INCORPORATING UNRELIABILITY OF TRANSIT IN TRANSPORT DEMAND MODELS: THEORETICAL AND PRACTIAL APPROACH

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ABSTRACT

Nowadays, transport demand models do not explicitly evaluate the impacts of service reliability of transit. Service reliability of transit systems is adversely experienced by users, as it causes additional travel time and unsecure arrival times. Because of this, travelers are likely to perceive a higher utility from higher reliable transport systems. In order to mimic and measure the impacts of service reliability on a transit demand model a three-step approach is proposed using intelligent transport systems data. The approach consists of determining the probabilistic distribution of transit trip times, defining demand patterns and estimating the average impacts of unreliability per passenger. This approach was successfully tested on the model of the city of Utrecht in The Netherlands. By adding service reliability as a variable parameter of transit systems the results of the demand model improved showing that the absolute difference between the observed and the estimated demand decreased by 18%. In addition, the proposed approach allows measuring the effects of expected changes in level of service reliability on traveler behavior. Finally, the authors have identified future research topics required to improve the estimation of those effects.

1. INTRODUCTION

Service reliability has been researched for a long time for both car traffic and transit, studying its cause and measuring the magnitude of its consequences. The consequences of unreliability have been statistically analyzed in terms of probability of occurrence and related impacts on operations and infrastructure performance. It is still not common practice, however, to include service reliability as an explanatory variable in transport demand models in order to measure its impacts on the demand component of the transport network (*1*).

Transit services have proven to represent sustainable transport solutions for mobility. Attention for studies related to transit quality and efficiency is growing for its potential to increase its cost-effectiveness in order to prove financial feasibility. In particular service reliability has been pointed out as a recommended direction to improve transport models (*2*) showing statistical significance to explain passenger behavior (*3*) and as a consequence nowadays several transit projects aim at improving service reliability.

Transit service reliability is the certainty with which service aspects (such as travel time, departure time and arrival time) match the scheduled aspects as perceived by the user (*4*). Both passengers and operators benefit from enhanced service reliability by predictable travel times and by lower costs respectively.

Due to the lack of a proper theoretical framework that enables evaluating and predicting passenger impacts in a network context, commonly service reliability is not taken into account in transport demand models nor in most cost benefit analyses (*5*). To the authors' knowledge currently transport demand models assume that transit is 100% punctual and the impacts of unreliability are only implicitly incorporated. This limits the prediction accuracy of the models and in addition it is not possible to estimate the impacts of expected changes of service reliability on transport demand and as a consequence on (societal) costs and benefits (*5*).

Developments and improvements of data availability in transit, such as automated vehicle location (AVL) and automated passenger counting systems (APC), enable detailed research in order to develop measures to improve service reliability at all levels of transit planning and operations as shown in (*4, 7,8* and *9*).

In this paper, a methodology is presented to integrate the estimation of the effects of service reliability on a static transit demand model. This project is a first step to harmonize standards in demand modeling concerning transit service reliability effects. The paper is organized as follows: the next section presents the state of the art of the impact of service reliability in discrete choice modeling. Section three provides the proposed approach developed to incorporate the effect of transit service reliability in a transport demand model. In section four the methodology is applied to a case study in the city of Utrecht, The Netherlands. Section five provides a discussion of the results and future research and finally conclusions are presented in section six.

2. STATE OF THE ART OF MODELING SERVICE RELIABILITY

The level of service reliability affects several choices made by travelers, such as mode, route and departure time. In literature, much research is available with regard to passenger choices as a function of service reliability. According to (*10*) and (*11*) service reliability of transit systems is considered critically important by most transit users because passengers are adversely affected by the consequences associated with unreliability such as additional waiting time, late or early arrival at destinations and missed connections, generating a disutility associated to the transport alternatives in question.

There are two main approaches to model the effects of service reliability known as the mean-variance approach and the scheduling approach (*3*). The mean-variance approach represents the effects of service reliability on mode and route choice as a function of the mean travel time, additional travel time and variance of travel time caused by unreliability, while the scheduling approach studies the impact of service reliability on the departure time choice as a function of the probability of early or late schedule adherence. To the authors knowledge there is no generalized theoretical preference for one of these two approaches. However, in order to implement service reliability in four step models the mean-variance

approach is suggested (*12*). The mean-variance approach consists on adding attributes of service reliability to the transit generalized cost function along with other transit attributes such as distance, travel time, waiting time, fare, and number of transfers.

