CHARACTERIZING THE DIFFERENCES ON PUBLIC TRANSPORT TRAVEL TIME RELIABILITY BETWEEN TRAVELLERS AND OPERATORS

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RESUMEN

El objetivo de este estudio es caracterizar la confiabilidad del tiempo de viaje para servicios de transporte público de largo similar, entregando una comparación entre distintos modos y comparando la confiabilidad experimentada por usuarios y entregada por operadores. Se provee evidencia respecto a diferencias significativas en la variabilidad del tiempo de viaje entre modos. Además, esta variabilidad crece con la distancia para todos los modos. Sin embargo, esta variabilidad es siempre menor a 5 minutos para el caso de metro, la cual es difícilmente percibida por los viajeros. Al tomar en cuenta la demanda de cada ruta, la mayoría de los usuarios de metro experimenta los viajes más lentos.
Palabras clave: Confiabilidad del tiempo de viaje; Transporte público; Experiencia de usuarios; Planificación de transporte.

ABSTRACT

This study focuses on characterizing travel time reliability for public transport routes of similar length, providing a comparison between different public transport modes, and comparing travel time reliability experienced by travellers and operators. This study provides evidence of significant differences among travel time variability for trips of similar length and different mode. This variability also increases with travel length for every mode. However, the variability is always smaller than 5 minutes for metro, which could hardly be perceived by travellers. When taking into consideration route demand, most metro travellers experience the slower trips.
Keywords: Travel time reliability; Public transport; Travaller's experience; Transport Planning

1. INTRODUCCTION

Travel time reliability plays an important role in public transport travellers' satisfaction and their perception regarding the level of service, as well as in operational costs (de Jong & Bliemer, 2015). Nevertheless, when planning public transport systems, travellers' behaviour has been usually modelled through traditional variables such as monetary cost, expected travel time and planned waiting time. Other elements such as crowdedness, excess waiting time, and mode/service reliability (understood as the certainty travellers have regarding their travel time, their arrival time or the comfort level they will experience inside the vehicle) are usually neglected from these behavioural models. This could lead us to erroneously predict the demand for new public transportation alternatives.

The availability of large volumes of automated data regarding the operation of public transport systems has increased over the recent years and represents a valuable source of detailed information which, properly processed, allows analysing and understanding the system's operation (Bucknell et al., 2017; Gschwender et al., 2016; Munizaga & Hurtubia, 2016). This type of information usually comes from sensors strategically placed within vehicles (such as GPS systems) and smartcard data from passengers boarding or alighting the vehicles. This kind of information lead us to understand travel times better than how it could before.

An application of this kind of information to characterize public transport level of service is the study by the BRT Center of Excellence (BRT, 2012), which compares the level of service of six Latin-American cities: Santiago, Chile; Porto Alegre, Brazil; Guadalajara, Mexico; Mexico City, Mexico; Bogota, Colombia; Lima, Peru. For each city, a socio-economic description of the population was made, as well as a description of the characteristics of the existing public transport system (such as the number of operators, subway lines, operation, fares, payment schemes, infrastructure, vehicles, information systems, quality perception, among others). Level of service indicators of the respective public transport systems were calculated by estimating travel, waiting and walking times for 400 representative trips in each city.

A relevant indicator within the study relates to travel time variability in the systems. To compute this indicator, the study defined two different types of variability: (i) an interpersonal variability, which accounts for the heterogeneity of the existing levels of service within the city, and (ii) an intrapersonal variability, related to how variable the same trip performed repetitively by an individual is (i.e. how reliable is the level of service). This second kind of variability is called day-to-day variability (DDTV) (Bates, 2009). However, when measuring these indicators, the travel demand is not adequately weighted (to account for the number of travellers performing each trip) when calculating an average variability, nor is there an in-depth analysis of the differences between modes and/or operating conditions.

Santiago, Chile has a public transportation system called Transantiago, where bus and metro services are integrated by fare (Muñoz et al., 2014). Regarding the bus services, there are mainly two types: regular services, which stops in every bus stop of the route and express services, which stops only in some of them. Besides, there are five lines of metro, where Line 1 is the one most heavily loaded during peak periods, as it runs though the city center.

