From delay to disruption: the impact of service degradation on public transport network

Alessio D. Marra[1,2] Francesco Corman[1]

[1]Institute for Transport Planning and Systems, ETH Zürich

[2]e-mail: alessio.marra@ivt.baug.ethz.ch

Abstract

Passengers in public transport networks (PTN) experience every day different kinds of disturbances, from small delays to big service interruptions. A strict boundary between delays and disruptions is not plausible, but rather there is a continuous range of disruptions with different characteristics and impact. Despite this, in disruption analysis the typical definition of disruption is a link closure for a certain amount of time. No attention is given to the relationship between delays and disruptions or to short-term disruptions. This is of particular interest in multimodal PTN, where a link closure is not often observable. The aim of this paper is to link delays to disruptions and identify the relationships between the disruption characteristics and their impact on the users. Real disturbances of the Zürich PTN are analysed to identify disruptions with different characteristics. Therefore, the disruption impact is observed on simulated passengers' paths. Using machine learning techniques, a strong dependence between the characteristics and the impact is identified and the most important features are highlighted.

Keywords

Disruption, Public Transport, AVL Data, Network Vulnerability, Features Importance

1 Introduction

PTNs are characterized by daily unexpected delays or failed trips. The impact of each of them depends by multiple factors, such as network characteristics and the entity of the disturbance. For instance, a missed run of a bus travelling in a city center can have a different impact if the bus travels in a rural area. In addition, combination of delays and failed trips can affect particular areas of the PTN more than single disturbances. Typically, a major exceptional event, in terms of duration and effects, is defined as a disruption. Nevertheless, there is not a clear distinction between small and big disruptions, but rather there is a continuous range of disruptions with different impact.

With this study, we aim to understand the impact of disruptions to the affected demand from their characteristics. In that way, knowing the characteristics of a disruption, public transport providers can better deal with unexpected events. To identify different disruptions, real disturbances of the Zürich PTN are grouped through a clustering algorithm. Therefore, the impact of each disruption is analysed on different ODs considering a range of possible paths for the passengers. Finally, the relationships between the disruption characteristics and the impact are analysed through feature importance metrics.

2 Literature Review

Typically, in previous works a disruption is defined as a node or a link failed for a certain amount of time, without traffic admitted through it (Cats and Jenelius (2014), Rodríguez-Núñez and García-Palomares (2014)). This definition can be consistent with a railway/metro network and with long disruptions. Instead, for buses, a disruption can be better defined from the operational perspective, taking into account delays or missed runs. In the literature of public transport disruption and vulnerability studies, most of the works are focused only on metro (Rodríguez-Núñez and García-Palomares (2014), Lu (2018)) or railways (Van der Hurk (2015)), instead of considering a multimodal PTN. In this sense, Leng et al. (2018) analysed the user's behaviour in a multimodal network, but they considered only railway disruptions.

Most of the previous works are focused on identifying critical link or station and few attention is given on analyse the impact of different types of disruptions. Burgholzer et al. (2013) described a disruption by its duration (2 hours the smallest), its time of occurrence and the capacity reduction. Cats and Jenelius (2018) analysed the relation between the extent of capacity reduction and its consequences on PTN performance, but they did not examine other disruption characteristics.

Focusing on the methodology, Mattsson and Jenelius (2015) identified two traditions in disruption analysis: topological vulnerability analysis, based on the topological properties of the transport network; system-based vulnerability analysis, that represents also the demand of the transport systems. In the second group, the interaction between demand and supply is simulated by means of transport system models. Typically, the passengers' behaviour is modelled as the shortest travel time (Van der Hurk (2015), Rodríguez-Núñez and García-Palomares (2014), Lu (2018)) or using discrete choice models (Cats and Jenelius (2014)). Therefore, the impact of a disruption is primarily measured based on the whole traffic in the network (Cats and Jenelius (2014), Cats and Jenelius (2018), Burgholzer et al. (2013)). To the best of our knowledge, the impact is never analysed on single ODs or considering the entire choice-set of a user.

A key missing aspect in literature is the analysis of short disruptions (in the order of minutes), although they are the most frequent disruptions people experience in daily trips. In addition, the relationship between disruptions and delays is seldom analysed. Instead, it is reasonable to think that they are linked phenomena and there is not a strict boundary between them.