For this research the destination and mode choice are modeled simultaneously through a gravity model using a deterrence function proportional to the generalized cost function. To model the variation in preference for route choice the Zenith method for transit assignment as described in (*13*) is used with a logit formulation dependent on the generalized cost function including service reliability attributes.

The following subsection provides an explanation of the attributes of service reliability to include in the transit generalized cost function in order to explain passenger behavior in a transport demand model.

2.1 Service Reliability Impacts on Passengers

Unreliability causes longer and uncertain passenger journeys (*4*). Figure 1 shows the passenger trip chain and its relation to vehicle processes. Transit vehicles are scheduled to leave a stop at a departure time with a time interval from its predecessor known as headway. The successive part of the trip is the in-vehicle time. In this phase, the passenger time aspects are similar to those of the vehicle. If a passenger makes a transfer, a new waiting time for the passenger will arise. This new waiting time is affected by the planned synchronization between the two connecting vehicles, the actual performance of this synchronization and the waiting regime of the connecting vehicle (*14*).

The magnitude of the delays caused on the passenger waiting time by the adherence to the schedule depends on the passenger arrival pattern. If passengers arrive randomly, the headway between successive vehicles determines the waiting time (*15*). If passengers arrive in conformance with the scheduled departure time, the deviation of the schedule adherence affects the waiting time (*6*). For example if the vehicle departs earlier than scheduled, passengers have to wait a full headway.

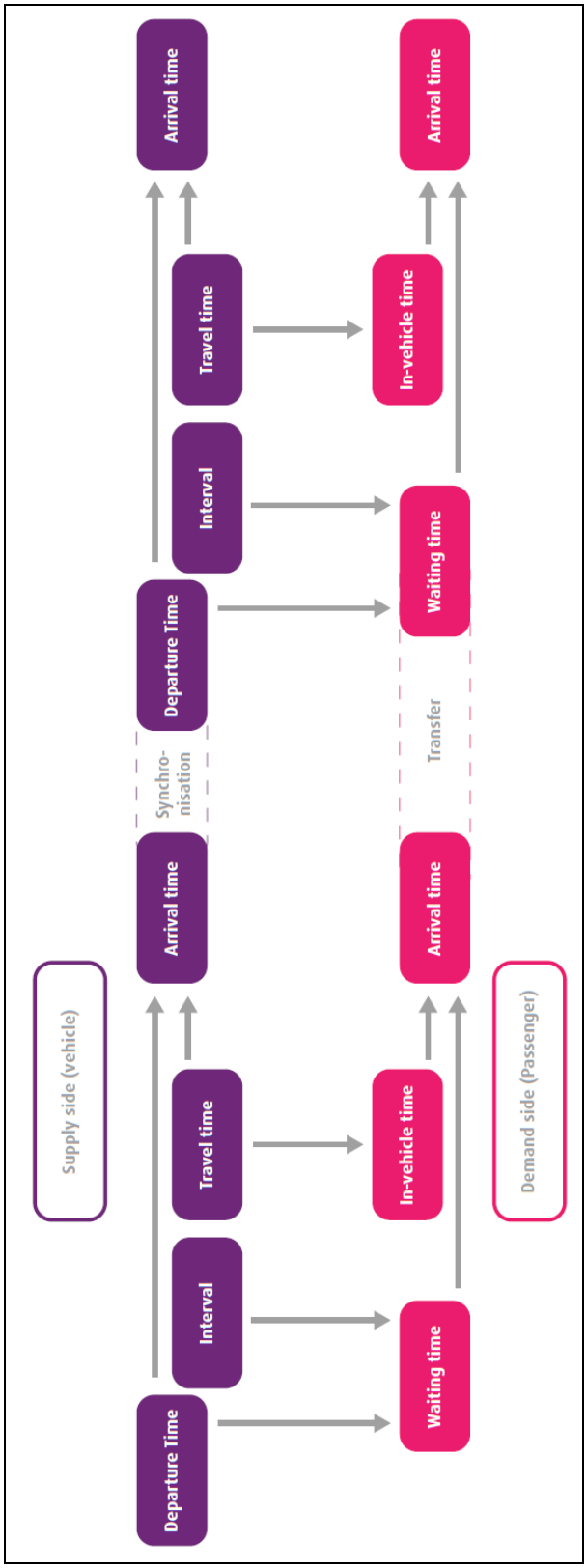

FIGURE 1 Interaction of passenger trip chain (below) and vehicle characteristics (above).

