Assessment of bus bridging strategies under unplanned public transit disruptions: a case study from Lyon, France

Benjamin Cottreau *[1,2], Ouassim Manout[2], and Louafi Bouzouina[2]

[1]Keolis
[2]ENTPE-CNRS-University of Lyon, France

Short summary

Unplanned service disruptions often occur on Public Transit (PT), with different levels of intensity. Growing urbanization and environmental issues are two main factors that put increasing pressure on PT. Therefore, service disruptions are expected to occur more often, maybe with tougher impacts than before on public transport demand. In this context, it is valuable to provide insights to PT operators, to develop suitable disruption management strategies. Using four different sources of data (counting, disruption, Automatic Fare Collection and Automatic Vehicle Location data), this paper intends to assess PT robustness, vulnerability and performance of bus bridging strategies towards subway disruptions. The case study introduced in this paper focuses on two of the most severe disruptions which took place between September 15$^{\text{th}}$ 2022 and October 15$^{\text{th}}$ 2022 on 7 stations of subway line A of Lyon (France). Findings indicate the valuable contribution of bridging buses, that strengthen PT robustness. The major stations rely more on alternative modes that are already available, whereas the minor stations mostly rely on bridging buses. This indicates the need for supply-based management strategies in these areas. Results also show the importance of having efficient buses, that substantially reduce the vulnerability of stations. Above all, this work intends to give a scalable framework to assess the efficiency of disruption management strategies.
Keywords: robustness, vulnerability, public transit, disruptions, bridging bus

1 Introduction

Metropolitan areas are facing environmental and demographic challenges, leading more inhabitants to use mobility services within these dense areas while public authorities are pursuing policies discouraging the use of individual and polluting modes of transportation such as cars. In Lyon, France, several decisions have been taken by public authorities that strongly incentivize citizens to use Public Transit (PT) (French Parliament, 2019, 2021; SYTRAL Mobilité, 2020). In this context of hard promotion and constant evolution, PT system of Lyon is under pressure and highly subject to unplanned disruptions. Therefore, PT operators have a significant interest in improving service quality, especially during disruptions that substantially affect costumers' perception of PT.
Unplanned disruptions occur spontaneously due to various factors; the most recurrent being rolling-stock or infrastructure damages, incivilities or safety issues. These events and their characteristics, namely duration, intensity, and location are often unknown in advance, which makes their real-time management challenging. From the PT operators' perspective, two kinds of strategies can be implemented, together or independently, to manage unplanned disruptions:

- **Supply-oriented strategies**, which rely on providing alternative PT supply to overcome the disruption, especially Bus Bridging (BB) services (Deng et al., 2018; Yin et al., 2018)
- **Demand-oriented strategies**, which essentially rely on providing relevant information to users (Leng & Corman, 2020; Drabicki et al., 2021; Rahimi Siegrist & Corman, 2021; Mo et al., 2022).

This work aims to provide a comprehensive framework that can be applied to assess both kinds of strategies and help PT operators understand demand fluctuations. A first analysis of disruption management strategies in Lyon shows that these are often supply-based and focus on providing BB when the subway service is disrupted. Demand-based strategies are limited and only give insights on whether the subway line is disrupted or not, but very little information on the duration of the disruption or other PT alternatives available nearby. For this reason, we focus in this research on the investigation of BB by addressing two research questions:

- What are the impacts of Bus Bridging (BB) strategies on demand under unplanned disruptions?
- More generally, what measures can be used and implemented to any kind of disruptions' management strategies ?

To answer these questions, we will focus on the concepts of **robustness** and **vulnerability** as defined by Rodríguez-Núñez & García-Palomares (2014), which give information about how the PT system reacts during disruptions. Robustness describes the ability of the PT system to absorb the shock in demand, while vulnerability refers to the effort that needs to be consented to keep the same levels of demand. We will also implement a measurement of the **performance** of PT network under disruption based on the average speed of the mode considered.
This work distinguishes itself from existing literature in three main aspects. First, we rely on a rich data set collected in Lyon, which includes information on disaggregate travel demand and PT disruptions along their characteristics for all PT modes (subway, tramway, and bus). Second, we assess the robustness, the performance and the vulnerability of the subway network in Lyon using different indicators that can be transferred to other PT systems or case studies. Third, we propose a multimodal framework, including spillovers from subway to others PT mode (tramways, bus and BB services).