3 Methods

The methods used to understand the impact of different types of disruptions on a PTN, can be divided in three parts. First, the concept of disruption is defined and several disruptions are identified; second, the impact of the disruptions is computed; third, the relationships between the disruptions' characteristics and their impact are analyzed.

3.1 Disruption Identification

The definition of a disruption as a link closure is not realistic in the case of a multimodal PTN. In fact, the network traffic is characterized by delays or missed stops, that can not be

described by a link closure. Therefore, it is necessary a new definition, that links delays and missed stops to disruptions, considering also short-term disruptions. We define an event as an arrival of a public transport means at a stop. Therefore, we define a disruption as a set of delayed or failed events (e.g. a bus that did not stop at a stop) near to each other in time and space. This definition is not strict, but it allows both to connect delays to disruptions and to consider disruptions with different characteristics, of which impact can be analysed afterwards.
To identify real cases of disruptions, AVL data are used, seeking clusters of delayed or failed events. To find the clusters, the ST-DBSCAN algorithm is used (Birant and Kut (2007)). This algorithm is a variant of the clustering algorithm DBSCAN, used to cluster spatio-temporal data. DBSCAN is a density-based algorithm that groups together points close to each other, based on a distance function. In ST-DBSCAN both a spatial distance and a temporal distance are used, to form clusters of points close in time and space. Given a set of delayed or failed events, the ST-DBSCAN is able to detect groups of events that satisfy our definition of disruption.

3.2 Evaluate Disruption Impact

Since we are considering short disruptions (formed by events with at least 6 minutes of delay), we decided to evaluate the impact of a disruption only on ODs directly affected by it, without considering capacity constraints. Therefore, we considered ODs starting from the center of the disruption at its beginning (the planned time of the first event of the disruption). The destinations are chosen randomly among the stops of the network. For each OD two choice set are generated to model the possible paths with and without the disruption. The first is based on the timetable, without considering disturbances in the network; the second considers as the only disturbances in the network the events of the disruption. In this way, we can evaluate the impact of a disruption comparing the two sets of alternative for a OD. Using the whole choice set, instead of a single optimal path, can better describe the disruption impact, since more possibilities for the user are taken into account.
We modelled the PTN as a graph $G = (N, A)$ from the AVL data. Each node in N is a triple (arrival/departure, tripId, stopId), representing the arrival or departure of a public transport means at a stop. The arcs in A model the trips in the network and the possible transfers.
For each OD the choice sets are based on the K-shortest paths (K-SPs) (Yen (1971)), choosing as cost function the total travel time with a transfer penalty of 5 minutes. The following paths are not considered in the choice set: paths passing two times at the same stop; paths with the same means but different stops of paths already selected (e.g. boarding on the same bus at a different stop). The walking speed for transfers is set to 1.4 m/s. Instead, the walking times from the origin to the first stop and from the last stop to the destination are set to 0, to give more flexibility to the user's choices. For modelling and computational reasons, the following constraints are added to the model: max distance to transfer of 350 meters; max waiting time of 20 minutes; the K-SPs are limited to a cost double the first SP cost or to K = 250.
The impact of a disruption on a certain OD is computed as the difference of the average travel cost of the two choice sets (equation 1). Full information on the disruption is assumed for the users. Each path is weighted by the probability to use it, computed using a multinomial logit model. The cost function used (C_j) is the same to build the choice set and the calibrated parameters are based on Montini et al. (2017).

$$impact(od, dis) = \frac{\sum_j^{j \in P(od,dis)} e^{-\beta C_j} C_j}{\sum_j^{j \in P(od,dis)} e^{-\beta C_j}} - \frac{\sum_j^{j \in P(od)} e^{-\beta C_j} C_j}{\sum_j^{j \in P(od)} e^{-\beta C_j}} \tag{1}$$

$$P(od, dis) = \text{choice-set for the given od and disruption.} \tag{2}$$

$$P(od) = \text{choice-set for the given od without any disruption.} \tag{3}$$

3.3 Features Analysis

Analysing the relationship between an OD and the impact, we can determine how much the impact of a disruption on the OD depends on its characteristics and which of these are more important. First, we extracted 19 features for each OD, describing size of the disruption, duration, total delay, service frequency and network metrics. For brevity, the comprehensive list is not shown, but the most important features are highlighted in Table 1. Therefore, the features importance to predict the impact is analysed computing the mutual information and using random forest regression.
The mutual information is a measure of the amount of information one random variable contains about another (Cover and Thomas (2006)). The formula is the following:

