Impact analysis of a new metro line in Amsterdam using automated data sources

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Extended Abstract
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Introduction

A new metro line (the north-south line) was opened in Amsterdam in July 2018, adding significant capacity to the existing urban public transport network consisting of bus, tram and metro modes. The opening of the metro line was accompanied by changes to the existing bus and tram network, such as removal of duplicate routes and addition of feeder routes.

Traditionally, the impact of such a network change was measured either ex-ante or post-op based on surveys or model forecasts (Vuk 2005; Knowles 1996; Engebretsen, Christiansen, and Strand 2017). However, with the availability of automated data sources such as the smart card data, the exact impact on transit demand and service quality can now be measured. However, so far this has been limited to analysing the changes in travel times and reliability at a trip level (Fu and Gu 2018), excluding transfers.

This research utilises smart card and AVL data to study the impact of the new line on travel patterns (passenger flows), travel times and reliability from a passenger perspective by considering journeys including transfers. The metrics are calculated at a stop-cluster level, enabling also a distributional analysis of the impacts. Such a post-op analysis of any policy intervention or network change could be used to refine the demand predictive ex-ante tools.

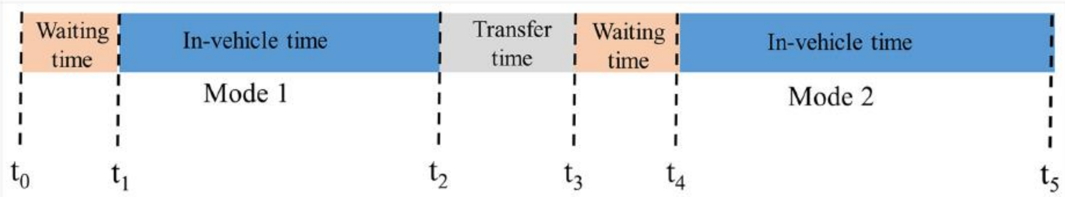
Methodology

The primary data sources for this study are smart card and AVL data from the urban PT network of Amsterdam. Both for ‘before’ and ‘after’ situation, a period of five weeks has been used for the analysis. The ‘after’ data starts 7 weeks after opening, providing enough time for travellers to get used to the new network. Data for the same period of the year (Sept-Oct) for 2017 and 2018 has been used to eliminate seasonal variations in demand. Both periods exclude school holidays in the Netherlands.

The Dutch smart card data provides information on both tap-in and tap-out (for more details see van Oort et al. (2015)). For transactions with missed tap-outs (~4.2%), destination is inferred based on Trépanier, Tranchant, and Chapleau (2007). Individual transactions (trips) are then combined to form journeys by matching with AVL data and using existing transfer inference algorithms (Yap et al. 2017; Gordon et al. 2013). The final database results in over 550,000 journeys per day.

For this research, the complete public transport journey as experienced by the passenger is looked at, from the time that the passenger arrived at the boarding stop to the time they reached the destination stop. Figure 1 shows the various components of travel time included for a typical transit journey with a transfer.

Figure 1 - Components of passenger experienced travel time for a transit journey with two legs (Dixit et al. 2019)



The waiting time for journeys starting with metro is included in the time between the last tap-out and first tap-in as measured by the smart card data (t_5-t_0 in Figure 1; tap-in/tap-out at the platform). The waiting time for bus/tram is not directly measured by the smart card data (t_5-t_1; tap-in and tap-out in the vehicle). Hence, it is estimated based on the observed headways from AVL data, using the methodology presented in Dixit et al. (2019). This is important because the 'after' situation has more metro trips, which are measured in a different way than tram and bus trips.

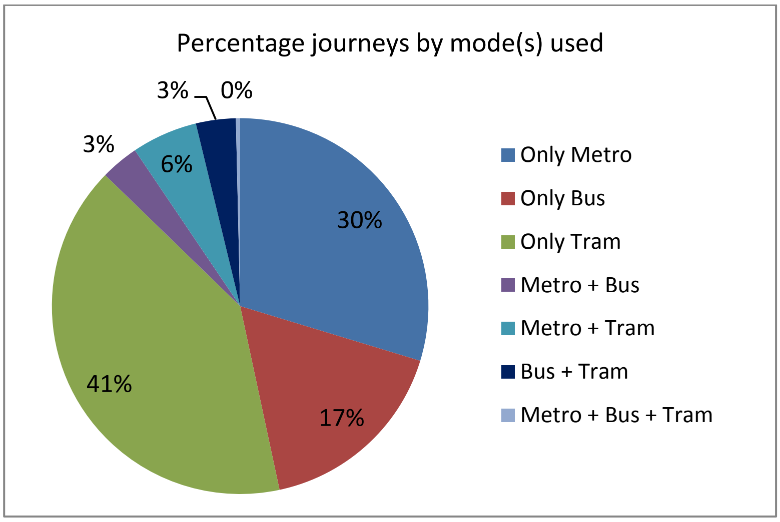
Expected Results

Currently the analysis has been carried out for the 'before' scenario. Additional results and comparison with the 'after' scenario will be added and presented during the conference. Some of the metrics that will be compared are shown below.