2 Methodology

The goal of the study is to compare trips' characteristics during a disruption with the same characteristics during a reference period (i.e. without disruptions). First, we propose a definition of a reference period. Second, we define the spatial boundaries of the study (i.e. the service area) and the trips' attributes that are used in this work. Third, once trips are defined, different sets of trips are considered, whether they start and end in the service area or not. Finally, for each station studied, three aggregated indicators are introduced, that respectively assess **robustness**, **vulnerability** and **performance**.

Definition of a reference period

The reference period is defined as a disruption-free period. This period is considered as the *steady state* of PT, which we want to compare with the disrupted state. The reference period is further characterized by distinguishing: (i) workdays from weekends and (ii) school holidays from the rest. Normal demand fluctuations are observed during weekends and holidays (Egu & Bonnel, 2021) that are not related to disruptions and need, as such, not to be confused with demand disruption. This yields 4 reference periods during each of which PT demand patterns are deemed similar. Consequently, travel demand during a disruption occurring on a day j at an exact time t is compared to the demand of the same time t of a similar normal period to the day j.
In the following, trips observed during a disruption period i will be compared to trips observed during the corresponding reference period ref. Next sections focus on the selection of relevant data for disruptions' analysis.

Trips' selection procedure and attributes

Let a disruption occur on a subway line L. $\mathbb{A}_{\mathrm{L}} = [a_1, a_2, ..., a_n]$ is the set of n stations of this line. For each subway station $a \in \mathbb{A}_{\mathrm{L}}$, we define the set $\mathbb{B}_a$ of reachable PT stops that are located within a walkable distance w from station a. The resulting area centered on station a is called the service area. These stops can be subway (other than line L), tramway, or bus stops. We suppose that $\mathbb{B}_a$ is the set of alternative stops that can reasonably be used as an alternative to L when a disruption hits stop a. We only assign the closest subway station a to each $b \in \mathbb{B}_a$. At the line level, the whole set of reachable stops $\mathbb{B}_{\mathrm{L}} = [b_1, b_2, ..., b_m]$ is defined as the union of the disjoint sets $\mathbb{B}_a$.
In Lyon, the Automatic Fare Collection (AFC) system collects data only when demand taps-in. The destination of PT users is unknown. A three-step method based on by Egu & Bonnel (2020) is used to overcome this issue. First, the inference procedure is used to infer the destination d and the arrival time t_d for each validation at an origin stop o at time t_o. Let's denote this trip leg

(o, d). Second, trip chaining allows to associate N trip legs $(o_k, d_k), k \in [\![1; N]\!]$ and build a whole trip from origin O to destination D, such as a trip (O,D) is defined as mentioned in equation 1:

$$(O, D) = \bigcap_{k=1}^{N} (o_\mathrm{k}, d_\mathrm{k}) \tag{1}$$

Third, each trip is weighted using counting data. We end up with a weight score associated to each reconstructed trip, that will be used as the final **Number of Trips (NT)**. Two other attributes result from the whole procedure: **Journey Time (JT)** is defined as the difference between original time t_O and destination time t_D and **Trip Length (TL)** is calculated as the number of subway stations that are crossed during a trip. For trips in $\mathbb{B}_L$, TL is also calculated using the number of associated subway stations that are crossed.

Sets of trips considered

Disruptions can have different impacts on PT trips depending if these trips were planned to be exclusively performed on the disrupted line or with transfers involving this line. Accordingly, the trips can be divided into two categories (Figure 1): the first group includes all trips starting from **and** ending within the service area of the disrupted subway line (grey circles in Figure 1). These trips as said to be **direct**. The second case corresponds to trips that include at least one transfer within the service area of the subway line. These trips as said to be **non-direct**.