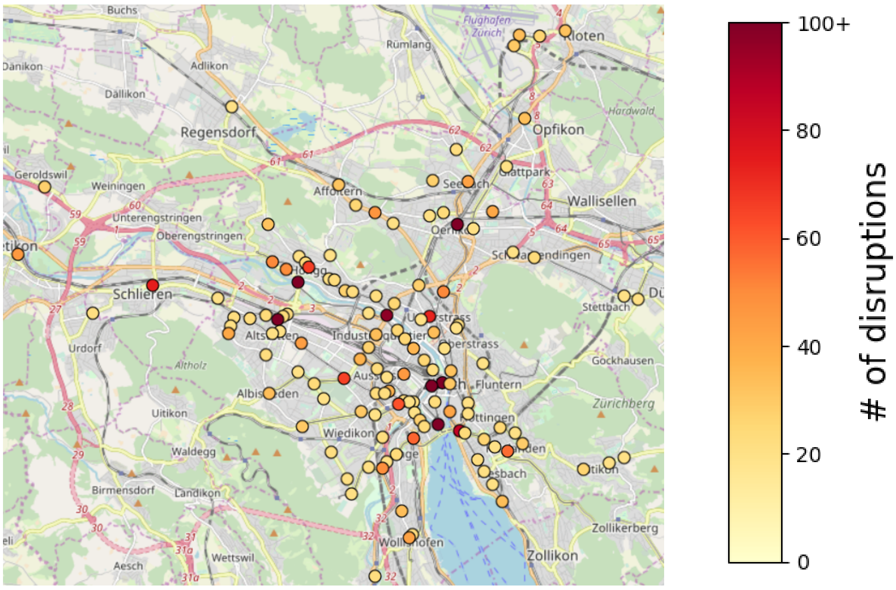
$$MI(X, Y) = \int_X \int_Y p(x, y) log(\frac{p(x, y)}{p(x)p(y)})\ dx\ dy \tag{4}$$

Therefore, it is possible to rank the features by their mutual information with the impact. Nevertheless, this measure does not capture the relationships among features and it is possible that a feature has a great importance only if combined with others. In contrast, a random forest regression considers multiple features in one single model. To fit the regression model, we used 67% of dataset as training-set and cross-validation to estimate the parameters. The regression can show how much the features are able to describe the impact, and can rank them based on the *Mean Decrease Impurity* (Breiman (2002)). Particular attention must be given to correlated features, since this metric tends to distribute their importance.

4 Experiments and Results

For our experiments, we used 8 months (01-08/2018) of AVL data of the city of Zürich to analyse realized disruptions. To identify disruptions with the ST-DBSCAN algorithm, failed events are considered as delayed events with a delay equals to the time difference with the next same event (same line at the same stop). Therefore, for each day, all the events with a delay ≥ 6 minutes and ≤ 3 hour are selected for clustering.
The following values are assigned to the ST-DBSCAN parameter: MinPts = 5, epsSpace = 250 meters, epsTime = 4 minutes, $\Delta\epsilon = \infty$ (not used) (for more details, we refer to Birant and Kut (2007)). Given the intentional ambiguity of the definition of a disruption, a precise tuning of these parameters is not possible. Therefore, they have been selected by manual experiments by the authors to have a reasonable number of disruptions per day and events per disruption. In our experiments, 2567 disruptions were detected (≈ 11 per day, with a median of 7 events per disruption) and the spatial distribution is shown in Figure 1. To avoid bias due to different timetables (e.g. during weekend), we considered only disruptions with

Figure 1: Distribution of disruptions in the city of Zürich (from 01-01-2018 to 31-08-2018).



events that can occur during an arbitrary working day, the 01-10-2018 (1332 disruptions). To evaluate the impact of the identified disruptions, for each one 10 different random ODs are created and the impact on each OD is computed, as explained in Section 3.2. The ODs not affected by the disruption (i.e. none of the disrupted means is useful to reach the destination) are discarded (35%). In total, 8630 OD pairs were analysed.

