Modelling and Assessing Resilience in Multimodal Transportation Systems

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ABSTRACT

Transport demand and operational concerns need to be aligned in large urban centers. As such, this dissertation aims to contribute to a more sustainable mobility solution by proposing and empirically testing methods to assess the resilience of a multimodal transport system. Resilience is seen in both static and dynamic settings, looking at aspects in the network topology and user's flow and demand. Our hypothesis is that the appropriate multi-layered and traffic-sensitive modelling of this network can promote the integrated analysis of different transport modes and support improved resilience analysis. To this end, we propose three major contributions, a robustness assessment model along with the analysis of dynamics and the demand and supply changes as a means to characterize resilience. Within this multilayer network, citizens' mobility patterns can be understood and represented. In particular we resort to the the use of agglomerative hierarchical clustering and weighted digraphs to this end. The results of this research allow decision-makers to understand the vulnerabilities and ongoing changes to the multimodal usage patterns within the network. Moreover, we highlighted the changes in passenger traffic demand during Covid-19 pandemic.

1 INTRODUCTION

Numerous studies attempt to optimize transportation systems planning and usage in urban scenarios [10, 40]. Among the studied solutions, the importance of a multimodal transportation system arises due to high demand of some traffic corridors. As the demand for transport services rises, so does the possibility of safety, efficiency and comfort concerns that affect users' daily mobility. This raises the question of how resilient are these transportation systems. This characteristic is applied both at a static - topological level - and at a dynamic level - demand response.

For this research, the city of Lisbon is used as an example to improve the integration of the current multimodal transport network. This analysis is fundamental in the context of the Lisbon Metropolitan Area (LMA), where the average occupancy rate for individual private transport (cars) is 1.60 passengers per vehicle, and the daily traffic inflow in the county of Lisbon is also the cumulative result of commuting traffic inflows between Lisbon and the eighteen municipalities that integrate the Lisbon Metropolitan Area (LMA) [30]. Several road traffic corridors are flooded daily with single occupancy vehicles that could possibly use other public transport alternative. Despite the stable establishments and the integration of the operators' systems with a single card, challenges to the integrated operation and multimodal planning of the public transport network still persist within LMA. The current study aims to contribute to the literature with a more comprehensive review of how to objectively model multimodal transportation systems and quantitatively assess their resilience. These concepts are applied to the Lisbon multimodal transport network in the context of the ILU project. More information about this project can be found at web.ist.utl.pt/rmch/ilu/.

The need for an objective and transparent coordination between different transport modes as a means to reduce congestion and failures in different streams has become apparent. To further understand the usage of multimodal transport, the inclusion of resilience assessment model offers a crucial perspective to the improvement of our public services. This starts by understanding how to quantitatively assess robustness [59]. However, there is a need to go beyond a monomodal rubostness assessment and focus on a method to assess the resilience of a transportation network with different modalities. In this context, the natural subsequent research question is: How to measure the resilience of a multimodal transport network covering several transport modes?

Moreover, there is also a lack of understanding of the changes in flow patterns of travellers within complex multimodal public transportation systems [45]. This statement is highly relevant since some measures to contain the pandemic have heavily impacted the transportation sector. In this sense, how can we assess resilience to continuously changing demand patterns?

This research aims to propose a method to assess the resilience of a multimodal transportation network. After comprehensively assessing topological resilience, the research aims at moving to a more dynamic view of traffic vulnerabilities. To this end, we propose the usage of pattern mining techniques to understand the flow of the travellers within a complex multimodal transportation network. The search for patterns aims to improve the management of different transportation modalities, by providing non-trivial and usage patterns to the knowledge base of the public transportation's information system. The main goals of this work are the following:

- Model the current multimodal transport system into a multi-layer network;
- Propose an assessment of multimodality that is sensible to topology and network robustness;
- Discover main differences in subway, bus, and tramways usage data (e.g. using passenger flow data before and after the COVID-19 pandemic or other disruptive events);
- Discover actionable public transport usage patterns;
- Measure resilience of a multimodal transportation system.

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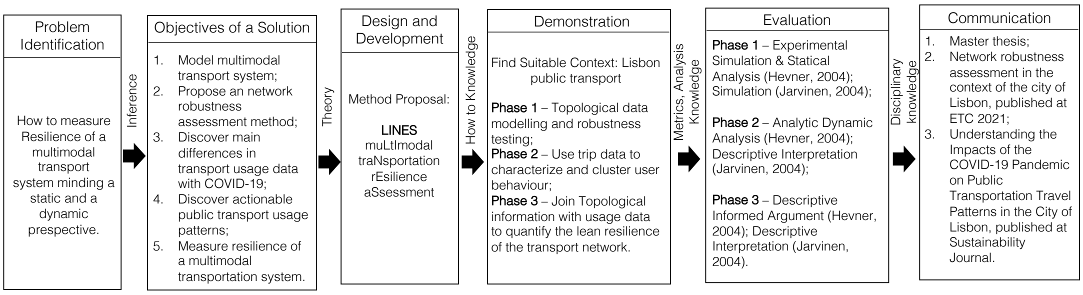

Figure 1: Methodological phases of the present research, based on Peffers et al [47] framework

	Build	Evaluate	Theorize	Justify
Construct	Public Transportation Lean Resilience	-	-	-
Model	-	-	Resilience model; User profile impact	Usage patterns; Clusters of users.
Method	Network resilience measurement process: LINES	Robustness testing comparing multi and singleplex	-	-
Instatiation	Network modelling; Usage patterns and resilience analysis Software;	Robustness tests; Cluster solutions	-	-

Table 1: Research outputs

2 METHODOLOGICAL APPROACH

To achieve the afore mentioned research objectives, a design science research methodology [27, 32, 47] was conducted. Figure 1 illustrates the research methodological phases. Phase 1 comprehends the problem identification and its scientific motivation. Phase 2 defines the objectives of the solution (research objectives). Phase 3 presents the design an development of the artifact - muLtImodal traNsportation rEsilience analySis (LINES) Process based on theory. Phase 4 describes the demonstration of the validity and usage of the artifacts to solve the problem. Phase 5 comprehends the various evaluation methods used to assess the demonstration phase and Phase 6 comprehends the communication of the process and the results.

To summarize the main contributions of the thesis, we present the March and Smith research output framework [39]. The main contributions of this research work ae on Table 1. These are mainly composed by design science research outputs.