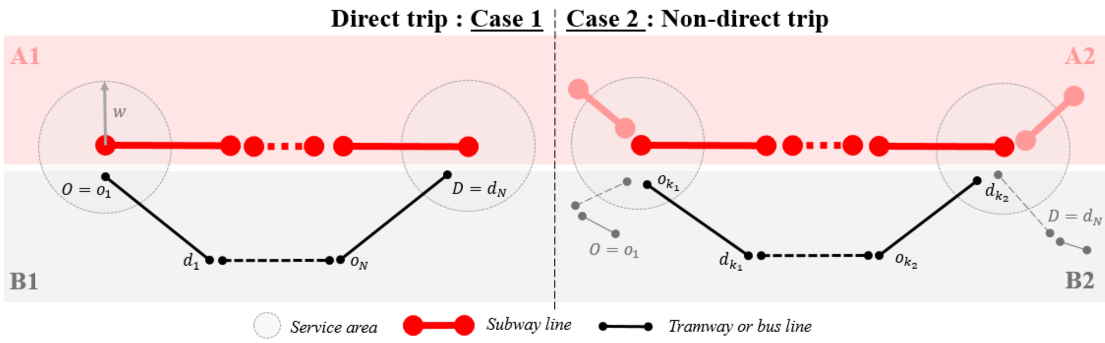

Figure 1: Cases considered in the study: direct trips (case 1) refer to trips that start and end at a stop close to a subway station; non-direct (case 2) trips refer to trips including a direct trip, with transfers before and/or after reaching a stop close to a subway station.

Evaluation of robustness, vulnerability and performance under disruption

Three indicators are used in this work to measure the impact of disruption on travel demand and to evaluate supply-oriented disruption management strategies. First, **robustness (R)** is measured using the percentage of disruption spillover. We evaluate spillovers by retrieving the Number of Trips (NT) starting from station a that switch to stops $b \in \mathbb{B}_a$ during disruption's interval of time Δ_i. We compare the difference between NT at stops b during disruption i and NT during reference period ref at stops b, to the number of trips NT_{ref} at associated station a during reference period ref. We also add to this equation the number of trips made from station a during disruption i, which is expected to be close to zero but must be taken into account. This variation is calculated using for each subway station a and disruption i using the ratio in equation 2. $R(a, i)$ can be interpreted as the share of lost demand at station a, absorbed by stops $b \in \mathbb{B}_a$ during disruption i. Robustness, when normalized for a station, varies in the range of (0-1) where a higher value indicates higher robustness of the station during a disruption.

$$R(a, i) = \frac{\sum\limits_{b \in \mathbb{B}_a} \sum\limits_{t \in \Delta_i} \Big[NT(b, t)_i - NT(b, t)_{ref}\Big] + \sum\limits_{t \in \Delta_i} NT(a, t)_i}{\sum\limits_{t \in \Delta_i} NT(a, t)_{ref}} \tag{2}$$

Second, **vulnerability (V)** is measured as the excess in the average journey time. We obtain this indicator by comparing the average Journey Time (JT) of alternative trips using stops $b \in \mathbb{B}_a$ during disruptions with the average JT of regular trips using subway station a, over the disruption period Δ_i. Values of JT are weighted by NT of each trip. As shown in equation 3, $V(a,i)$ can be interpreted as the mean additional amount of time needed to reach a destination in $\mathbb{A}_L$ under disruption i, starting a trip at b instead of a. Vulnerability, when normalized for a station, varies in the range of (0-1) where a higher value indicates higher vulnerability of the station during a disruption.

$$V(a,i) = \frac{\sum\limits_{b\in\mathbb{B}_a}\sum\limits_{t\in\Delta_i} JT(b,t)_i.NT(b,t)_i}{\sum\limits_{b\in\mathbb{B}_a}\sum\limits_{t\in\Delta_i} NT(b,t)_i} - \frac{\sum\limits_{t\in\Delta_i} JT(a,t)_{ref}.NT(a,t)ref}{\sum\limits_{t\in\Delta_i} NT(a,t)_{ref}} \tag{3}$$