Due to the stochastic nature, the impacts on individual passengers are variable; however in an aggregated way passengers mainly experience the following three effects (*16, 17* and*18*):

i. Impacts on duration of travel time components, being in-vehicle time and waiting time, which lead to arriving early or late;

ii. Impacts on passenger perception of the transit mode depending on the variability of travel time components, being departure time, arrival time, in-vehicle time and waiting time, which lead to uncertainty of the actual travel time;

iii. Impact on the probability of finding a seat and of crowding, affecting the level of comfort of the journey.

This paper focuses on the first two aspects, namely the travel time related aspects. More detailed research on crowding may be found for instance in (*19*).

To calculate the passenger effects of unreliability actual departure times per stop, actual dwell times, actual headways and actual trip times available by AVL systems or forecast tools such as illustrated in (*20*), are translated to passenger effects using APC data.

In an aggregated way, service reliability leads to an extension of passenger average travel time, since average waiting time per passenger may be extended due to irregular, early or late vehicles. To express the effect of service reliability on passengers an indicator called average additional travel time per passenger is introduced (*18*). The second effect of service variability is the variance of passenger travel time.

Figure 2 illustrates the average additional travel time per passenger (T^{add}) and the variability of actual travel time relative to the scheduled travel time (4). It is important to note that $T^{journey,\ sched}$ consists of the scheduled waiting time and the scheduled in-vehicle time. The latter is directly related to the scheduled vehicle trip time and is thus controllable being a function of schedule design (e.g. tight or loose schedule). Figure 2 shows that the additional travel time is distributed, due to variability of the operations. In some cases individual passengers may even arrive earlier than scheduled, when waiting and or in-vehicle time is shorter than planned.

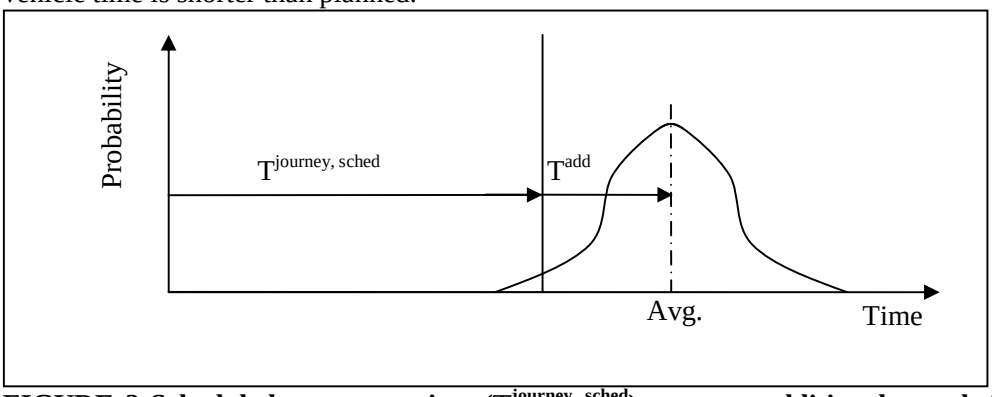

FIGURE 2 Scheduled passenger time ($T^{journey,\ sched}$), average additional travel time per passenger (T^{add}) and variance.

Table 1 shows a matrix of four components that represent the passenger impacts of service reliability (*4*). However, if operations are not controlled in any way (e.g. by holding vehicles), no additional in-vehicle trip time arises (compared to the average trip), so only the three remaining components shown in the matrix with the numbers 1, 2 and 3 are investigated.