In this city, Munizaga & Palma (2012) proposed a methodology to estimate a public transport trip matrix using the validations made with the payment card and the geographical position of the buses. This trip-matrix is used in this research to characterize travel time reliability for public transport routes of similar length in the city during the morning peak period. Additionally, the evolution of travel time variability as travel length increases is analysed. This study also compares the travel time reliability actually experienced by travellers (weighting each route by its demand) with the travel time reliability that an external entity (such as the operator or a central controller) would observe, based solely on the vehicles' operation.

This document is structured as follows. Section 2 describes the methodology applied to obtain all the different travel time distributions for bus, express bus, and metro services. Section 3 shows an illustrative sample of the results obtained, as well as the proper analysis of those figures. Finally, Section 4 presents the main conclusions and elaborates on how these results should steer following research and public transport planning models.

2. METHODOLOGY

To characterize travel times across the city, a two-step approach is applied. The first step consists on a statistical analysis of actual travel times of all travellers on a given week, while the second step consists on weighting every route by its demand, in order to compare traveller's experience and an external observation of travel time distributions.

2.1 First step: individual travel time analysis

For bus trips, the data comes from smartcard transactions and GPS information. This information was extracted from a trip-leg table obtained with the methodology proposed by Munizaga & Palma (2012), in which for each smartcard validation, public transport service is indicated as well as the moment and place in which the traveller boards and alights the bus. This information is estimated from the GPS information delivered by the vehicles every 30 seconds, the geo-referenced bus route and the geographical position of the stops along the route. The resulting trip table has the boarding and alighting time for every bus trip-leg made by at least one individual.

With this information, it is possible to construct travel time distributions for any service between any pair of stations within the network (categorizing that pair AB by the distance range D_i in route that separates them) that has at least one trip made by some user.

$$h_{bus}^{AB,D_i} = \frac{\text{Number of trips such that } k \cdot t^* \leq tv_{bus}^{AB} \leq (k+1) \cdot t^*}{\text{Total number of trips}} \quad \forall AB \in D_i \tag{1}$$

Where t^* is the width of the histogram intervals y k represents a given interval to be calculated. In this study, we consider $t^* = 5$ minutes.

Even though the previous database contains information about metro trips, the information regarding travel times is not accurate, as the same average travel time is assigned to all travellers. Therefore, travel times in metro must be imputed to all travellers' trips. The information used to impute metro travel times consists on arrival and departure times for every train at every station which was provided by Metro de Santiago. Similar to the previous case, it is possible to obtain travel time distributions by distance range for every pair of stations that belong to the same line. This is, for a pair AB of stations in the line L:

$$h_{metro}^{AB,D_i} = \frac{\text{Number of obs such that } k \cdot t^* \leq tv_{metro}^{AB} \leq (k+1) \cdot t^*}{\text{Total number of trips}} \quad \forall AB \in D_i \tag{2}$$

Based on all available information, a comparison between public transport travel time reliability is performed across route lengths and modes for all recorded trips.

2.2 Second step: demand weighting

In order to obtain travel time distributions from a point of view of the user's experience, it is necessary to weight each distribution associated with each origin-destination pair by the travel demand of that pair. This will use the information obtained through smartcard use information. In addition to the service used, and boarding and alighting place, this matrix contains an expansion factor for each observation. Adding all the expansion factors of those trips that had the vehicle, boarding and alighting place, it is possible to obtain a measure of the demand for that trip in the service.

However, the smartcard demand information used for the metro services contain information of trips between any two stations within the entire metro network while the metro travel times are within the same line. For this reason, a proper transformation of the data available must be done. One way to solve this is to separate each metro trip between any pair of stations that belong to different lines into its trip legs. It must be considered that for some pair of stations there is more than one reasonable route. To solve this issue, we assign a choice probability to each of these routes. The weighting chosen consists of using the proportions of choice by the users, obtained from an appropriate route choice model (Raveau et al., 2014). This model is based on an origin destination survey conducted within the metro system. As any specific trip leg that involves a transfer station will be part of multiple origin-destination pairs within the network, the sum of the demand of all those multiple pairs must be computed to have the actual demand of every trip leg in the metro system.

