. The estimated constant parameters are the following: a = 0.841, b = 2.52. During all estimations the dataset was grouped based on the F/C ratios in 5% intervals. Figure 4 illustrates the accuracy of the VDF estimation.

Based on the standard deviation values a function can be developed, which can describe the relationship between the standard deviation of travel times and F/C groups. Setting out from the shape, a standard cubic function turned out to fit the data points as three stages of the function can be observed. For very low F/C ratios the standard deviations of travel times are higher and decrease up to around the saturation level of 0.35 where the function has a local minimum. For higher F/C values the standard deviation is constantly increasing to the local maximum point (around 1.25 F/C value) from which there is a slight decrease. The reason is quite logical and well-described in the literature (see de Jong and Bliemer (2015) or Eliasson (2006)).

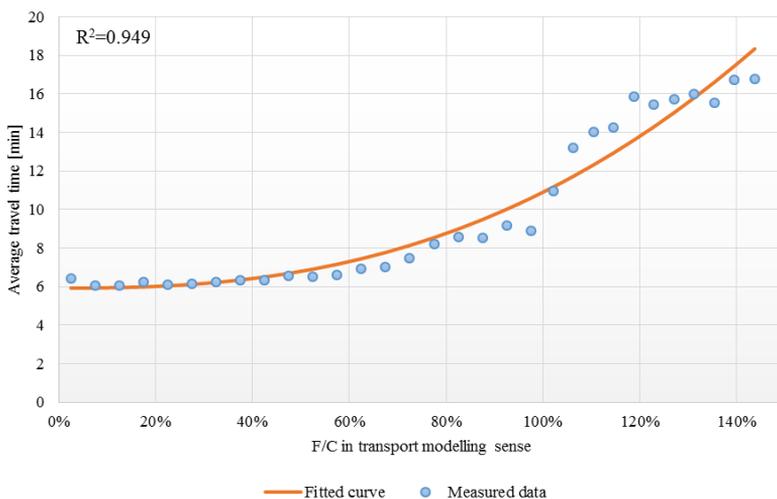


Fig. 4. Measured and modelled mean travel times (route no. 4)

For very low traffic volumes the traffic state could be ‘instable’ and the variability of travel times might be higher than normally expected. As traffic volume increases, the traffic state is becoming ‘stable’ up to the local minimum point. From this point the traffic starts to become heterogeneous and travel time variability is increasing with the saturation level. Then towards a heavy congestion state traffic is about to become homogeneous due to queuing, in which state the variability of travel times is decreasing. The process is also illustrated by the density plots of the travel time observations for specific saturation groups (see Figure 5).

One can note that the higher standard deviation values in case of very low saturation levels should be disregarded in the forecasting model as the higher variability of travel times is presumably coming from the higher level of freedom in choosing cruising speed. It means that this higher variability is reflecting a nearly free-flow traffic state in which the heterogeneity of car drivers is more perceptible. Despite the phenomenon is not correlated with congestion it is a feature of the proposed model. However, this issue can yield further considerations, analyses and possible modifications of the model. Then standard deviation is described by Equation (3):

$$std = a \cdot \left(\frac{F}{C}\right)^3 + b \cdot \left(\frac{F}{C}\right)^2 + c \cdot \left(\frac{F}{C}\right) + d \cdot t_0 \quad (3)$$

As a result of a multiple linear regression analysis the estimated parameters are the following: $a = -2.532$, $b = 6.515$, $c = -3.588$ and $d = 0.298$. Figure 6 illustrates the accuracy the forecasting model of the standard deviation (TTR). It should be stressed that all measured data (travel times and standard deviation) were calculated for F/C groups (steps of 5%) as the forecasting problem was approached from a transport modelling point of view in which the saturation level (F/C ratio) has the largest influence. The standard deviation function has a point of inflection at around 0.85 F/C ratio, which seems to be theoretically appropriate as the boundary between ordinary and hyper-congestion should be somewhere around 1 but a lower value is also possible. It should be also stressed out, that the shape of the function comes from the above mentioned theoretical considerations (i.e. to adequately describe the phenomenon) and not because it provides the best fit to the data points.

Kouwenhoven and Warffemius (2016) suggests to not only calculate the raw standard deviation but to use a correction for the expected travel times. Then the deviation of the real travel times is calculated from the predicted travel times. In this study mean travel times and standard deviation values are calculated for F/C groups in which there can be data from different days and time periods which makes it impossible and unnecessary to determine expected travel time values. Therefore, this correction was not relevant for this research.