3 BACKGROUND

The concept of multimodality is central to this research. Claudia Nobis [46] states that: "*multimodality* is defined as the use of at least two modes of transportation — bicycle, car, or public transportation — in 1 week". However, multimodality is more "commonly defined as the use of more than one transport mode to complete a trip" [19]. This is the undertaken stance by this work. The concept of *crossmodality* can also be used as a synonymous of multimodality.

According to Buehler and Hamre [9], multimodality is a sub-field of intrapersonal variability of travel behaviour, that is characterised by four dimensions: modal, purpose, spatial and temporal. Hence, the spatiotemporal data driven nature of the approaches proposed in this research, as these dimensions are markedly present. The focus of the analysis performed is a contribution to more sustainable mobility planning and management. Hence, defining it is important. This has as its primary objective increasing urban accessibility and delivering high-quality, long-term mobility and transportation to, through, and within the city [15]. The more interconnected and diversified sustainable mobility alternatives are, the more efficient and resilient the transportation system as a whole will be [55].

The definition of transport resilience is defined by four main dimensions: robustness, redundancy, resourcefulness and rapidity and these have major effects on: fewer repercussions, reliability and quicker recuperation [53]. Nevertheless, the way these dimensions are understood and measured has been a fairly active research theme. First, we may look at topological features such as centrality [13, 33] and connectivity [59], these may be used to characterize robustness and how the network can be affected based on simulations. On a dynamic prospective, the throughput, travel time [22] and weighted networks' [41] that result from these measurements may also characterize resilience in terms of functionality. Additionally, there is a stance firstly introduced by Bruneau et al. [8], where resilience is characterized by a curve based on the time to recover from a initial degradation event. This stance originated the resilience triangle and the resilience index, later formalized by Reed et al. [48]. This resilience index in the context of a networked infrastructure can be calculated as

$$R \; \frac{{}_{t_1}^{t_2} Qtdt}{t_2 - t_1}, \qquad (1)$$

where Qt is the system functionality between t_1 and t_2. This index offers a generalization of the concept of resilience. As we may measure the resilience of any dimension regarding system qualities. In the context of our work, we may instantiate Qt as the ratio between the transportation demand and supply.

Hierarchical clustering has been used in the context of spatiotemporal data in the transportation sector [4] and particularly to analyse smart card data [56]. This method is characterized by both distances and linkage. The Euclidean distance, also called L_2 distance and the Manhattan distance also called L_1 distance are not prepared to measure temporal dependencies in time series another family of metrics is introduced. Cross-correlation based distances are very common in time-series analysis and describes the correlation between two curves as one of them is shifted. The concept of linkage is core to hierarchical clustering since it is what determines the distance between sets of observations. To assess the generated solutions we use the silhouette score and the Calinski Harabaz Index. The first is a metric that measures both the cohesion within the clusters, resulting in a bounded metric between 1 and -1. Where -1 would be complete dissimilarity and 1 the opposite. The value of 0 indicates that the that element is between two clusters. Further on we use the average value for this metric of all elements in all clusters, as the reference silhouettes. The Calinski Harabaz Index measures dispersion inter and between clusters and it is not bounded like the silhouette. This metric measures the distance of every element to the centroid of a cluster, the average of all dimensions of the elements in a said cluster. The idea of this metric is to calculate the variance within, and between clusters, these are covariance measure that equating to a ratio, result is an index.

Since we have different connection types within the whole transportation system, we cannot model such a network with a simple monoplex network. Instead, we use multiplex networks. This kind of representation allows us to analyse the intralayer, interlayer and the global picture of connections. According to previous literature [18], multilayer networks are the optimal solution to represent this kind of metropolitan transportation systems as as each transport mode should be represented in different layers, and they should also be kept separate to guarantee efficient coverage.

The modelling of multimodal transportation systems recurring to multilayer networks has been previously proposed to analyse urban transportation systems [3]. Different authors have modelled and assessed multimodal transport networks [3, 17, 20, 58]. Orozco et al. [44] were able to extract data from different multimodal transport networks from cities all across the globe. His study is relevant not only because of the extraction task but because it studies the overlap between layers within the networks extracted and city clustering based on network similarity. Are urban multimodal networks in fact more resilient if they exhibit high levels of overlap between different modal layers? To understand the multimodality behaviours, previous studies [19] propose the use of indices from other disciplines to quantitatively measure the usage within different transportation modalities, *e.g.* bus, metro, train.

The concept of network resilience is inherently linked to the passenger flow and demand patterns within a transport network [31]. The vulnerabilities of such a network are dependent of topological features and on their disruption by severe events. The mere fluctuation of volume of urban transport users may be viewed as a disruptive event for the system. As such, it is important to dig deeper into the types of usage that can be found as a means for Design-for-Resilience. The understanding of user behaviour can be considered to design systems that can withstand stronger specific vulnerabilities [51]. Ivanov [31] noted that resilience capabilities are frequently seen as passive plans, ready to use in a emergency scenario, and there is an increasing demand for what is called the lean resilience. This is an agile, data driven approach to actively reconfigure a system as a means to manage resilience continually. This is an emerging trend of research as of this year (2021), COVID and post-COVID changes are felt abruptly in the world of transportation [25]. This concept has been previously introduced in the context of supply chain, however here we apply it for the first time in the context of public transportation. Hence, based on previous literature [25], we define public transportation lean resilience as a measurement regarding resilience comprising passenger flow and transportation supply with continuous adaptability.

Recent studies have approached the passenger demand change understanding by identifying different usage profiles applying different clustering techniques. This is the case since individual travel patterns provide higher detailed description than zonal commuting behaviour analysis [49, 57], since we can detail what kinds of users are coming from where. Additionally, Ma et al. [38] noted that understanding these usage profiles may be a useful tool for targeting and fare reduction to improve public transportation adoption, and Lathia and Capra [36] concluded that it was also a way to effectively measure if the incentives had taken effect. To describe the commuting patterns most studies have collected smart card data similar to the one available in the city of Lisbon. Distinctively, Kung et al. explored the usage patterns based on mobile phone location data [35]. Ma et al. [37] clustered users according to the number of days, stops, routes and time in transportation, clustering them in three categories: Absolute commuters, Average commuters and Non-commuters, using a variant of K-means. However, this generalization led to a large number of Non-commuters given the strong assumption that there are only three commuter profiles. Nevertheless, the distribution of departure times showed fair results, with a clear separation of profiles.