This allows us to compare travel time reliability indicators from a travellers' perspective and an operational perspective (i.e. between passengers and vehicle's perspective). This way, travel time reliability indicators obtained on the first step are transformed into traveller experienced travel time distributions.

This is:

f_m^{AB,D_i}	Travel time distribution for mode m, service S_i between the pair AB
d_m^{AB}	Trips demand for mode m, service S_i between the pair AB

$$f_m^{D_i} = \frac{\sum_{AB \in D_i} f_m^{AB,D_i} \cdot d_m^{AB}}{\sum_{AB \in D_i} d_m^{AB}} \tag{3}$$

3. RESULTS

In this section, we perform a graphical analysis to compare the travel times according to distance ranges for the different public transport services that exist in the city. The results shown in Fig.1 show how travel time increases as travel distance increases. However, it is possible to see how travel time increases more rapidly for bus-based services than for metro. Within bus-based services, there is a significant difference in the average travel time between bus and express bus services, but there is not enough evidence to suggest a significant difference between their variability. This fact will be analysed more detailed in the following analysis.

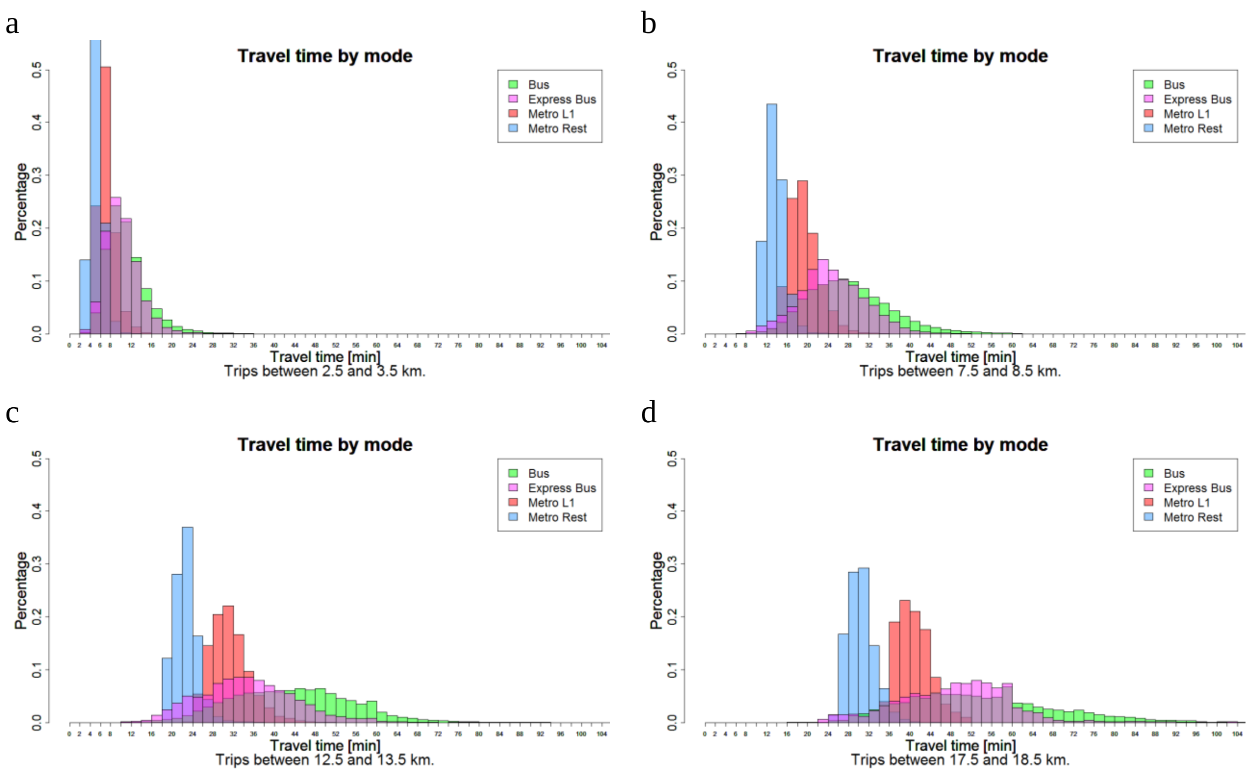

Fig. 1. Travel time distributions by mode and distance range.
(a) between 2.5 and 3.5 km; (b) between 7.5 and 8.5 km; (c) between 12.5 and 13.5 km; (d) between 17.5 and 18.5 km;

Regarding metro services, there is a significant difference in the speed of Line 1 of the Metro service compared to the other lines, and therefore Line 1 is shown separately from the others. Also, it can be seen a broader dispersion for Line 1 in comparison to the rest of the lines, but, as mentioned in the case of buses, this will be of further analysis in the following analysis.