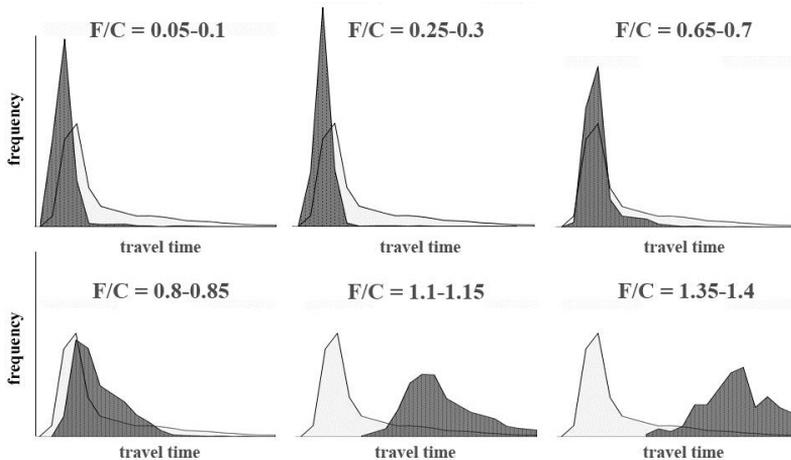


Fig. 5. Frequency of observed travel times for different F/C groups (route no. 4, dark grey – actual F/C group, light grey - total)

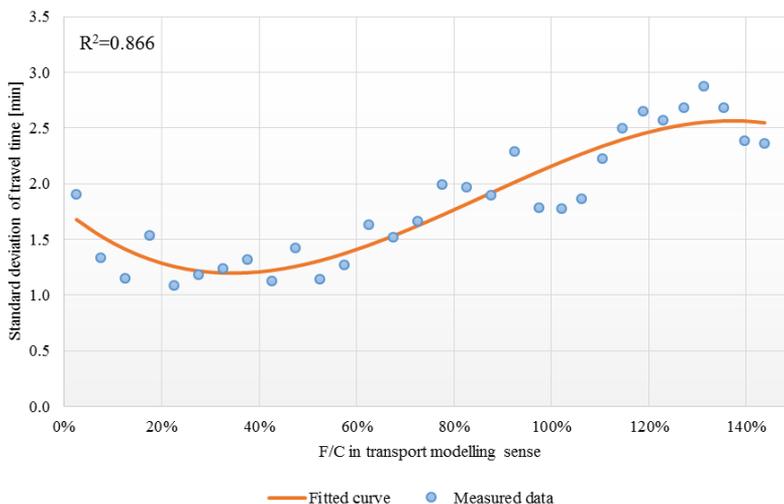


Fig. 6. Measured and modelled standard deviation of travel times (route no. 4)

The role of route length as an explanatory variable for standard deviation was also analysed but it was found that based on the data from Budapest it is not significant. However, other studies proved that it can also have an important role as on the one hand congestion is more likely and on the other hand delays could be compensated along a longer route. In this study there was not a big difference between the distances of the analysed routes and that might be a reason why length has not proved to be a significant factor.

Alternatively, other TTR forecast models were tested on the available dataset. This required another approach of analysis as most of the other methods are using mean delay (ratio of mean travel time and free-flow travel time) as an explanatory variable for standard deviation. The study of Eliasson (2006) seemed to be especially interesting to compare the results with. So based on its method, our daily data was split into 30-minute time periods. One can note that Eliasson used a 15-minute interval based on the implicit assumption that travellers base their decisions on this 'time resolution'. However, due to the measurement intervals previously mentioned, only a 30-minute split was possible. Applying this splitting, 672 data points could be created for the same 14 workdays we analysed before.

Analysing the relationship of absolute standard deviation and mean travel time as well as relative standard deviation (standard deviation divided by

mean travel time) and relative increase in travel time (travel time divided by free flow travel time minus 1), the same findings can be found as by Eliasson (see Figure 7):

- standard deviation in absolute terms tends to increase with travel times;
- relative standard deviation increases with congestion but decreases for higher congestion levels.

A comparison of forecast methods was also carried out based on mean delays calculated by the calibrated VDF for each 5% F/C group as it would be normally measured during a project assessment. After some calibration model fit was adequate for all methods with R^2 values around 0.7. Only the NZTA model showed a lower value of 0.55. Results are illustrated by Figure 8 and they show that the method developed on the Budapest case has the best fit with a 1.5 sum of squared differences. The other models are slightly underestimating the standard deviation for lower F/C values and sums of squared differences are in the range from 1.9 to 2.2. It does not mean that the proposed model is universally better as the proposed model was designed based on the Budapest case and it is not surprising that it has the best fit. However, the results show that TTR can be forecasted based purely on the saturation level with similar accuracy to the existing models that predicts TTR based on mean-delay.

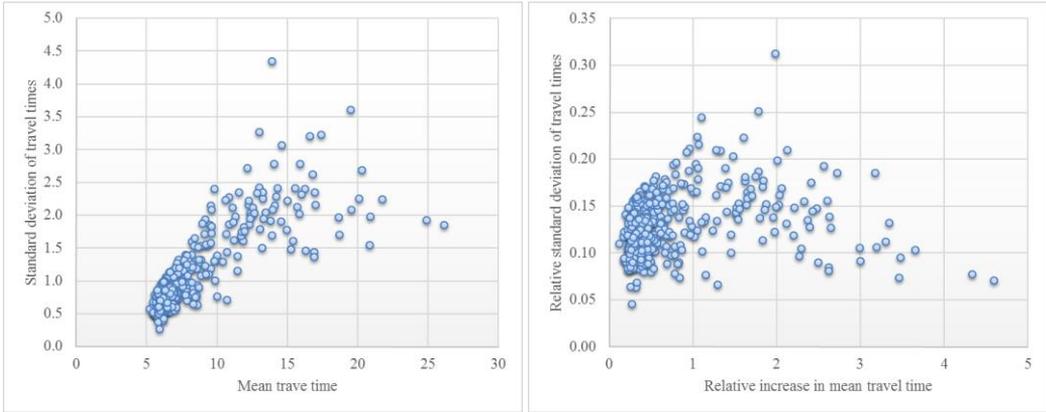


Fig. 7. The relationship of standard deviation and travel time (route no. 4) – each dot representing a 30-minute time interval