Other perspectives in transport user profiling include clustering the usage times. The usage times can be formally described as the array containing the number of validations each user has in a specific timespan, this can be though as a daily usage profile. Naturally, when we think about comparing the distance between two curves Dynamic Time Wrapping (DTW) comes to mind. However, He et al. [26] effectively demonstrated that a metric such as cross-correlation distance (CCD) would yield drastically better results compared to (DTW), based on an exclusivity and homogeneity criteria. A cross-correlation distance is characterized by a maximum lag to which two time-series can diverge from one another, effectively working as a way to change the granularity of the time series. This means that a similar task can be achieved by lowering the granularity of the time intervals and defining distances between the curves using a less computationally costly distance metric. Morency et al. [43] used an hourly observation granularity and calculated clusters of users based on k-means and the hamming distance. Agard [1] used k-means clustering to group user weeks with similar patterns, with four time-spans per day and five week days. Later on, Ghaemi et al. [24] proposed the usage of hierarchical approach that allowed for a better interpretability of the clusters via a dendogram. The author argues that this is a considerable advantage since it does not only help to understand the user behaviour, but also may be used with other kinds of environmental data and that may help the decision making in the planning process.

To answer the need for measuring resilience of networks, Klau and Weiskircher [34] noted in their robustness and resilience review that, a network should be considered resilient if it sustains a high number of node failures before it turns disconnected. In that sense, performing node percolation tests is a way to measure resilience. Measuring this property in transport networks has been the focus of several studies. Sulivan et al. [52] has evaluated system-wide robustness by finding critical isolating links in road networks. They reduced the link capacity and measured the travel time as a means to measure robustness, this allowed for a dynamic perspective as well. Later on Zhou et al. [60] have done a similar study, but induced the vulnerabilities by blocking lanes instead, same as deleting an edge, which ranked the links by how critical they were building upon the much earlier work who did just that [50]. These studies were very much related with the earlier study of reliability done by Chen et al. [12], where they measured the reliability of networks given the demand change based on models of route choice. This study extended capacity reliability to network equilibrium models as well as taking into account the route-choice actions of drivers. Later on Al-Deek and Eman [2] measured the reliability by network capacity and travel time by changing demand and inducing link degradation and non persistent congestion. These studies are in fact very important because they showed how different demand levels affects the capacity reliability in an analytical way. It is important to note that reliability is fundamentally different to resilience. Reliability usually measures the interruption of service. Resilience, on the other hand, measures the ability to recover from such interruption in service [14]. The importance of the study of system resilience increases due to the limited ways where systems are either successful or failed in a binary view of reliability system efficiency. Studies of network resilience have also been done in the context of multimodal transport. Montes-Orozco [42] recently showed that the same idea of percolation could be used in multiplex networks. This notion opens this test for the world of multimodal transport network resilience. On the other hand, Cats et al. [11] defined a framework to assess robustness. This helped the description of robustness assessment as an economic problem. This kind of assessment is highly relevant for the present research as it provides a baseline to understand the impact of disruption scenarios in specific links, quantifying the criticality.

With this research, we aim to objectively model and assess the resilience of a multimodal transportation system. We have seen that resilience is relevant since it is a stepping stone to minimize the impact of vulnerabilities in the system caused by usage patterns or other disturbances like natural disasters. By understanding the patterns of users' flows and topological characteristics that weaken the system, we can plan better strategies to avoid and mitigate negative impacts. In this sense, we will use a network representation capable of capturing dynamic aspects such as passenger demand over time. The search for patterns in such a network allows for assessing the resilience of the network, both in responding to variations in demand and identifying vulnerabilities. This analysis is then followed by studying emerging patterns, such as the dynamics of the system. Given the abrupt mobility changes faced due to the SARS-CoV-2 outbreak, we seek to understand the demand change in the present context. To further understand how to adapt the current transportation systems to yield better multimodality resilience, we will be combining the outputs from the previous two phases to assess the resilience of the system with the available topological and usage information. In this section, we list the main goals and the specific activities to tackle these challenges. Figure 2 presents a Work Breakdown Structure diagram with the main activities of the LINES Process.

A way to assess the static resilience of a network is by removing sets of nodes and understanding network metrics' behaviour. The simplest one is injecting *random* failures in the network, i.e., randomly removing nodes from the network. We based our attack strategies on the ones defined by Holme et al. [28]. We attack nodes as well as edges to be able to compare efficiency in strategies. We use attributes from the network, such as *degree* and *centrality* to target attacks according to relevance. We used the six following attack strategies for nodes and edges: Random removal, Initial Degree removal (ID), Initial Betweenness removal (IB), Recalculate Degree removal (RD), Recalculate Betweenness removal (RB) and Multimodal Hubs removal along with *Multimodal Hubs removal*,removing entities that connect layers. To understand the impact of the removals

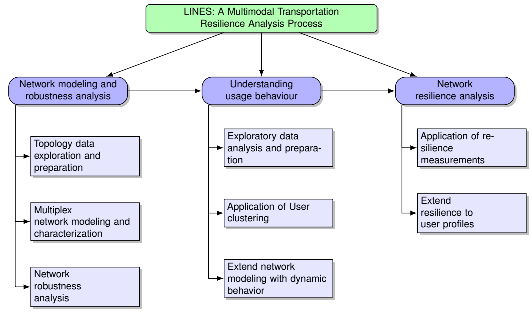

Figure 2: Interconnectivity of each activity of the proposal using a WBS diagram, integrating the methodology for assessing the resilience of a multimodal transportation system.

we use network metrics such as size of the largest strongly connected component (SCC), average path length (APL) and number of isolated components (IC's).

The assessment of the cluster quality will be done according to the metrics introduced: the silhouette score and the Calinski Harabaz index. These metrics measure the cohesion and separation of the clusters, helping us understand which kind of clustering method is the most adequate. These are adequate measure since the cluster cohesion and separation is what allows us to assess how different the usage profiles are. These two metrics were previously used by Tang et al. [54] to analyse the quality of clusters produced by different algorithms regarding behavioural analysis of smart card data. To further assess the quality of the clusters generated we look at size of the cluster and distribution of users per cluster, we aim to generate clusters that have sets of users that have similar behaviour and not unbalanced macro clusters that include every user type and have few homogene characteristics. Interpretability is also a criteria. It can be further assessed by field experts, through the visual analysis the results.