TABLE 1 Passenger Impacts of Service Reliability

	Additional travel time	Travel time variance
In-vehicle time	*na*	*2*
Waiting time	*1*	*3*

Finally the passenger impacts of service reliability are represented by three attributes that are added to the generalized cost function: additional waiting time, in-vehicle travel time variance and waiting time variance. The proposed generalized cost function is shown in Equation 1.

$$GC = \alpha + \beta_1 d + \beta_2 \left(\hat{T} + \hat{W} + \frac{\beta_3}{\beta_2} v \right) + \beta_4 f + \beta_5 N \quad (1)$$

Where:

GC = generalized cost in €

d = distance in *Km*

$\hat{T}$ = average travel time in *hours*

$\hat{W}$ = $W + T^{add}$; average waiting time in *hours*

v = $v_{in-vehicle} + v_{waiting}$; variance of both in-vehicle and waiting time in *hours*

f = fare in €

N = number of transfers

α = alternative specific constant in €

β_1 = elasticity measure of distance in *€/Km*

β_2 = elasticity measure of travel time a.k.a. value of time in *€/hour*

β_3 = elasticity measure of variance of travel time a.k.a. value of reliability in *€/hour*

$\frac{\beta_3}{\beta_2}$ = reliability ratio

β_4 = elasticity measure of transit fares

β_5 = elasticity measure of the number of transfers in *€/transfer*

In order to calculate the additional waiting time component, two situations have to be distinguished: high frequency transit systems (with random arrivals of passengers at the stop) and low frequency transit systems (with planned arrivals of passengers at the stop).

If passengers arrive randomly, exact departure times and punctuality are not relevant anymore, because passengers do not use a schedule. In that scenario, the additional travel time is calculated using the coefficient of variation (CoV) of the actual headways ($\tilde{H}_{l,j}^{act}$). A generic formulation to estimate the expected waiting time per passenger is given by Equation 2(*15, 21* and *22*), according to the following assumptions:

- The examined period is homogeneous concerning scheduled departure times, trip times and headways (for instance rush-hour on working days in a month);
- The passenger pattern on the line is assumed to be fixed;
- All passengers are able to board to the first arriving vehicle.

$$E(\tilde{T}_{l,j}^{waiting}) = \frac{E(\tilde{H}_{l,j}^{act})}{2} * (1 + CoV^2(\tilde{H}_{l,j}^{act})) \quad (2)$$

Where:

$\tilde{T}_{l,j}^{waiting}$ = passenger waiting time for line *l* at stop *j*

$\tilde{H}_{l,j}^{act}$ = actual headway of line *l* at stop *j*

$CoV(\tilde{H}_{l,j}^{act})$ = coefficient of variation of actual headways of line *l* at stop *j*

If the service is regular, the coefficient of variation equals zero and the average waiting time will be equal to half the headway. In the case of irregular service, the additional waiting time may then be calculated using Equation 3. Assuming no change in the actual vehicle trip times, the total average additional travel time per passenger will be equal to the average additional waiting time per passenger.

$$E(\tilde{T}_{l,j}^{Add,waiting}) = \frac{E(\tilde{H}_{l,j}^{act})}{2} * (CoV^2(\tilde{H}_{l,j}^{act})) \quad (3)$$

Where:

$E(\tilde{T}_{l,j}^{Add,waiting})$ = average additional waiting time per passenger due to unreliability of line *l* at stop *j*

For low frequency services it is assumed that passengers plan their arrival at the first stop of their trip according to the schedule and therefore another method of calculating additional travel time is necessary. Equations 4 and 5 show this method (*6*). Passengers are assumed to arrive randomly within a range of the scheduled departure time minus τ_{early} and plus τ_{late} and if the vehicle departs within this time window it is assumed that passengers do not experience any additional waiting time. Research about empirical values of τ_{early} and τ_{late} is presented in (*4*). It is important to note that there is a difference between driving ahead of schedule and driving late. Driving ahead (i.e. departing before the scheduled departure time minus τ_{early}) leads to a waiting time equal to the headway (H_l^{sched}*;* assuming punctual departure of the successive vehicle). Especially in the case of low frequencies, this leads to a substantial increase in passenger waiting time. Arriving late creates an additional waiting time equal to the delay ($\tilde{d}_{l,i,j}^{departure}$*)*. Just as before, the additional waiting time is first calculated per stop.