Finally, we use a **performance metric (P)** which is calculated for each trip as the ratio between TL (i.e. the distance) and JT (i.e. the journey time). The performance metric is then averaged using NT as a weight. As shown in equation 4, $P(a,i)$ gives a notion of the average speed of all alternative modes starting from $b \in \mathbb{B}_a$. In this study we will be particularly interested in comparing performance between BB and other modes available under disruption. Performance, when normalized for a station, varies in the range of (0-1) where a higher value indicates higher performance of the station during a disruption.

$$P(a,i) = \frac{\sum\limits_{b\in\mathbb{B}_a}\sum\limits_{t\in\Delta_i} NT(b,t)_i.\frac{TL(b,t)_i}{JT(b,t)_i}}{\sum\limits_{b\in\mathbb{B}_a}\sum\limits_{t\in\Delta_i} NT(b,t)_i} \tag{4}$$

3 Results and discussion

Case study

We use enriched data, combining AFC, Automatic Vehicle Location (AVL) and counting data to retrieve trips from September 15$^{\text{th}}$ 2022 to October 15$^{\text{th}}$ 2022, and end up studying a total of 1 472 890 trips. During this period, two major disruptions occurred on all the subway lines. The first disruption occurred on October 6$^{\text{th}}$ 2022 between 15:51 and 20:03 (Disruption 1) and the second one occurred on October 14$^{\text{th}}$ 2022 (Disruption 2) between 17:21 and 20:25. During these periods, the operator provided BB as subway alternatives. The reference period has been defined using 17 days not included in these disruption periods and not impacted by other minor disruptions.
In this research, we focus on a single subway line (line A) to demonstrate the contribution of our research. This study can be easily transferred to the rest subway lines. Line A has 14 stations. However, only 7 of them have been covered by BB during the disruptions, namely SOI, BON CUS, FLA, GRA, REP and CHA. For these $n = 7$ subway stations, a total number of $m = 77$ alternative stops have been identified within their service area, defined by distance threshold $w = 500m$. Table 1 indicates the number of alternative stops for each subway station and the station's weight according to counting data (the higher the score, the more users are counted at this station).
Results are shown using radar plots in Figure 2. For each radar plot, the left-hand side indicates value of all indicators in the case of direct-trips (1), while the right-hand side shows the value of the same indicators for non-direct trips (2). Robustness (R), Vulnerability (V) and Performance (P) have been normalized using min-max function at the station level.

Subway station (a)	**SOI**	**BON**	**CUS**	**FLA**	**GRA**	**REP**	**CHA**
Number of alternative stops (b)	23	12	2	9	12	2	17
Station's weight	0.16	0.11	0.07	0.09	0.14	0.07	0.36

Table 1: Numbers of alternative stops associated with each subway station belonging to line A, where the bus bridging strategy has been implemented. Station's weight is calculated as the share of each station in the counting data during the reference period. Stations are sorted according to their location.

Results and discussion

Robustness: Raw value (i.e. before normalization) of robustness for the considered stations is estimated to lie between 20% (for disruption 2) and 24% (for disruption 1), meaning that the alternatives stops absorb between 1 trip out of 5 and 1 trip out of 4 of all the trips impacted by the disruption on the subway line.

Without providing for BB, the robustness index is high for stations that have a combination of a high number of alternative stops and a high station's weight. The CHA station (table 1) has the highest robustness index (between 0.25 and 0.48), followed by BON (0.11 and 0.17 for direct trips and 0.53 and 0.73 for non-direct trips) and SOI (0.07 for direct trips and between 0.21 and 0.31 for non-direct trips). Despite having characteristics relatively similar to that of BON (see Table 1), GRA has a lower robustness (between 0 and 0.06). These values are closer to REP (between 0 and 0.01), FLA (between 0 and 0.02) and CUS (0.01 and 0.02 for direct trips). CUS has relatively a higher robustness (0.11 and 0.15) for non-direct trips.

The deployment of BB increases the robustness of the PT system. BB significantly improve the robustness for stations that have low robustness in the reference scenario: between 79% and 100% of robustness in bus bridging scenario is due to the presence of this mode of transit for FLA, GRA and REP. This contribution is between 23% and 70% for SOI, BON and CHA. BB have a sparser impact on CUS, with values that lies between 50 and 85%.