When the transport can recover from the demand overload of users, the transportation is seen as lean resilient and thus we will measure lean resilience based on centrality and the equilibrium between the transportation supply and the demand for the transportation. This will be quantified with the resilience index Qt as defined by Reed et al. [48] We measure Qt as the ratio between the demand and the supply for transportation in a defined time period, using a data driven approach, by measuring the smart card validations and estimating supply levels. The result of this approach is a better prescription of the resilience in the context of multimodal networks.

4 RESULTS: NETWORK MODELLING

This section describes the process of modelling and assessing of the robustness of a multimodal transport network, highlighting the differences between a single-layer and a multilayer perspectives. This work is published in the proceedings of the European Transport Conference 2021 [6].

Firstly, the criteria used for the inference of the multiplex network is identified, followed by an analysis of the resilience of the topology and routing. This analysis will be extended during the thesis to the dynamic aspects (flows) in the network.

To transform route planning from General Transit Feed Specification (GTFS) data files of each mode into a network, we joined the shapes and the stops of each one of the transportation modalities: CARRIS , CP , FERTAGUS , METRO , RODLISBOA , SULFERTAGUS , TRANSTEJO , TST . This merge describes each line and stops connected to one another via their order, within the line. Given the structure of the data, we created a directed graph (digraph) for each transportation modality (bus, railway, riverway, subway, tram), forming a layer for each. We resorted to digraphs for each layer because transport does not always flow in both directions within the same path. This allows us to create each layer of our multilayer network. We apply a multilayer representation because the edges of different layers have different types that represented different realities. Modelling such characteristics was not possible with a single layer (or monolayer) network. Now that we have each layer, we also have to represent the possible multimodality interactions, i.e., the possibility to change different means of transportation within a trip. These links are of extreme importance because they allow us to assess the connectivity of the transportation system as a whole. To accurately understand where these edges could be located, we created a script that extracted the Lisbon city map and calculated the walking distance between every two stations and combined it with a standard coordinate distance calculation to get faster calculations. After getting this result, we selected the pairs of stations from different modes and linked them based on distance. We connected the eight modes of transportation in the Lisbon city using the described method. By programming a 3-dimensional method, for visualizing such network, using the geographical information available, we were able to see its structure, see Figure 3 for more detail.

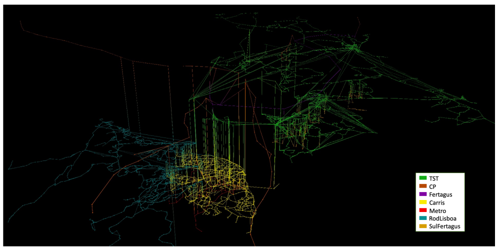

Figure 3: Multilayer Lisbon transport network topology on a 3D representation with all the layers

We modeled 1502 edges representing multimodal changes. The average in and out-degree are approximately the same at 1.4917, which means that the majority of the edges are reciprocally directed. As we are studying a directed network, it is essential to assess the strongly connected components (SCC's). These are graph partitions, where the nodes are connected through a path, i. e. transport users can go from one station to any other station within the component (or subset of total stations) but not to other components. It is quite normal to have many single-node SCC's in unidirectional lines. This is precisely the case in this network. We observe 417 SCC's in the whole network. As some layers such as METRO and CP have only bidirectional relationships between nodes, this can contribute to a higher number of SCC's in the whole network. Some layers such as METRO and have only bidirectional relationships between nodes. The giant strongly connected component has 7,512 nodes which are about 94% of the total nodes of the network. The number of SCC's per each layer are: CARRIS : 67, CP : 3, FERTAGUS : 1, METRO : 1, RODLISBOA : 263, SOFLUSA : 1, SULFERTAGUS : 6, TRANSTEJO : 3, TST : 177. The fact that the number of SCC's of the layers summed is higher than the SCC's in the multilayer network means that the multimodal edges are well placed on improving network connectivity.

How many stops do we have on average between each station? To answer this question we look at the average path length in number of stops between two stations (not the length of the path itself). For the largest mutually connected component, the Average (shortest) path length (APL) is about 34.6878. This means that on average to get from a station/stop to any other on the network, we have to go through about 35 stations/stops before reaching the destination (this number includes multimodal travels as well). Per layer, this value is usually smaller (METRO : 7.7176, CP : 10.2072, FERTAGUS : 5.0, CARRIS : 25.8734, RODLISBOA : 36.9525, SULFERTAGUS : 34.7543, TRANSTEJO : 1.5, TST : 43.3558). However, each layer covers a smaller area than the composition of all the layers. In the case of TST , the APL is higher than in the composition of all the layers. This means that multimodality can be useful for passengers to avoid many stops and additional transfer time.

Which stations connect travellers from different parts of the city? In the case of transportation networks, it is interesting to measure the betweenness centrality to understand what are the nodes that connect different communities of stations, i.e. sets of interconnected stations within a region. In the multilayer network, we identify some stations that have a very high centrality (Figure 4), these are mostly from TST , this may be a sign that TST is kind of bridging layer in some zones. The left skew on the betweenness centrality may indicate the same type of distribution on node criticality since the betweenness centrality on the node measures the number of shortest paths that include that node. So these results are similar to the ones found in the literature [11].

Are the central stations directly connected with one another? To understand the role of degree-degree correlations, we look at degree assortativity. This measures the degree similarity of connected nodes concerning their degree. In Figure 5, we see the same pattern described by Arruda et al. [17]. This is reasonably simple to understand since the assortativity is influenced by the high number of multimodal hubs that connect to one another.

How do different attack strategies affect the connectedness of the network? We attempt to answer this question by analysing the behaviour of the size of the largest strongly connected component - SCC - over time for the duration of the simulation. By implementing the different extraction strategies discussed previously. For each iteration, we compute the largest SCC and its size. This size decreases with the removal and if a critical station is removed the size decreases even faster. Ergo the strategy which has a faster decrease has a more significant impact on the network. This means that networks that exhibit a steeper decrease sooner, as the percentage of iteration

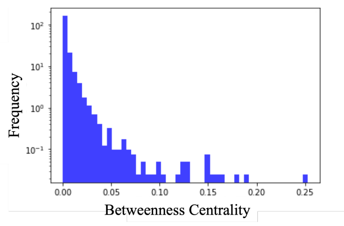

Figure 4: Betweenness centrality distribution

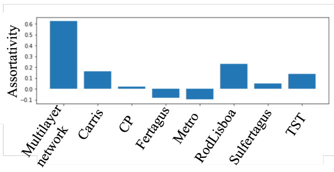

Figure 5: Assortativity distribution of each layer and network.