$$\begin{cases} \tilde{T}_{l,i,j}^{Add,waiting} = H_l^{sched} & if \quad \tilde{d}_{l,i,j}^{departure} \le -\tau_{early} \\ \tilde{T}_{l,i,j}^{Add,waiting} = 0 & if \quad -\tau_{early} < \tilde{d}_{l,i,j}^{departure} < \tau_{late} \\ \tilde{T}_{l,i,j}^{Add,waiting} = \tilde{d}_{l,i,j}^{departure} & if \quad \tilde{d}_{l,i,j}^{departure} \ge \tau_{late} \end{cases} \quad (4)$$

$$E(\tilde{T}_{l,j}^{Add,waiting}) = \frac{\sum_i E(\tilde{T}_{l,i,j}^{Add,waiting})}{n_{l,i}} \quad (5)$$

Where:

$E(\tilde{T}_{l,i,j}^{Add,waiting})$ = *average additional waiting time per passenger due to unreliability of vehicle i of line l at stop j*

H_l^{sched} = *scheduled headway at line l*

$\tilde{d}_{l,i,j}^{departure}$ = *departure deviation of vehicle i at stop j on line l*

τ_{early} = *lower bound of arrival bandwidth of passengers at departure stop*

τ_{late} = *upper bound of arrival bandwidth of passengers at departure stop*

$n_{l,i}$ = *number of vehicles i on line l*

Based on the average additional travel time per passenger per stop of a line, the average additional travel time per passenger on the complete line is calculated. To do this, the proportion or percentage of boarding passengers per stop is used ($\alpha_{l,j}$), as shown by Equation 6. Please note that using the proportion of passengers makes the indicator independent of the actual number of passengers.

$$E(\tilde{T}_l^{Add,waiting}) = \sum_j (\alpha_{l,j} * E(\tilde{T}_{l,j}^{Add,waiting})) \qquad with \qquad \sum_j \alpha_{l,j} = 1 \tag{6}$$

Where:

$\alpha_{l,j}$ = *proportion of passengers of line l boarding at stop j*

The following section describes the proposed approach to obtain to translate operational data into the reliability attributes described on this section in order to be able to estimate the impacts of service reliability in a transport demand model.

3. THREE-STEP APPROACH

The objective in this paper is to incorporate service reliability in transit modeling in a static transport demand model by including the impacts of service reliability on passenger behavior. Therefore a three-step approach is proposed. Figure 3 shows the three steps consisting of:

Step 1: Analysis of transit schedule adherence, using AVL data;

Step 2: Calculation of passenger impacts caused by service reliability, using APC data and determination of the average additional travel time;

Step 3: Translation of passenger impacts into travel time units;

After the three steps are completed, the results are imported into existing static transport demand models that are able to calculate the effects on transit demand and on network performance.

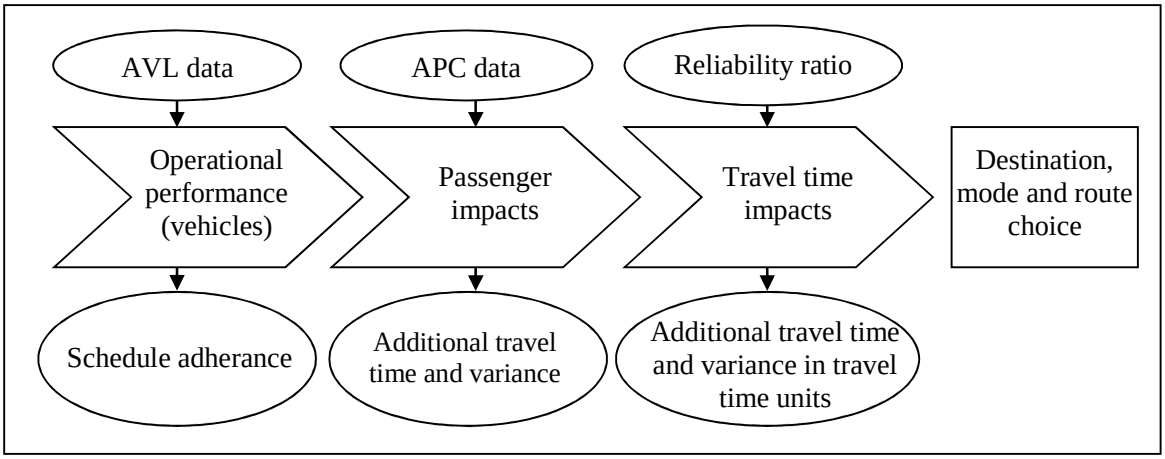

FIGURE 3 Three-step approach for incorporating service reliability in a transport model (consisting of vehicle performance analysis, calculation of passenger impacts and translation of these into travel time units)

Step one provides insight into performance characteristics such as trip time, dwell time and schedule adherence by comparing the schedule to the operational performance obtained from AVL data. Early or late departures and the difference between scheduled and actual headways are determined.