The relationship between the features of each OD and the impact are analysed as explained in Section 3.3. The random forest regressor gives an $R^2 = 0.53$ (i.e. half of the variance in disruption impact depends on the identified features), that can be considered an acceptable value, even if there are not studies with which to compare the results. This proves that it is possible to predict the impact of a disruption (as defined by the authors) from its characteristics. The results of the features importance analysis are shown in Table 1. Given the complexity of the task and the high correlation among the features, the values in Table 1 must be judged as useful to make general conclusions, and not as strict rankings. The most relevant feature in both the metrics is the *frequency*. This proves that a high-frequency service can contrast delays or single failures. Slightly less important are three network metrics (out-degree, closeness and betweenness centrality), proving that the impact of a disruption is dependent by its location in the network. These metrics are computed on a static network with a node for each stop and arcs weighted by the travel time. Compared to them, the duration and the size of the disruption have a lower influence. The disruption density (events/Perimeter) has a slight influence. Interesting is that network metrics of the destination have low influence on the impact, proving that it is more important to go away from the disrupted zone. The relationships between some features and the impact are shown in Figure 2.

Figure 2: Relationship between features and impact.

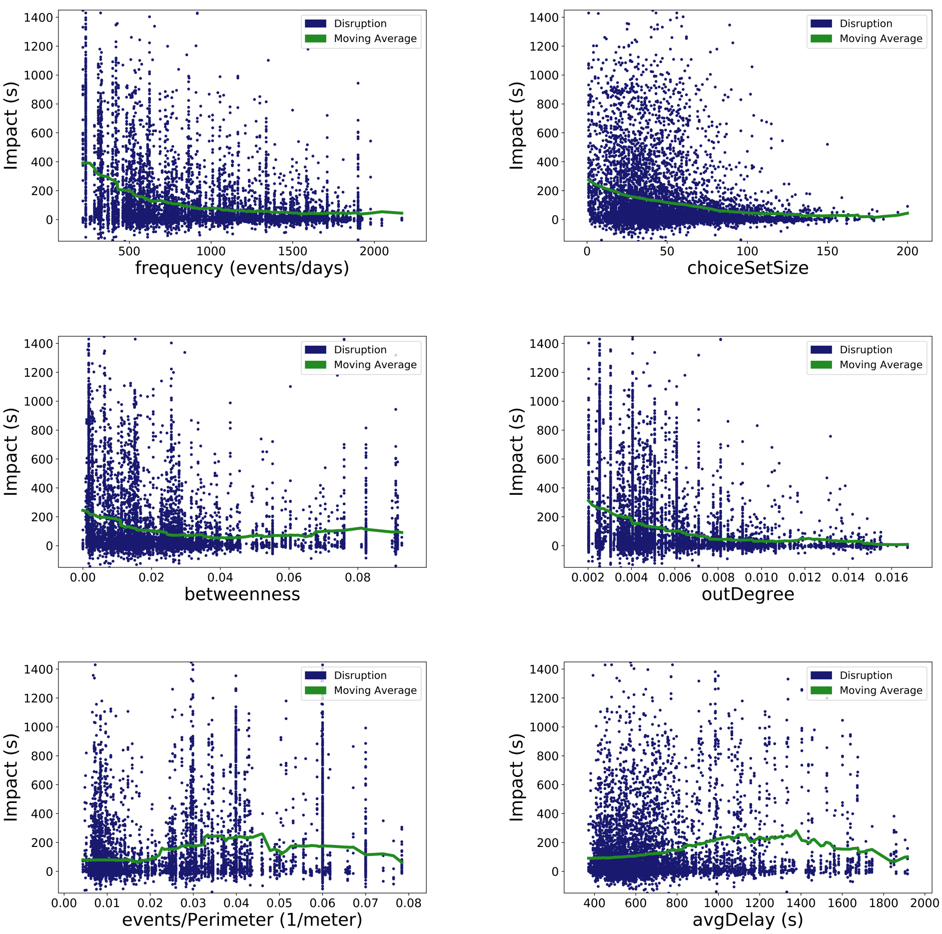


Table 1: Feature importance: features rankings based on mutual information (MI) and mean decrease impurity (MDI). A subset of model's features is shown. The mark (AVG) means that the feature is computed as the average among the events of the disruption.