Ridership & Transfers

The majority of journeys in the 'before' scenario consist of only one mode, with most of them being made by tram (Figure 2). With the new network, some of the tram journeys will be replaced by metro and intermodal transfers are expected to increase. The distribution of flows over different OD pairs (stop cluster level) will also be compared between 'before' and 'after' situations.

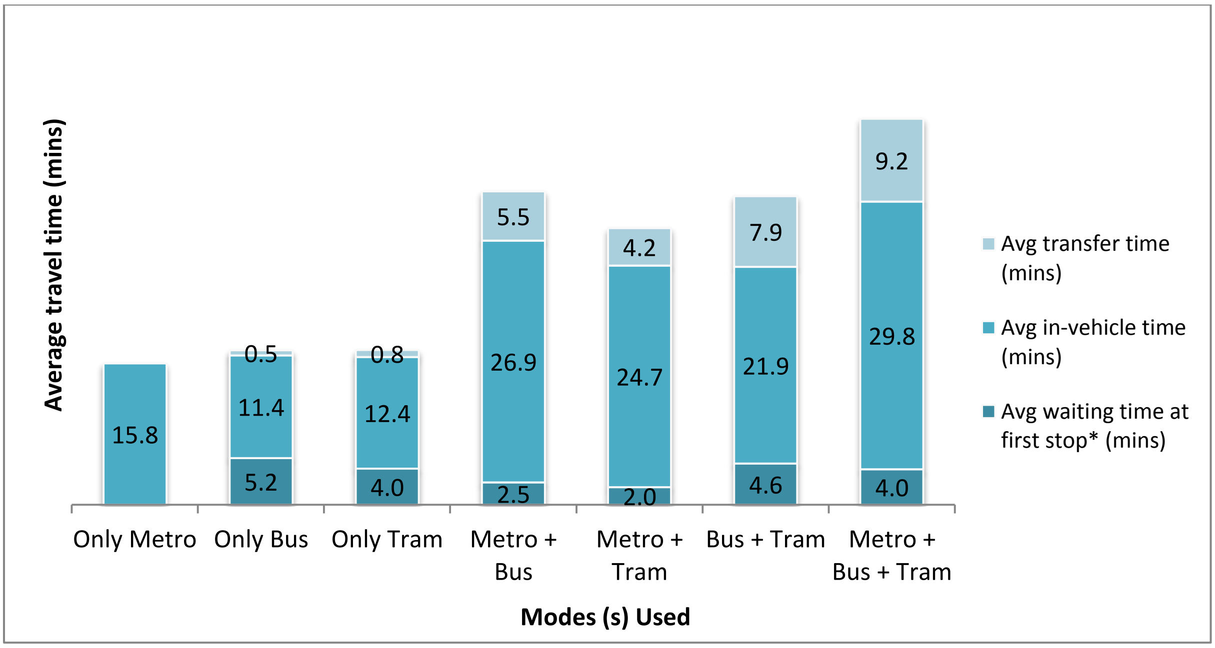
Figure 2 : Distribution of journeys by mode(s) used 'before' the north-south metro line



Journey Times & Speeds

The journey times and their distribution over OD (stop-cluster to stop-cluster) pairs will be compared to establish the proportion of OD pairs for which there is a loss/gain of travel times. The different components of journey time will also be analysed for each type of journey (Figure 3).

Figure 3 - Distribution of travel time by mode(s) used 'before' the north-south metro line



** Average waiting time at first stop is calculated for bus and tram modes only*

In the 'before' scenario, the share of waiting time is higher for bus than for tram due to lower frequencies on average. It should be noted that journeys that include metro have larger shares of in-vehicle time due to the tap-in and tap-out taking place on the platform instead of in the vehicle.

In addition to journey times, the average speed for each OD pair will be calculated based on the Euclidean distance travelled and the experienced journey time. Since this can be compared across different journey lengths, it will be used to give an insight on the efficiency of connections, and how it changes after the new metro line.

Reliability

Reliability will be measured and compared in terms of Reliability Buffer Time (RBT), using the methodology developed in Dixit et al. (2019) for journeys including transfers. RBT for each mode as well as the distribution over different OD pairs will be calculated. Changes are expected in journeys specifically with tram and metro modes. In general, the entire network is expected to become more reliable.

Conclusion

Our study analyses the impact of a major public transport network change on transit ridership and quality using automated data sources. The analysis is done from a passenger perspective by considering the whole journey from origin transit stop to destination transit stop. In addition to providing an evaluation of the implemented scheme, such an analysis could be used to validate or improve the ex-ante models for performance and ridership predictions.

Acknowledgments

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