In *Step two* the travel time impacts are estimated by defining the average additional travel time, the waiting time standard deviation and the in-vehicle travel time standard deviation. Depending on the

passenger arrival pattern the average additional waiting time is calculated with either Equations 2 and 3 or 4 and 5.

In *step three* the average additional travel time can be directly added to the *base in-vehicle travel time* (which in the transport demand model is estimated by multiplying the vehicle speed by the travelled distance) providing an *average travel time* ($\check{T}$). The estimation of the standard deviation of the travel time and waiting time depends on the probability distribution function of the travel time pattern. Once the standard deviations caused by the unreliability have been determined they are multiplied by a *reliability ratio* to transform the standard deviations into travel time units. Various values for this reliability ratio are found in literature ranging from 0.70 (*17*) to 1.40 (*23*).

The effects of service reliability as obtained from step three, may be added to the network in the transport demand model. For this purpose the following two strategies are proposed:

Reliability effects at the stop level. Reliability data is calculated for every section between two stops and for every stop. The reliability that is experienced within the in-vehicle travel time is included on each section. The impacts of unreliability that are experienced at the boarding stop are included at the stop in the model as a boarding additional waiting time. Consequently, when searching a route through the transit network, the boarding penalty applies to all passengers boarding at a specific stop, while the section reliability applies to all passengers traversing this section. Therefore, on a journey on one transit line, a passenger experiences exactly one boarding penalty and several reliability effects on all sections. In figure 4a an example trip is shown: if a passenger boards at stop 1 and alights at stop 3, he or she experiences the reliability at stop 1 and 2 and on two sections.

Reliability effects at the line level. A value of reliability is estimated for the transit line as a whole, by using Equation 6. This value is attached to the network as an unreliability factor (F_l), which is applied to the travel time for every transit line. In figure 4b an example trip is shown: if a passenger boards at stop 1 and alights at stop 3, a reliability value proportional to the travel time between those two stops is applied.

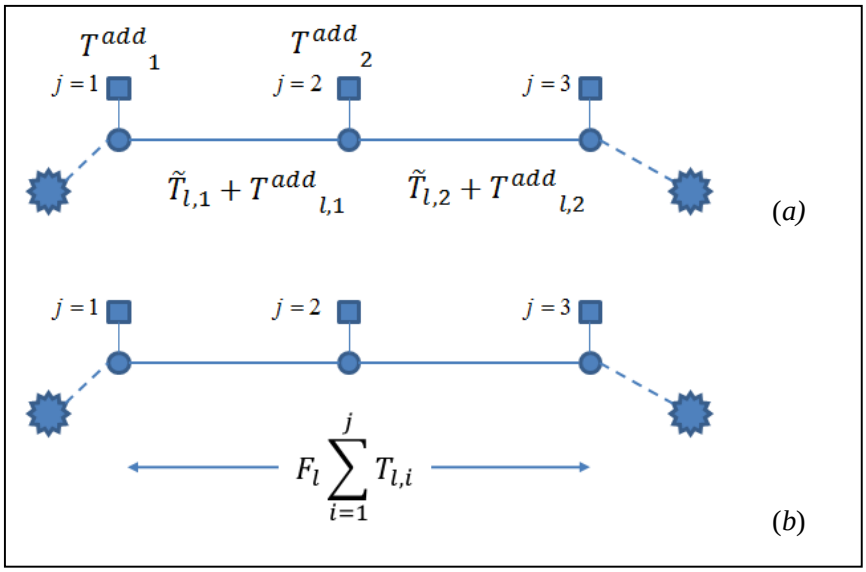

FIGURE 4 Reliability effects at the stop level (*a*) and reliability effects at the line level (*b*).

After the service reliability data is incorporated, existing modeling techniques are applied to calculate expected ridership. The following section describes the application of this approach to a case study in Utrecht, The Netherlands.