From this result emerges two groups of stations: the set of "major" stations composed of SOI, BON and CHA, that have a relatively high robustness index without bus bridging strategies, and the set of "minor" stations for which bus bridging strategies substantially improve the robustness, even if robustness values are still low.

Vulnerability & Performance: As the vulnerability index is based on journey time, it is important to distinguish short trips (i.e. direct trips) from long trips (i.e. non-direct trips). For direct trips and non-direct trips, raw values (i.e. before normalization) of vulnerability are respectively estimated to 16 and 25 minutes for disruptions 1, and 9 and 17 minutes for disruption 2. These values correspond to the average additional journey time that a user should expect to endure under a disruption.

From direct trips' perspective, when BB improve performance index at CUS, FLA, GRA or REP, vulnerability substantially decreases. This statement does not hold for major station like CHA, BON and SOI, where performance of BB have less importance in the set of alternative stops available. From non-direct trips perspective, vulnerability index increase in most case, regardless of the evolution of performance index. Decrease in vulnerability are observed for FLA, REP and GRA (maximum 0.06 points of difference). This observation can be explained with two hypothesis. First, vulnerability increases for non-direct trips because better options are available. The starting and/or the ending point of these trips are usually located far from subway stations. During reference period, it is rational to reach a subway station. However, when the subway is not available, other routes appear more relevant to the user rather than reaching a subway station and taking a BB. Second, from minor station as FLA, REP and GRA, it can be worth using a less efficient mode such as BB, as few options are available for the chosen route.