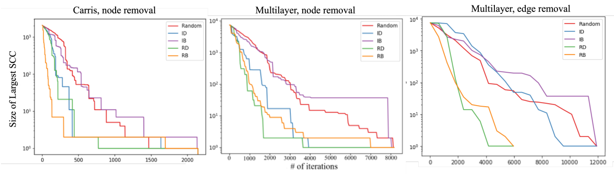

Figure 6: Evolution of SCC size along node attack strategies for a single layer, CARRIS (left) all layers (middle) and edge removal in multilayer network (right).

steps, are less robust. In the same fashion, a high-performance extraction strategy is one which the SCC descends faster. To compare different strategies, we use the discrete AUC and a normalized AUC to compare the resilience of the different layers and the multilayer network. The normalized $AUC \subset 0,100$ allows us to compare the values of networks with different sizes, and is calculated using the following formula:

$$AUC_{Normalized} \sum_{i0}^{\chi} \frac{\tau_i}{V} \cdot \frac{100}{\chi}, \tag{2}$$

where χ is the number of steps of the simulation, τ_i is the size of the largest strongly connected component at timestep i, and V is the number of nodes of the network. This measurement allows us to compare the different resilience side by side. It is important to note that this metric might have a higher variability (for both inflation and deflation) in smaller networks given the granularity. Observing table 2, the most resilient layer is FERTAGUS , and the least resilient layer is RODLISBOA .

	Strategy				
Network	Random	ID	IB	RD	RB
CARRIS	9.8306	4.9715	8.1610	4.4104	**1.2501**
CP	10.7915	17.3442	14.5977	9.4074	**6.0337**
FERTAGUS	27.5555	30.2222	27.9999	24.8888	**22.2222**
METRO	17.9930	18.3006	16.9550	11.8800	**10.2652**
RODLISBOA	7.0540	2.7484	6.7469	1.7580	**0.6569**
SULFERTAGUS	2.4251	1.6707	12.4929	2.9098	**0.8832**
TRANSTEJO	19.0	20.0	20.0	**15.0**	20.0
TST	5.7429	2.5852	7.3845	2.1839	**0.6288**
Multilayer	11.4000	6.6333	10.7513	**5.9189**	8.7007

Table 2: Normalized AUC across all networks: RB is the most effective node removal strategy in all the networks, with the exception of TRANSTEJO and the multilayer network.

Looking at the table 2, we can see that the RD and RB strategies usually yield the best results across all layers. Nevertheless, the RB strategy tends to have a faster descent among the different layers as we can see in Figure 6. Moreover, the IB and Random strategies seem to have the least impact on the size of the largest SCC. There seems to be no particular reason why the ID strategy has a better result than the RD. However, this is the case in SULFERTAGUS , and it should be investigated further. We postulate that this happens because there may be fairly large components that have nodes with a high degree; however, removing nodes from these components does not affect the size of the largest component. So, this phenomena probably has more to do with the metric we are using than the strategy itself.

How do node and edge targeting affect the average path length? To understand the evolution of path length when targeting stations and pathways, we calculated the APL only for existing paths along with the network. So, if there was no path using the transportation system between two points, this was not accounted for. It is important to note that this strategy may not be the best to measure robustness on road transportation since alternative paths may be available on roads that are not on the normal route. So, we expect the APL to reduce along each time step quickly. We ran the result for each layer and the whole network as well.

Regarding the results for station and pathway targeting of the CARRIS network on Figure 7, the RD is the best strategy, this is consistent in all layers. This means that removing the stops with the highest degree has the highest impact on the length of stations one can reach. RB providing an efficient strategy indicates a lower network robustness. In the multimodal network with all the layers we see that RB is a strategy that promotes a fast decrease the APL. This indicates a lower network robustness.

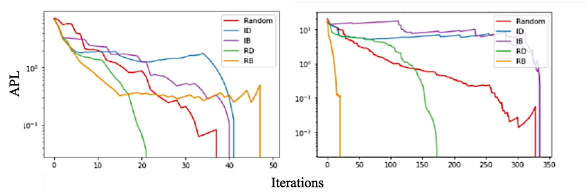

Figure 7: Evolution of APL along node attack strategies for METRO (left) and SULFERTAGUS (right).

How many nodes do we have to delete to fragment the network into isolated components? Figure 8 shows the evolution of isolated components for each strategy in the CARRIS layer. In these graphs we clearly see that RD had the best results, this is the only one that stopped before the end of the simulation, because there are only isolated components when it stops. We obtained about the same results in every layer and for multilayer network is also very similar. This means that the only effective strategy to measure the vulnerability of disconnecting the network from different parts of the city is RD.

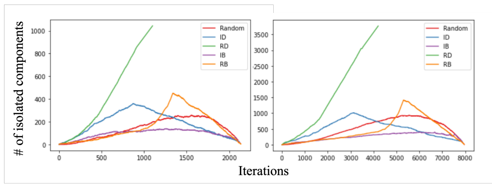

Figure 8: Evolution of the Isolated components (IC) in the CARRIS layer (left) and Multi-modality network (right) for node removal.

What is the impact of removing nodes vs edges? We observed that attacks to nodes are more efficient than attacking the edges, as we need more removals to get the same increase of IC's and decrease of APL and decrease of SCC. As Figure 6 shows, it takes much more iterations to destroy a network by attacking the edges.

Should we recalculate the degree and betweenness after each attack? RB and RD removal strategies can be very effective, yet not so computationally efficient. Recalculating degree after each node removal has proven to be beneficial, since it allows for an better assessment of robustness in both metrics.