4. CASE STUDY: CITY OF UTRECHT

The first approach of incorporating service reliability in a demand model was applied in the transport model of the Utrecht region in The Netherlands. Utrecht is the fourth largest city in The Netherlands with over 300,000 inhabitants and is facing several challenges with regards to transit. Funding is reduced, while quality is required to increase. The main issue while planning and designing transit is predicting the impact of service reliability on demand and its benefits (*5*). Although a transport model (VRU3.0) is available, service reliability was not accounted for until recently.

The VRU3.0 model is a multimodal transport model, containing car, bicycle and transit (train, tram and bus). Its study area consists of the 9 municipalities cooperating in the region of Utrecht, with an influence area that covers the Netherlands and some parts of Belgium and Germany. It contains 4,400 transportation zones, approximately 50,000 links, 5,000 transit stops and 900 transit lines.

To deal with the research question concerning service reliability the proposed three-step approach was applied as follows.

The first step is to analyze historical operations with AVL data. AVL systems are of great help to provide databases of historical performance with regards to travel time and reliability and APC data allows obtaining an exact demand pattern over distance and over time. Although such data has already been available for many operators, it is just since recently that this valuable data is also becoming available to Dutch transit authorities, researchers and developers. Most transit operators and authorities are involved with the initiative called *Transit Information without Borders* (GOVI in Dutch), aiming at making a wide range of transit information available from planned timetables, fares, vehicle location and punctuality (*24*).

GOVI was designed to facilitate data communication between vehicles and the land side enabling dynamic passenger information. An additional benefit is that all the actual and scheduled vehicle positions and times are logged in a database. Although this database was not the objective of the GOVI system, it is extremely helpful to monitor and analyze transit performance through statistical analysis making it possible to compute travel time distributions. Figure 5 shows an example of the processed data.

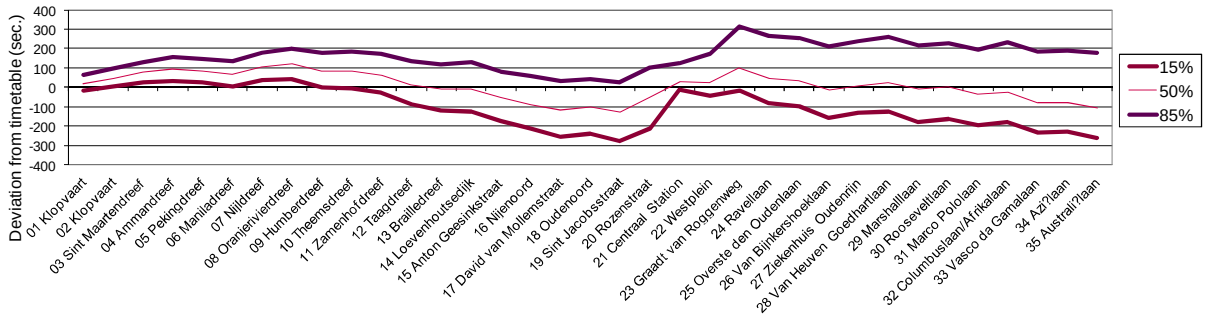

FIGURE5 Example graph, punctuality development, bus line 7 Utrecht, evening rush hour.

The second step is to transform the findings of step one into the average additional travel time and standard deviations. Depending on the type of transit line and the passenger arrival pattern Equations 2 and 3 or 4 and 5 were used to calculate the average additional waiting time. The standard deviation of additional waiting times was calculated as suggested in (*11* and *25*) and the standard deviation of in-vehicle travel time is derived from operational data of the vehicle trip time variance assuming a normal distribution.

In order to estimate the reliability ratio (step three) for this study the value of time (VOT) and the value of reliability (VOR) were used. The values are taken from (*26*) which were corrected by inflation to year 2011, as shown in Table 2.

TABLE 2 Value of Time and Value of Reliability in 2011

Travel purpose	Value of time (€/hour)	Value of reliability (€/hour)
Business	10.00	14.00
Commuter	17.44	24.42
Other	6.33	8.86

This survey states that service reliability is valued 40% higher than travel time. Using these insights, the values of standard deviation where multiplied by a 1.4 factor to be added in travel time units to the generalized cost functions of the demand model. The waiting time portion of the travel time includes now the reliability effects consisting of: scheduled waiting time, average additional waiting time and additional waiting caused by variance.