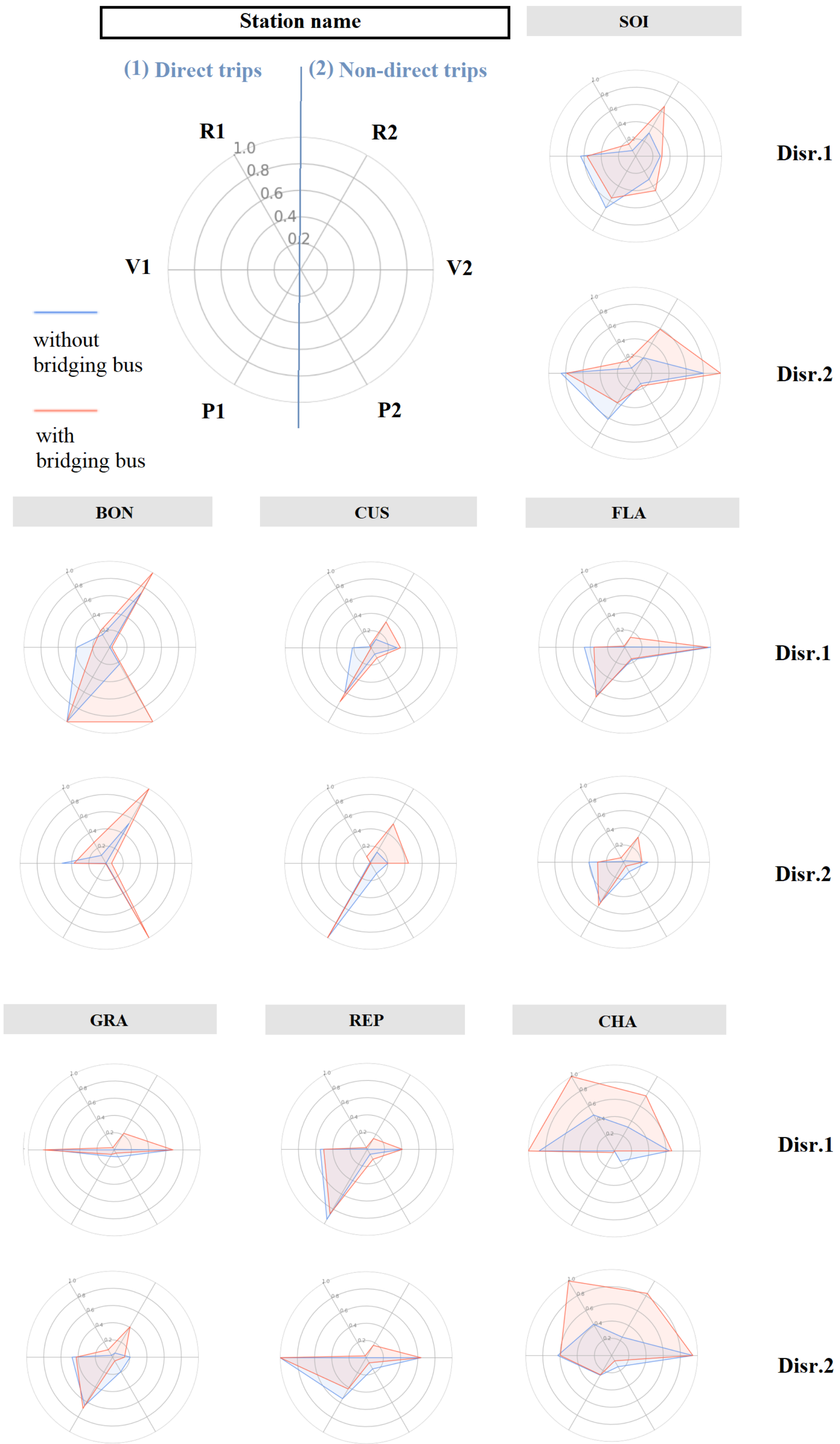

Figure 2: *Radar plots* - The left-hand and right-hand side shows the Robustness (R), Vulnerability (V) and Performance (P) indicators in the case of direct-trips and non-direct trips respectively. The red and blue curves correspond to a disruption management strategy with and without BB respectively. *Disr.1* stands for the disruption occurring on October 6^{th} 2022 and *Disr.2* stands for the disruption occurring on October 14^{th} 2022

4 Conclusions

This paper addresses the following questions: *what are the impacts of Bus Bridging (BB) strategies on demand under unplanned disruptions? What measures can be used and implemented to any kind of disruptions' management strategies ?* First, trips are retrieved using Automatic Vehicle Location (AVL), Automatic Fare Collection (AFC) and counting data. Relevant trips are filtered with a distance threshold, and split into two categories which are direct trips and non-direct trips. Second, three indicators are set up in order to assess the impact of subway disruptions, evaluating respectively robustness, vulnerability and performance. Finally, this methodology has been applied to two major disruptions, focusing on the implementation of bus bridging strategies and comparing the evolution of the chosen indicators in both cases.

Results highlight the valuable contribution of BB, that strengthen PT robustness. The major stations (CHA, SOI, BON) rely more on alternatives stops that are already available, whereas minor stations (CUS, FLA, GRA, REP) mostly - and sometimes fully - rely on BB. This indicates the need for supply-based management strategies in these areas. Findings also show the importance of having efficient buses, that substantially reduce the vulnerability of stations. For the set of minor stations, when BB improve the performance of alternative options available around a subway station, a decrease in vulnerability is observed for direct trips. This observation does not hold for the set of major stations, where performance of other alternative stops have a more significant impact on vulnerability. For non-direct trips, values of vulnerability mostly increase with bus bridging strategies, regardless the value of performance index. The work on these trips needs to be further investigated as their starting and ending point are out of the service area defined in this paper. Providing demand-based management strategies for these specific trips seems more relevant.

These results could help PT operators in managing disruption by reinforcing usual PT lines at major station, and focusing BB strategies on minor stations. The same methodology needs to be further investigated in order to provide more precise insights on where to send relevant information about disruptions, especially in remote stops that are outside the studied service area. To go further, clustering techniques can be used to exploit this methodology and asses a higher number of disruptions (>2) simultaneously.

Acknowledgements

This paper is part of the "Mobility in the Big Data Era" chair. The authors are thankful to KEOLIS for providing the data on PT use in Lyon.