5 RESULTS: USAGE BEHAVIOUR

This research is focused on a multimodal prospective , more specifically on the public transport operators METRO and CARRIS ., among the largest operators in the Lisbon metropolitan area. This section aims to discover main differences in subway, bus, and tramways usage data. In the context of the ILU project, we have conducted a study [5] that assesses the main differences in terms of multimodal public transport demand pre and post COVID-19. Additionally, we aim to discover actionable public transport usage patterns. The information gathered from this section is derived from the smart card usage data. Table 3 shows an example of such data. Individual trips correspond to smart card validations at METRO stations and CARRIS buses and tramways, monitored through an integrated fare collection system.

date	fleet number	route number	variant	plate number	trip number	direction	stop number	card ID (anonymized)	type of title	title code	stop identifier	stop name
24/10/2019 10:03:50	201	76B	0	1	6	CIRC	7	321	Viagem CA/ML	3032779	100318	R. Cruzeiro /Tv. Pardal
23/10/2019 12:52:06	201	734	8	1	13	DESC	17	789	Viagem CA/ML	3032779	816	Martim Moniz
24/10/2019 15:49:36	201	76B	0	1	16	CIRC	3	987	Viagem CA/ML	3032779	13401	Boa Hora

Table 3: **Sample of smart card validation data.**

In this study we consider all the individual trips recorded throughout a typical pre-pandemic month, October 2019, and a post-pandemic month, May 2020. Along these periods, a total of 38.845.645 and 14.867.335 trips were observed at the METRO and CARRIS networks, respectively. An illustrative set of anonymized raw trip records from CARRIS is provided in Table 3. From this kind of data we can extract usage patterns that are more detailed than the trivial kind of pattern we see.

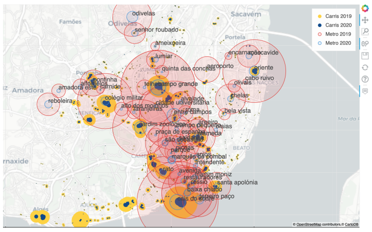

Figure 9: **City view of demand variations (2019 vs 2020) along** METRO **and** CARRIS **stations**

Figure 9 geographically displays the demand at subway stations (transparent circles) and bus-tramway stations (opaque circles) before the pandemic (red-yellow coloring) and during the pandemic (light-dark blue coloring). A general decrease in passengers' demand is observed across METRO (subway) and CARRIS (bus-tramway) networks across the Lisbon metropolitan area. The demand contraction on the METRO demand per station (red to light-blue circle ratio) is considerably higher than the observed contraction on the CARRIS demand per stop (yellow to dark-blue circle ration). With greater detail, we can observe that the demand across commuting routes leading to Amadora and Odivelas (outside the Lisbon area) was less impacted than the ones leading to Parque das Nações (north-eastern side of the city of Lisbon), consistently across the two modes of transport. On the south waterfront zone (Cais do Sodré to Algés) we observe a clear decrease in the demand at CARRIS stops. According to the gross reported income per tax household [29], Amadora and Odivelas, reporting on average 18 157,00 and 19 100,00 euros respectively, have a lower income than the Lisbon municipality (city center), reporting 25 548,00 euros. Generally, the observed degree of demand changes appears to be also correlated with the average land cost near the stations, which serves as a proxy for the household income and working roles that require circulation along the city. Demand changes have a lower magnitude in peripheral stations and in zones with lower income. To further understand the causes of this trend further studies are necessary. Figure 10 provides a coarser-grained view of the daily changes in demand, and the associated variability, across the major lines of the subway network and the major clusters of buses. Generally, the higher the number of stations in the city periphery, the lower the demand contraction.

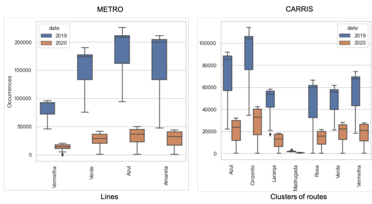

Figure 10: **Daily validations along the lines of** METRO **network and the seven clusters of routes of** CARRIS **network for 2019 versus 2020.**

To clearly assess differences on the degree of demand change within the METRO network, we plotted the demand over the 20 stations with the highest change (left stations in Figure 11) and the 20 stations with lowest change (on the right) across the two time periods. The difference within this mean of transportation is a staggering order of magnitude in all stations. The three stations suffering highest demand contraction are: Aeroporto (Lisbon airport), Cidade Universitária (University of Lisbon) and Saldanha (commercial, business and service district in central Lisbon). With less than ten percent of their demand from the previous year, Aeroporto had the most noticeable change due to air travel restrictions held during the reference pandemic period. Cidade Universitária also had a considerable change in demand. This station serves many students as it is one of the main hubs for students to reach several university campi. Saldanha is a working pole, with a high concentration of large business offices. The Saldanha station similarly suffered a significant change in demand due to remote working enforcement rules by the Portuguese government.

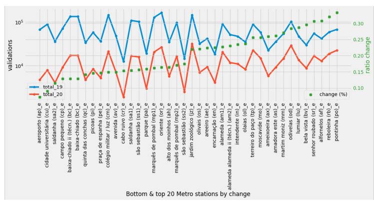

Figure 11: **Demand for** METRO **stations in 2019 versus 2020 and ratio, top and bottom 20 stations**

The changes in demand observed along the CARRIS bus-tramway network reveals a considerably different reality (Figure 12). For the stations with top differences in demand, the variation yields two orders of magnitude, while some stations did not witness significant changes in demand. In fact, the six stops yielding the least decrease actually show increased levels of demand for 2020. A higher demand in a particular stop may be due to a lack of options on other means of transportation.

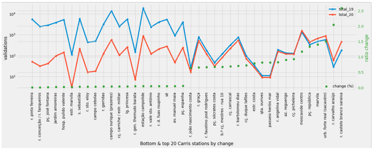

Figure 12: Demand for CARRIS stations in 2019 versus 2020 and ratio, top and bottom 20 stations

Now based on the differences previously seen, we choose to analyse the behavior of the users in a pre pandemic scenario. Even though the study of behaviours during quarantine and post COVID-19 scenarios might yield more updated results. We resort to clustering algorithms that allow us to separate the users based on their usage. This analysis is relevant to understand the resilience of the transport system to certain user types, also further improve incentives to nudge the usage of the system itself, as suggested in previous literature. To preform the clustering, we used aggregated smart card validations, from random a subsample of 1000 users, per hour for each user along periods of 24 hours.