Although the dispersion of the performance of express bus services shows that many of them have a level of service similar to that of regular bus services, there is a portion that resembles both the best lines of Metro and Line 1. It will then be important to understand what conditions make these services show such a level of service.

The relationship between travel time dispersion measures of the histograms shown before and distance can be seen in Fig. 2. The selected dispersion measures for the analysis are the standard deviation of travel time and the difference between the 95th percentile and the average travel time, which in the literature has been called "Reliability Buffer Time" (Engelson & Fosgerau, 2016). Overall, it can be seen that both dispersion measures increase with travel length for every mode with the exception of the last segment of Line 1. This happens as it is only one metro line analysed, the number of OD pairs for every travel distance range decreases from a point. In the end, for last range with information, there is only one origin-destination pair analysed, which is from one end to the other, so the variability is expected to be smaller.

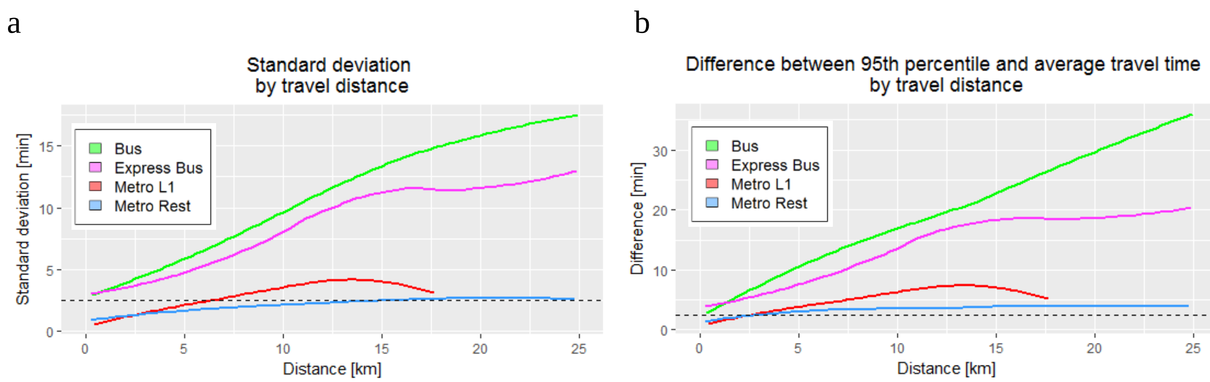

Fig. 2. Relationship between dispersion measures and travel length.
(a) Standard deviation; (b) Difference between 95th percentile and average travel time.

However, the dispersion is always smaller than 2.5 minutes for metro (with the exception of Line 1) when the standard deviation is considered as the measure of dispersion, which could hardly be perceived by travellers. Considering de reliability buffer time, the dispersion is almost eight minutes for Line 1 and always smaller than five minutes for the rest of the lines. The differences obtained between these two different measures are relevant because, on one hand, standard deviation measures longer and shorter than average travel times in the same way, while reliability buffer time only measures the difference between the longer travel times and the average.