References

Deng, Y., Ru, X., Dou, Z., & Liang, G. (2018, November). Design of Bus Bridging Routes in Response to Disruption of Urban Rail Transit. *Sustainability*, *10*(12), 4427. Retrieved 2023-11-27, from http://www.mdpi.com/2071-1050/10/12/4427 doi: 10.3390/su10124427

Drabicki, A., Kucharski, R., Cats, O., & Szarata, A. (2021, December). Modelling the effects of real-time crowding information in urban public transport systems. *Transportmetrica A: Transport Science*, *17*(4), 675–713. Retrieved 2023-09-20, from https://www.tandfonline.com/doi/full/10.1080/23249935.2020.1809547 doi: 10.1080/23249935.2020.1809547

Egu, O., & Bonnel, P. (2020, August). How comparable are origin-destination matrices estimated from automatic fare collection, origin-destination surveys and household travel survey? An empirical investigation in Lyon. *Transportation Research Part A: Policy and Practice*, *138*, 267–282. Retrieved 2023-08-10, from https://linkinghub.elsevier.com/retrieve/pii/S0965856420306030 doi: 10.1016/j.tra.2020.05.021

Egu, O., & Bonnel, P. (2021, May). Medium-term public transit route ridership forecasting: What, how and why? A case study in Lyon. *Transport Policy*, *105*, 124–133. Retrieved 2023-08-22, from https://linkinghub.elsevier.com/retrieve/pii/S0967070X21000627 doi: 10.1016/j.tranpol.2021.03.002

French Parliament. (2019). *Loi n° 2019-1428 du 24 décembre 2019 d'orientation des mobilités.* (https://www.legifrance.gouv.fr/loda/id/JORFTEXT000039666574)

French Parliament. (2021). *Loi n° 2021-1104 du 22 août 2021 portant lutte contre le déréglement climatique et renforcement de la résilience face à ses effets.* (https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000043956924)

Leng, N., & Corman, F. (2020, March). The role of information availability to passengers in public transport disruptions: An agent-based simulation approach. *Transportation Research Part A: Policy and Practice*, *133*, 214–236. Retrieved 2023-11-27, from https://linkinghub.elsevier.com/retrieve/pii/S0965856419305075 doi: 10.1016/j.tra.2020.01.007

Mo, B., Von Franque, M. Y., Koutsopoulos, H. N., Attanucci, J. P., & Zhao, J. (2022). Impact of Unplanned Long-Term Service Disruptions on Urban Public Transit Systems. *IEEE Open Journal of Intelligent Transportation Systems*, *3*, 551–569. Retrieved 2023-07-26, from https://ieeexplore.ieee.org/document/9858090/ doi: 10.1109/OJITS.2022.3199108

Rahimi Siegrist, M., & Corman, F. (2021, November). Modeling and Quantifying Interaction of Information and Capacity in Public Transport Disruptions. *Journal of Advanced Transportation*, *2021*, 1–21. Retrieved 2023-06-01, from https://www.hindawi.com/journals/jat/2021/5398316/ doi: 10.1155/2021/5398316

Rodríguez-Núñez, E., & García-Palomares, J. C. (2014, February). Measuring the vulnerability of public transport networks. *Journal of Transport Geography*, *35*, 50–63. Retrieved 2023-06-01, from https://linkinghub.elsevier.com/retrieve/pii/S0966692314000180 doi: 10.1016/j.jtrangeo.2014.01.008

SYTRAL Mobilité. (2020). *Extrait du registre des délibérations, comité syndical du 17 décembre 2020.* (https://www.sytral.fr/TPL_CODE/TPL_DELIBERATIONLISTE/PAR_TPL_IDENTIFIANT/5491861/TELECHARGER/1/491-deliberations.htm)

Yin, H., Wu, J., Sun, H., Qu, Y., Yang, X., & Wang, B. (2018, July). Optimal Bus-Bridging Service under a Metro Station Disruption. *Journal of Advanced Transportation*, *2018*, 1–16. Retrieved 2023-11-27, from https://www.hindawi.com/journals/jat/2018/2758652/ doi: 10.1155/2018/2758652