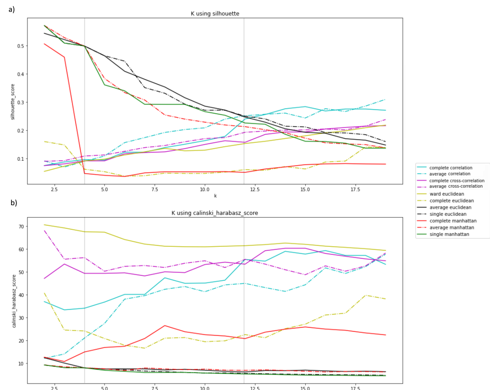

Figure 13: Cluster performance using Silhouette Score (above) and the Calinski Harabaz Index (Below)

We see that the Manhattan distance has a good silhouette score, however the distribution of user behaviour per cluster is highly unbalanced. It is important to note that the silhouette is measured based on the distance chosen for clustering. This means that correlation-based clustering has a lower intra-cluster correlation and progressively, as it decreases the number of series per cluster, the clusters get more cohesive. It interesting to see this same effect in the Ward Euclidean as well. On the other hand, the remaining distances start with a high silhouette and progressively lower as the inter-cluster distances. The described effects are outlined in Figure 13 a). On the Figure 13 b), we can observe that the Ward Euclidean agglomerative hierarchical clustering has the the best Calinski Harabaz score, which measures the inter and intra-cluster variability in a non bounded way. This metric is followed by the remaining clustering based metrics. This is a particularly interesting result since this may mean that correlation may be a worse way to join the clusters. It is important to note that since we are analysing time-series and the euclidean space does not capture the temporal interdependence of observations we expect the results from this analysis to have poor quality results. However, this is used as baseline to compare the further clustering solutions. This yielded particularly inbalanced cluster profiles, grouping users that are not similar and getting low average values. Within the correlation based metrics, we see that the cross-correlation is a better performer with average linkage when we have few clusters and with a complete linkage between 12 and 18 clusters. Nevertheless to actually understand the efficacy of the cluster formation we look at the balance between the clusters formed. The cross correlation metric shows promising results. This is expected since it is an adequate metric to compare time series, as it captures the distance between the time series minding time dependence and was also proven to yield better cluster formation in the context of smart card data by Ghaemi et al. [23]. Below we look further into cluster formation to understand the generated clusters and how they can be useful. The average linkage yields a value for inter and intra cluster correlation that is higher than other methods for a lower number of clusters (at most 10). However, the dendogram generated by average cross-correlation shows that the best cutting point is at about 16 clusters. At this number of clusters, the complete linkage yields a better cluster cohesion (Calinski-Harabasz). This resulted in inbalanced cluster sizes and many clusters with low average values per hour. This leaves us to wonder if in fact the complete cross-correlation actually yelded better results, so we test that. We consider 4 and 6 cluster which are clear cutting points on the dendogram.

A more balanced number of users per cluster in both cutting points (Figure 14). Even though, the formation with 6 clusters has a better balance, the average values per cluster for the solution with 4 clusters have distinct usage behaviour between clusters and fairly high average values per hour in each cluster, which means that the elements on the cluster are more similar.

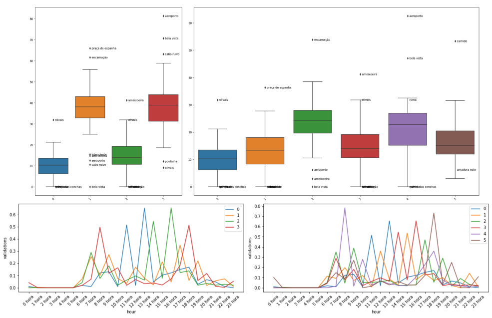

Figure 14: Clusters generated by Complete Cross-correlation

To better understand the results yielded from the cluster formation, we look at the average number of validations per hour during the 24 hour period. This will from now on be denoted as the user profile. In Figure 14 we see the user profiles generated. Based on the user journey profiles, we can further proceed with the spatial characterization of the usage. This analysis starts with the station usage. On the left box plot of Figure 14, we see the outliers identified for exceptionally high and low percentage of a certain user profile. We were able to map the origin and destination of each user and calculated the shortest path within the preexisting lines from one station or stop to another. Using this method we weighted the METRO network with the number of users that go through each pathway (or edge of the graph) at every hour of the day. In Figure 15, we see the user demand in two of the 24 time-spans of the day, at 9AM and 5PM on a typical Tuesday. The weighted digraphs generated show a heavy flow of users towards the city center at 9AM. On the 5PM weighted graph, we see the inverse pattern. Users travelling outwards from the city center, many of them traveling from stations outlined before.

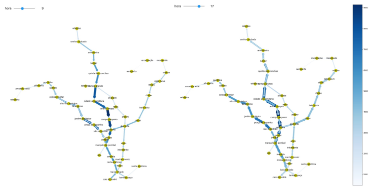

Figure 15: METRO **user demand throughout the network in the 10th of October of 2019 at 9AM on the left and 5PM on the right.**

6 RESULTS: NETWORK RESILIENCE

In this section we aim to measure the resilience of a multimodal transportation system. Nevertheless to actually measure the resilience of the network to demand changes, we need to measure the dynamics of the network transportation supply. So we might ask if the supply for transportation is in fact keeping up with the demand, and what consequences does the lack of equilibrium entail. To acquire a viable model of what the Lisbon public network is offering, we calculated the flow of vehicles based on the established schedules in GTFS data.Figure 16 depicts the METRO network and the weighted edges represent the paths that each route has to go through. This was inferred based on the stop times that allow us to know what are the progression of stops for each specific route (including the temporary buses). Since the nature of this data is spatio-temporal we use two distinct time-spans: 9AM and 5PM .The weighted graph regarding the supply levels is calculated using the schedule with an hourly granularity. Per each time there is a scheduled vehicle at a particular hour, the route is calculated based on the secession of stations of each passage. And the weight of the segments of the graph that belong to the line are incremented with the vehicle capacity. This process is done iteratively through the complete schedule. The representation of the weighted graph uses hue and line thickness according to the weight of the segment, to accentuate the value and priority level of the segments.

We applied this technique to the METRO network, however we used the average carriage values that have much less variance. These have on average about a maximum occupancy of 170 passengers, using the official METRO website data [21]. We also assume a length of 3 carriages, totaling a 510 maximum occupancy. These assumptions are made since we were unable to get more detailed data.

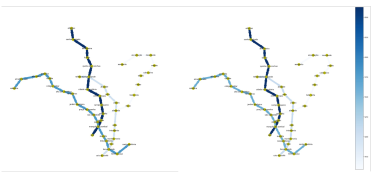

Figure 16: METRO **supply in the 10th of October of 2019 at 9AM on the left and 5PM on the right.**

The METRO supply levels (Figure 17) seem to be identical at both time-spans (9AM and 5PM). This may be adequate if the user types are equal and demand the transport equally at those hours. However, as we have seen that is not the case, so this may be an indication of low resilience in the afternoon. There is a clear pattern of outwards mobility from the city center with high congestion in the same zones and yet again an aggravated effect on the red line from Saldanha to Oriente. Even though the information in this document is static we can easily transpose this to a real time monitoring system that shows the over demanded segments thorough the day, outputing a representation similar to the left graph on Figure 17, which highlights the low resilience links. This would bring further actionable information.