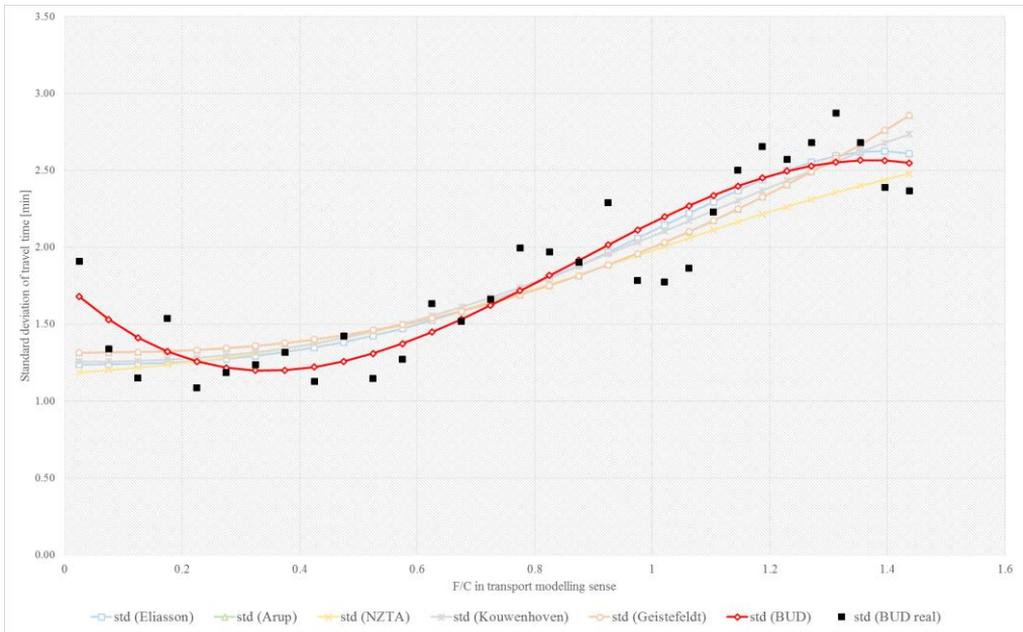


Fig. 8. Comparison of TTR forecast models (route no. 4)

5. Conclusion

Assessment of TTR as a fundamental factor in travel behaviour has become an important aspect in both transport modelling and economic appraisal. Improved reliability could provide a quite significant economic benefit if it is calculated in CBAs for which the theoretical background has already been set (definition of VOR). However,

methods to forecast TTR as well as travel behaviour models including TTR effects are rather scarce and there is a need for development. Another important aspect could be the influencing factor of reliability in travel demand management and related policy-making as restrictive road projects (e.g. traffic calming projects) might decrease TTR in the whole transport system which besides the positive effects

of these interventions could mean an undesirable loss for the society. In addition to these, forecasting TTR might present new opportunities in the provision of real-time traffic information. Therefore, this paper aimed to analyse reliability, focusing exclusively on urban road transport as it is presumed that the issue is mostly significant in this setting. However, it is quite likely that assessment of TTR can be relevant in other settings such as long-distance or public transport trips as well.

This research pointed out that besides existing mean-delay-based models, TTR can be forecasted based on the volume-capacity ratio with adequate accuracy. The novelty of this result is that the issue of interdependence (endogeneity) of previous models can be resolved. Then it becomes possible to forecast TTR independently of travel time (or mean delay) which makes it easier to include TTR in travel behavioural models.

However, due to the limitations of travel time measurements and data (detailed in section 3.2) the proposed model and all of the results are based on route-level analyses with certain constraints (e.g. to use the maximum F/C value to characterise the saturation level of the route). In spite of the facts that (1) in another paper of the authors the validity of the speed-flow function was proved for urban routes and (2) other functions that forecasting TTR on a link-level provides very similar results, the proposed model is only valid for the route-level and not necessarily valid for its shorter sections (links) with different technical parameters. It should be noted that routes may consist of different link types and TTR at given F/C ratios might vary greatly across these types. However, the result of this paper suggests that the base model described in section 4 could still be used with proper calibration in appraising urban road projects.

Anyway, as a consequence of the shortcomings of this research, it should be also stressed that further analyses would need to check the validity and the universality of the results. Providing that sufficient data was available, it would be preferred to do the estimations on a link-level and to assess the difference between cities, road types, seasons, days, etc. Plus, a following further research might be able to develop TTR forecasting methods for urban public transport trips and cycling.

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