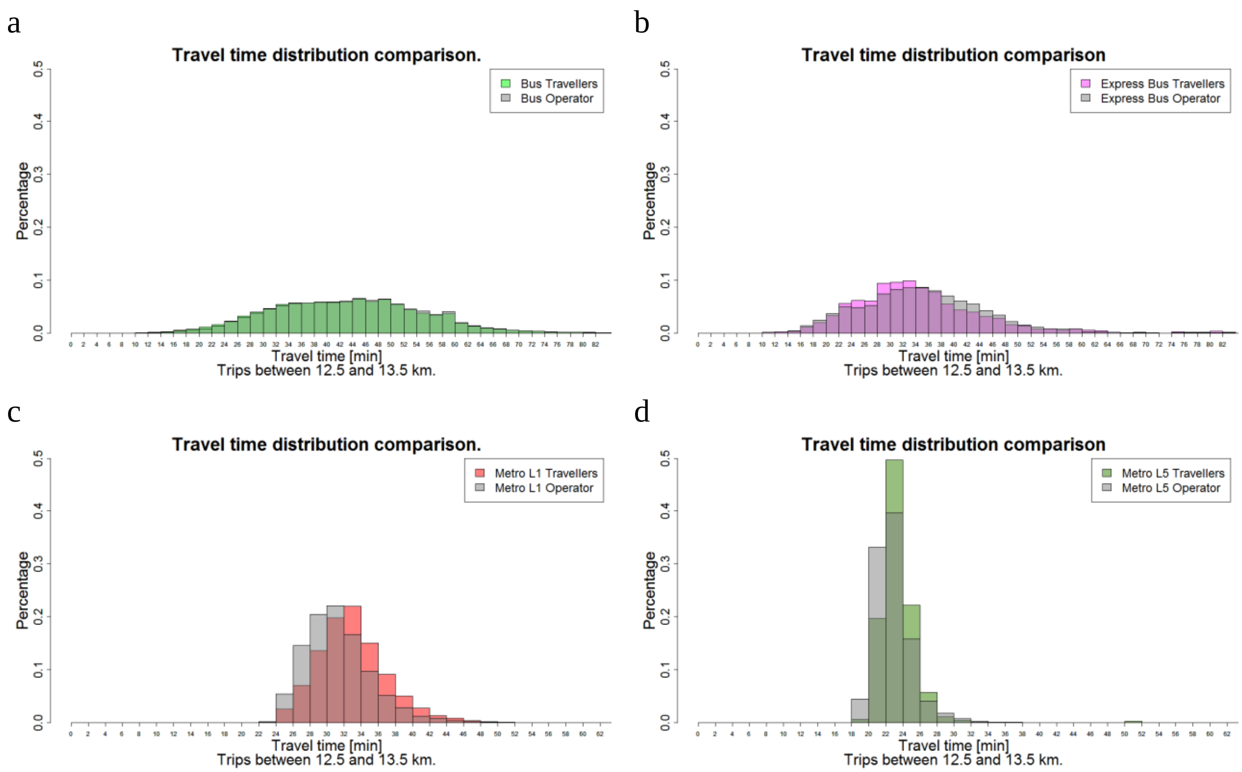

Fig. 3. Travel time distributions comparisons for trips between 12.5 and 13.5 km.
(a) bus; (b) express bus; (c) metro line 1; (d) metro line 5

For the second part of the analysis, every public transport route was properly weighted by its demand. By doing this, a comparison between travel time distributions obtained before (as in Fig.1.) and weighted distributions was conducted. As an example, the comparison for bus, express bus, metro Line 1 and metro Line 5 for trips between 12.5 and 13.5 kilometres are shown below. These figures are representative of what happens for the remained distance ranges.

As can be seen in the Fig. 3, for regular bus services there are not significant differences between the distribution of weighted and non-weighted travel times. For express bus services, a significant difference can be seen showing that travel time distribution based on user experience is faster than the one based on operators point of view.

For the case of metro lines, the situation is the opposite: travellers tend to travel between those origin-destination pairs that are slower than the average. This causes a spread towards the larger travel times in their travel time distribution.

In order to test these hypotheses, average and reliability buffer times for every range distance were computed and compared between the travellers and operators point of view. These results are shown in Fig. 4 and Fig. 5, respectively. Overall, both average travel time and reliability buffer time increases with travel length.