Figure 17: METRO **lean resilience using supply and demand in the 15th of October of 2019 at 9AM (left) and 5PM (right).**

To understand the resilience towards a certain user (a user centered resilience) behavior type we used the sub samples obtained from the clustering solution and weighted the edges based on the ratio of demand for the supply levels of a particular hour. The usage profile from cluster 0 was previously interpreted as "lunchtime commuters". These exert more pressure to the system in the city center, particularly from Saldanha to Cais do Sodré and between Entrecampos and Cidade Universitária. The usage profile from cluster 1 was seen as the long workday commuters, these exert overall higher levels of stress to the system than user profile 0 for example. However this is expected since the cardinality of users is considerably different. There is a lot of stress from Marquês de Pombal to Cais do Sodré and moderate levels in the pathways: Jardim Zoológico - Marquês de Pombal, Baixa Chiado - Alameda and Alameda Oriente. Cluster 2, previously understood as part-time workday commuters with shifted intervals, has strains along the Marquês de Pombal - Baixa Chieado pathway, and generates medium levels of strain from the city center to Laranjeiras, Campo Grande and Oriente. Lastly, users belonging to cluster 3 have a have a considerable presence in all lines, particularly, particularly from Campo grande to Terreiro do Paço. with noticeble presence in Olivais to Alameda, Collegio Militar to São Sebastião and Alameda to Cais do Sodré.

It is clear at this moment that there could be some incentives to alleviate the strain in transport by increasing the level of transport by the number of the demand-supply ratio achieved from the analysis. This can be achieved by implementing a gamification system that attributes usable points for good behavior like in other smart city gamification systems [16]. The use of past and current data could be used to generate agent based systems to decide under those circumstances [7]. The study of these incentives and the implementation of similar techniques to the ones used in this research could yield extremely interesting results. To understand the resilience of the METRO network, we rely on two perspectives 1) a dynamic, by identifying the low resilience links and 2) a static, the topological critical nodes (in case of layers). By comparing them side by side (in Figure 18). On the left we see the number of times each segment exceeded capacity throughout the day (these are regarded as low resilience since they were not resilient to user demand) and on the right the betweeness centrality of each edge. We see that the betweeness centrality is important to understand robustness impact but without a data driven perspective, this metric is nothing but a hunch to discern usage patterns. Most of the pathways that exceeded user capacity do not have a particularly high betweeness.

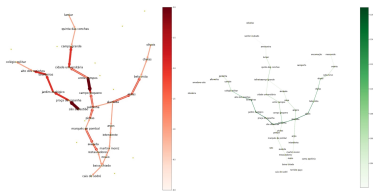

Figure 18: METRO **low resilience links in accordance with demand supply dynamics on the left and topological criticality on the right in accordance with betweeness centrality.**

7 CONCLUSIONS

The main goal of this research is to objectively measure the resilience of multimodal transport networks, both dynamic and topological, contributing to a sustainable transport system. To support the proposed solution, a method for measuring multimodal transport resilience, additional concepts of resilience applied to multimodal transport networks and public transport and time series clustering were introduced along with a set of studies developed in this context. Here, we proposed a multiplex network modelling and its assessment, the pattern exploration in this network using dynamic weights based on demand-supply ratios. To describe the generated solution, we conducted an agglomerative hierarchical clustering of passengers for further understanding specific usage behaviour. The evaluation of the described solution is based on network metrics and cluster cohesion and separation indices. Results show that the strategies that depend on recalculating metrics are generally more effective. We also showed that the resilience tests required removing about half the network nodes to leave all the remaining nodes wholly disconnected. This phenomenon happens in all layers and the multilayer network, suggesting that betweenness targeting is the best way to measure robustness across the different strategies. Results indicate that higher assortativity phenomena in multilayered networks, in contrast to single layers, highlight the importance of inter-modal hub redundancy. Based on the robustness tests, we concluded that the most effective method for targeting nodes is RD (recalculate degree). However, in some cases, RB (recalculate betweenness) yielded better results for multilayer APL decadence (both for nodes and edges strategies), although it showed higher variability. For decreasing the size of the largest SCC, RD yielded better results for the multilayer network. However, for most of its individual layers, the best strategy was RB. To divide a multimodal network into disconnected regions, high degree station failures have a higher impact than high betweenness station failures. However, to yield the same result in a single-mode network, betweenness is a more relevant metric, highlighting the impact of the network topology as the vulnerabilities linked to a multimodal network considerably differ from a single layer network. The gathered results in this study suggest that robustness can be objectively measured using network metrics and percolation simulations. The impact of such simulations can be compared regardless of the network size or structure in any multimodal transportation scenario. Moreover, research findings seem to indicate that we can use the targeting techniques to understand network recoverability (resilience stance) by focusing on stations with hub characteristics (higher centrality) or high betweenness. As practical implications of this study allow practitioners and urban transportation policymakers to tackle the impact of negative disruption in multimodal transportation networks. To assess the resilience of a multimodal transportation system, we applied a resilience metric on an hourly basis based on the equilibrium between demand and supply of service. This allowed us to conclude that the resilience of the network is not only dependent on the topological features such as the betweeness centrality. The strain of different types of users on the network service was analysed, yielding fairly different results for each user type. This is an important analysis since different usage patterns within the same network with different levels of service throughout the day have varying results. This implies that the differentiation of user profiles can be induced to improve the distribution of users in off-peak hours. The possible solutions may involve gamification. The generated resilience graphs for the public transport of the city of Lisbon aim to improve the lean resilience of the public transport network towards pasengers' demand variation using real-time data. These can reproduce accurate representations regarding the regarding the uptake of users by the system, hence the resilience measurement. In the analysis of lean resilience, a future direction points to the analysis of the resilience of inter-modal pathways (or links). Nevertheless, we have contributed to add knowledge on this issue since we empirically showed that for the Lisbon public transport network, the criticality of these links is not measured necessarily by the betweenness centrality of the links but rather from the link degree. This finding is important for the city mobility managers because more attention could be given to the redundancy of high degree stations. This study presents innovative solutions to understand public transportation multimodal resilience for the city of Lisbon.

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