Similarly, in-vehicle travel times were calculated, consisting of scheduled in-vehicle time and additional in-vehicle travel time caused by variance. After all the calculation of new waiting and in-vehicle times for all stops and links were performed both strategies were tested by incorporating these values in the transport model in the generalized cost matrix for all origin and destination pairs. Finally regular calculations on expected transit demand were performed.

This approach is one step towards a full incorporation of service reliability in transit modeling. The next section presents the results from both approaches and demonstrates the success of this method.

5. DISCUSSION OF RESULTS

To illustrate the added value of this approach, the results of the synthetic model (the model results before calibration) with and without taking service reliability impacts into account are compared. These results indicate that the explanatory power of the model has changed and the method was beneficial.

For an area in the southern part of the Utrecht area, mainly consisting of the town of Nieuwegein, we compared the synthetic model results with 24 count values, using both strategies to incorporate reliability. Data was available for the buses and tram lines operated by the region of Utrecht. Below, the main findings of applying the three-step approach are presented. Table 3 summarizes them.

TABLE 3 Results of applied approach (including service reliability) in Utrecht model compared to case without service reliability

Impacts	**Strategy 1** *Reliability effects at the stop level*	**Strategy 2** *Reliability effects at the line level*
Transit counts Improved fit Worse fit	 15 9	 13 11
Absolute difference observed values and model results	18% improvement	No improvement
Other impacts	Possibility of calculating impacts of improved service reliability	Possibility of calculating impacts of improved service reliability
Other impacts	Data provision for cost benefit analyses (with regard to service reliability impacts)	Data provision for cost benefit analyses (with regard to service reliability impacts)

Strategy 1: Reliability effects at the stop level
From the 24 transit count values, 15 synthetic model results show an improved fit and 9 results show a worse fit. In total, the absolute difference between observed values and the synthetic model results decreased by 18% (from 3,300 to 2,700; on a total amount of 9,300).

Strategy 2: Reliability effects at the line level
From the 24 count values, 13 synthetic model results show an improved fit and 11 results show a worse fit. In total the absolute difference between observed and synthetic model results is at a similar level of approximately 3,300.

Both strategies show a slight improvement concerning the fit of the synthetic model data to count data. Further, the assignment showed that a shift took place from less reliable bus lines to more reliable tram lines, which is in line with the expectations.

In addition to improved prediction quality, this approach also yields other valuable opportunities. Since we succeeded in incorporating service reliability impacts in the transport model, we are now also able to calculate the impacts of expected changes in the service reliability on transit demand. This is of great help to find optimal choices in both network and timetable design. The third benefit of our approach is that the result of the service reliability impacts on passengers are directly available as input for cost benefit analysis which was hardly possible until now (*5*).

From the literature review, the approach of including both travel time extension and standard deviation in the transport demand model seems the most appropriate choice in static modeling. However, this will be subject to future research.

Research is still needed on the value of the reliability ratio. In this research an estimate based on the ration between the value of time and the value of reliability has been used. However, other researchers found that the variation of this ratio is rather large, depending on the purpose of the trip and / or the socio economical characteristics of the passenger.

Ultimately it is recommended to apply the methodology presented in this article to more transit lines to determine if in general a stop or line approach, or maybe even a mode approach, yields better results.

6. CONCLUSIONS

This paper dealt with service reliability in transit (modeling). Service reliability is considered very important, both from a passenger and an operator perspective. Surprisingly, this quality aspect is not explicitly considered in transport demand models, which limits the prediction accuracy of the models and in addition, it is not possible to calculate the impacts of expected changes in level of service reliability. Finally, service reliability time impacts that are necessary for cost benefit analyses are not available as model output.

In the long term, improvements of transport models will be necessary, but to deal with service reliability and ridership on the short term, we developed a three-step approach to incorporate service reliability when calculating expected ridership. We applied this approach with success in a case study in the city of Utrecht in The Netherlands. The three-step approach consists of analyzing operational performance, calculating passenger impacts and finally transforming these into travel time impacts. Transport models are able to deal with these and therefore all their standard functionalities can be used. The three-step approach proved to be a promising approach for the short term. We will continue our research to deal with service reliability in a more detailed way. To achieve that, utility functions could be adjusted in a way that service reliability will explicitly taken into account in the choice processes, instead of the presented approach where service reliability impacts are translated into travel time units.

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