Feature	MDI	MI	Description
frequency	0.140	0.209	Number of events per day (AVG)
choiceSetSize	0.107	0.083	Size of the timetable choice set
betweenness	0.083	0.178	Betweenness centrality (AVG)
avgTravelCost	0.081	0.033	Avg. travel cost in the timetable choice set
distance	0.072	0.027	OD distance
outDegree	0.065	0.192	# of reachable stops (AVG)
closeness	0.052	0.204	Closeness centrality (AVG)
closenessDest	0.050	0.037	Destination closeness
avgDelay	0.049	0.075	Delay (AVG)
betweennessDest	0.041	0.017	Destination betweenness
events/Perimeter	0.037	0.130	# events / disruption perimeter
duration	0.030	0.037	Disruption duration
events	0.013	0.022	# events

5 Conclusions

The classical definition of PTN disruption as a link closure has been overcome in this study. A new definition is given, in order to represent disruptions with different characteristics and linked with small disturbances in the PTN. This fills the gap in the literature on short (in the order of minutes) disruption analysis in multimodal public transport. We modelled the disruption impact on single ODs affected by the disruption, allowing to consider the impact in a fine-grained level and to analyse it for different types of OD. We showed that there is a high relationship between the impact of a disruption and its characteristics. The service frequency and network metrics of the disruption area play a key role on the disruption impact. In contrast, destination's metrics are not so relevant. In addition, the impact generally increases with the density or the delays of the disruption. This paper represents a first step in the analysis of different types of disruption and several future directions are possible. In particular, we aim to test our methods on different cities, using other disruption identification techniques or a different impact function.

References

Birant D, Kut A, 2007. ST-DBSCAN: An algorithm for clustering spatial-temporal data. Data & Knowledge Engineering 60(1):208–221

Breiman L, 2002. Manual on setting up, using, and understanding random forests v3.1. Statistics Department University of California Berkeley, CA, USA

Burgholzer W, Bauer G, Posset M, Jammernegg W, 2013. Analysing the impact of disruptions in intermodal transport networks: A micro simulation-based model. Decision Support Systems 54(4):1580–1586

Cats O, Jenelius E, 2014. Dynamic Vulnerability Analysis of Public Transport Networks: Mitigation Effects of Real-Time Information. Networks and Spatial Economics 14(3):435–463

Cats O, Jenelius E, 2018. Beyond a Complete Failure: The Impact of Partial Capacity Degradation on Public Transport Network Vulnerability. Transportmetrica B: Transport Dynamics 6(2)

Cover TM, Thomas JA, 2006. Elements of Information Theory (Wiley Series in Telecommunications and Signal Processing). Wiley-Interscience, New York, NY, USA

Van der Hurk E, 2015. Passengers, Information, and Disruptions

Leng N, De Martinis V, Corman F, 2018. Agent-based simulation approach for disruption management in rail schedule. In: Conference on Advanced Systems in Public Transport and TransitData (CASPT 2018)

Lu QC, 2018. Modeling network resilience of rail transit under operational incidents. Transportation Research Part A: Policy and Practice 117:227–237

Mattsson LG, Jenelius E, 2015. Vulnerability and resilience of transport systems - A discussion of recent research. Transportation Research Part A: Policy and Practice 81:16–34

Montini L, Antoniou C, Axhausen KW, 2017. Route and mode choice models using GPS data. In: TRB Annual Meeting Online, Transportation Research Board (TRB)

Rodríguez-Núñez E, García-Palomares JC, 2014. Measuring the vulnerability of public transport networks. Journal of Transport Geography 35:50–63

Yen JY, 1971. Finding the K Shortest Loopless Paths in a Network. Management Science 17(11):712–716