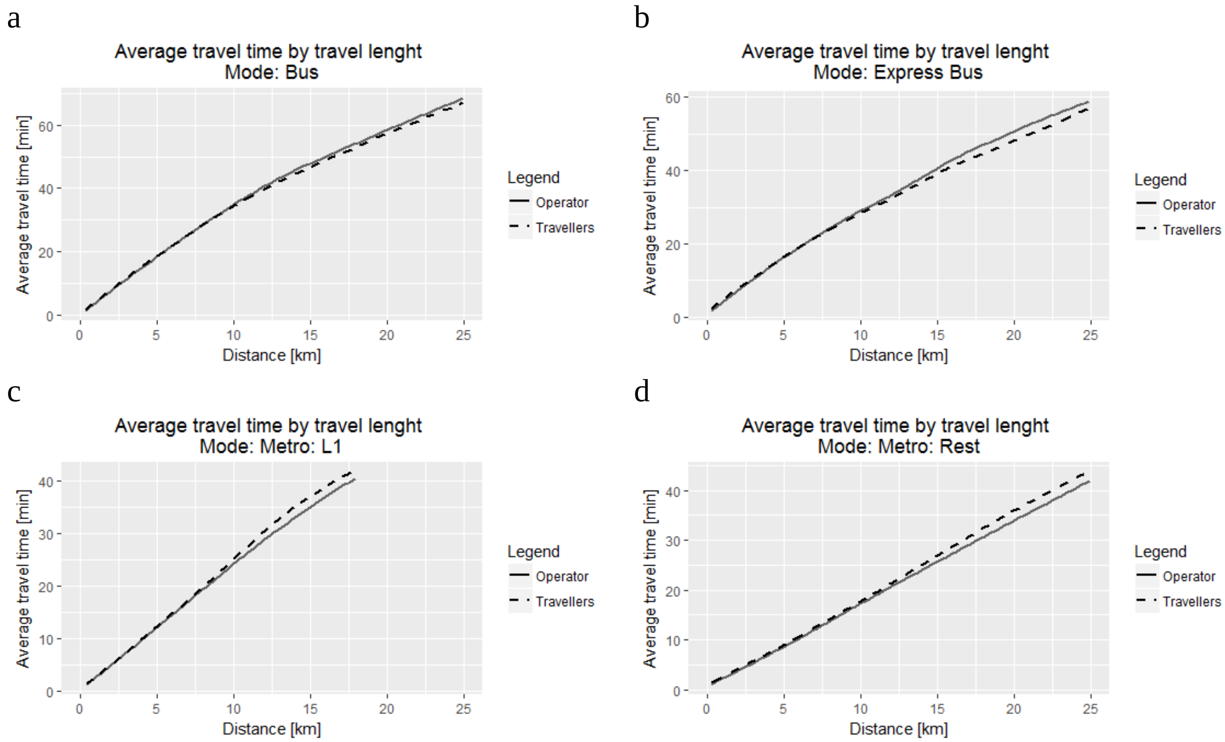

Fig. 4. Average travel time by travel length compared between operator's and traveller's point of view. (a) bus; (b) express bus; (c) metro line 1; (d) metro rest of lines

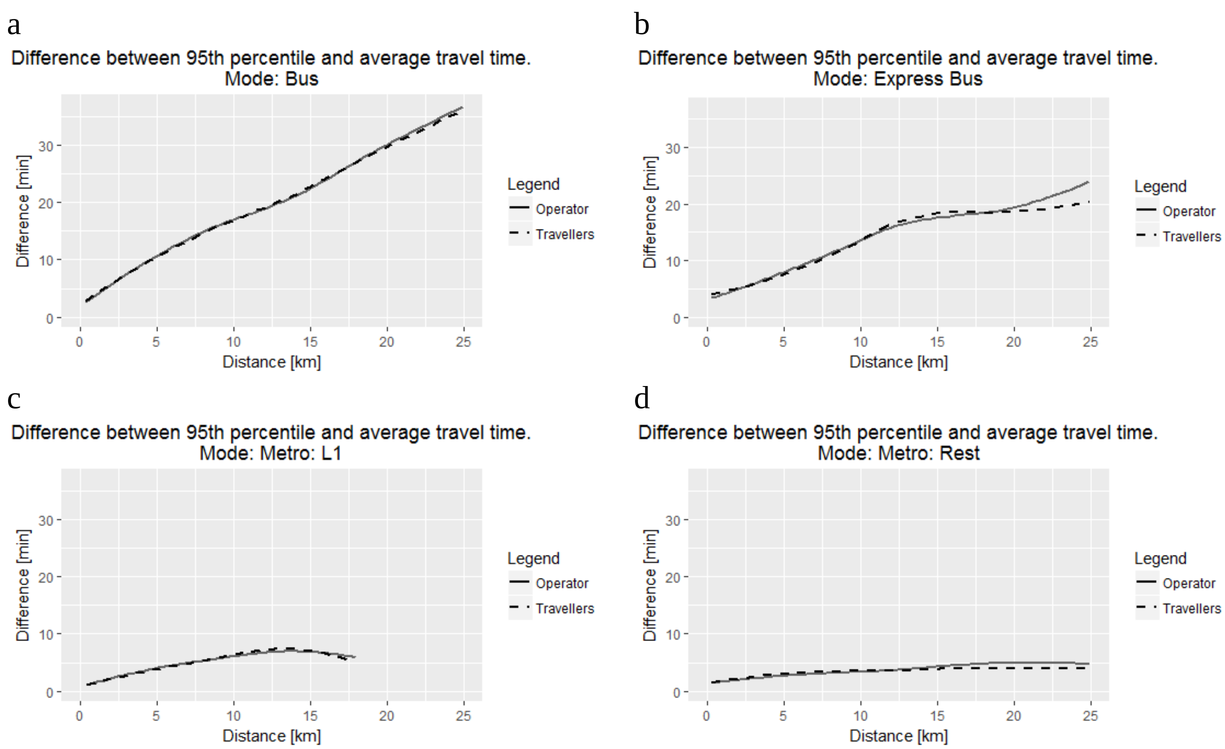

Fig. 5. Difference between 95th percentile and average travel time compared between operator's and traveller's point of view.
(a) bus; (b) express bus; (c) metro line 1; (d) metro rest of lines

Regarding average travel time, as explained in Fig. 3 express bus services show a significant and faster difference when considering user's experience, while the opposite happens analysing metro lines: metro's experienced average travel time are up to five minutes larger than average travel time compute in the typical way (i.e. non-weighted).

Regarding reliability buffer time, there are not significant differences between weighted and non-weighted dispersion measures for all the modes with the exception of the last segment of express bus services. However, this difference doesn't have an impact on average travel time.

4. CONCLUSIONS

This study provides evidence of significant differences among travel time dispersion (measured as the standard deviation or the difference between 95th percentile and average travel time) for trips of similar length and different mode. This dispersion also increases with travel length for every mode. However, the dispersion is always smaller than 2.5 minutes for metro (considering the standard deviation), which could hardly be perceived by travellers. When taking into consideration route demand, most metro travellers experience the slower trips; this causes a spread in the travel time distributions towards larger values.

Transport modellers should consider these results to improve project evaluation and decision-making processes by better understanding the effects of travel time reliability on public transport travellers. Classical public transport policy evaluation considers the non-weighted average of travel time as a main attribute of the level of service for each alternative. This research has evidenced that there are significant differences for all modes (with the exception of regular buses) between weighted and non-weighted average. As behavioural models consider traveller's experience, further research should evaluate the impact this change in average travel times has on choice models' predictions. Also, it is not clear how similar would be this situation when comparing experienced and externally observed waiting times. This variable has a direct relationship with crowding inside the vehicle, which makes it an interesting research subject.

Regarding how the results were presented in this research, being able to intuitively visualize reliability differences between different alternatives available will bring different benefits. On one hand, it allows us to understand why certain services are used to a lesser extent than predicted by conventional models that ignore the uncertainty in the level of service. The figures shown in this paper comprehended every service within certain distance range but the methodology is applicable for any subset of services desired to analyse. For example, it should be interesting to compare only those bus-based services that directly compete on demand with the metro system (i.e. bus services that run exactly above the metro).

On the other hand, this way of visualization allows identifying opportunities for improvement in the system by identifying similarities in the level of service between bus-based services and metro. This would allow us to recognize those characteristics that make the operation of these metro-like buses better than the others. For example, it would be interesting to analyse the differences in travel time dispersion generated by certain infrastructure, such as bus corridors or the presence of off-board payment stops.

Finally, this visualization allows the generation of an intuition regarding the perception that users have about the public transport system in the city. Public transport travellers' dissatisfaction is not completely understood and this type of analysis would lead us to better understand if variability over relevant travel attributes has an impact on travellers' choices.

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