Modelling and Assessing Resilience in Multimodal Transportation Systems

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Knowing is not enough; we must apply. Willing is not enough; we must do.

Johann Wolfgang von Goethe

Abstract

Currently, more than 50% of the global population lives in urban areas. This brings various mobility challenges, particularly pushed by commuting needs in the public transport network to get to work, school, university and several other places daily. In this context, transport demand, city information and operational concerns need to be aligned. As such, this thesis 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 flow and demand. Our hypothesis is that the appropriate multi-layered and traffic-sensitive modelling of this network can promote the integrate analysis of different modalities and characterize resilience. 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 study allow decision-makers to understand the vulnerabilities and ongoing changes to the citizen multimodal patterns in a multimodal transportation network. Moreover, we highlighted the changes in passenger traffic demand during Covid-19 pandemic.

Keywords

Sustainable mobility; Multimodality; Resilience; Traffic patterns Multiplex networks; Spatiotemporal pattern mining; Geolocalized time series; Hierarchical clustering.

Resumo

Atualmente, a população global vive maioritariamente em áreas urbanas. Esta realidade constitui um desafio à mobilidade urbana, principalmente impulsionada pelas necessidades de deslocação na rede de transporte público para finalidades laborais, académicas, entre outras. Neste contexto, a procura de transporte, informações sobre a ocupação na cidade, e a operação dos sistemas de transporte carecem de alinhamento. Assim, esta dissertação visa contribuir para uma solução de mobilidade mais sustentável, propondo e testando empiricamente métodos para avaliar a resiliência de um sistema de transporte multimodal. A resiliência é medida em configurações estáticas e dinâmicas, observando os aspectos da topologia da rede e o fluxo e a procura dos utilizadores. Considera-se a hipótese de que a modelação usando uma rede multicamada apropriada e sensível ao tráfego pode promover a integração de diferentes modalidades e caracterizar a resiliência. Para este fim, propomos três grandes contribuições: um modelo de avaliação da robustez; a análise da dinâmica de utilização da rede incluindo perfis de utilização e das mudanças de procura e oferta, e por fim caracterização da resiliênca. Dentro desta rede multicamada, os padrões de mobilidade da população podem ser compreendidos e representados. Em particular, recorremos a princípios de agrupamento hierárquico aglomerativo e dígrafos pesados para esse fim. Os resultados deste estudo permitem apoiar a decisão e planeamento da mobilidade urbana, compreendendo as vulnerabilidades e as mudanças correntes nos padrões multimodais da pouplação numa rede de transporte multimodal. Adicionalmente, o trabalho oferece uma análise das mudanças na procura de tráfego de passageiros durante a pandemia de Covid-19.

Palavras Chave

Mobilidade sustentável; Multimodalidade; Resiliência; Padrões de tráfego; Redes Multiplex; Prospeção de padrões espaço-temporais; Séries temporais geolocalizadas; Agrupamento hierárquico.

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Acronyms

3D	Three Dimensions
APL	Average shortest path length
AUC	Area Under Curve
CML	Lisbon City Council
CCD	Cross Correlation Distance
CML	Câmara Municipal de Lisboa
CP	Comboios de Portugal
DTW	Dynamic Time Warping
EWE	Extreme Weather Event
ERA	Excellence in Research for Australia
GTFS	General Transit Feed Specification
IB	Initial Betweenness removal
IC	Isolated Component
ID	Initial Degree removal
ILU	Integrative Learning from Urban data and the situational context for city mobility optimization
INESC-ID	Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento
LINES	muLtImodal traNsportation rEsilience aSsessment
LMA	Lisbon Metropolitan Area
LNEC	Laboratório Nacional de Engenharia Civil
OD	Origin-Destination
RB	Recalculate Betweenness removal
RD	Recalculate Degree removal

RodLisboa Rodoviária de Lisboa

SCC Strongly Connected Component

TST Transportes Sul do Tejo

WBS Work Breakdown Structure

Part I

Foundations

1 Introduction

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1.1 Context and Motivation

An estimate of approximately 55% of the world population lives in urban areas [12]. However, such areas represent only a small percentage of the total surface area. Therefore, daily commuting patterns and mobility services' consumption are dependent on factors such as the usage of natural resources and impact time in transportation, pollution, quality of life, among others, yielding extreme importance in the field of sustainability. In this context, numerous studies attempt to optimize transportation systems planning and usage in urban scenarios [13–15]. 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.

The measurement of resilience in engineered systems is defined as "the ability to anticipate, prepare for, recover, learn, and improve from an external disturbance regime that comprises a series of chronic low-intensity and infrequent acute shocks, which disrupt functionality" [16]. In the context of this study, this characteristic is applied both at a static - topological level - and at a dynamic level - demand response. The focal point of the study of the network dynamics is on guaranteeing resilience to demand change on nodes or links varying over time depending on the flow of travelers. To seek understanding of the network resilience, it is important to look not only at the topological features to know where are the rupture points [17] but comprehend usage patterns in a greater detail [18]. This research aims to model and assess resilience in multimodal transportation systems while exploring social equity, decarbonisation and reliability issues. Furthermore, new legislation on anti-pandemic measures [19] require the need to meet standards of social distance, avoiding the excessive accumulation of users at stops and vehicles. It is important to study how they impact the resilience of the network since it has been shown that the anti-pandemic measures have an impact on the usage of public transportation [20].

According to Heinen and Mattioli [21], an improved articulation of multimodality aspects within a transport system is significantly associated with lower weekly carbon emissions. This leads us to believe that a successful implementation of this kind of network is a viable long term solution in the urban scenario for promoting carbon neutrality. However, according to Clifton and Muhs [22], the study of multimodal transportation systems "has historically been underrepresented in travel surveying efforts. This lack of consideration has implications for widely accepted statistics for non-motorized travel behaviour (walking, bicycling, among others) and affects researchers and professionals in travel modelling, urban planning, public health, and urban design".

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 LMA [23]. 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.

Additionally, as noted previously in a general sense, it is essential to consider the impact of natural hazards to disrupt a working transportation system as well. Previous literature [1] denotes the natural hazard risk in different zones of the LMA (see Figure 1.1). This map shows us the spatial distribution of risk for earthquakes, flooding and landslides for the county of Lisbon. This stresses the importance to understand various risk impacts on the structure of the network. Along with the general risk from natural incidents, other incidents through the city have a higher rate of incidence, these usually have a more localised effect [2]. Such incidents may be caused by faults in energy and water suppliers, traffic accidents and fires that disable stations and pathways. Elvas et al. [2] rendered a map of incidents from such a diverse standpoint (see Figure 1.2). This shows us that a study on the impact of network robustness at a local level is relevant.

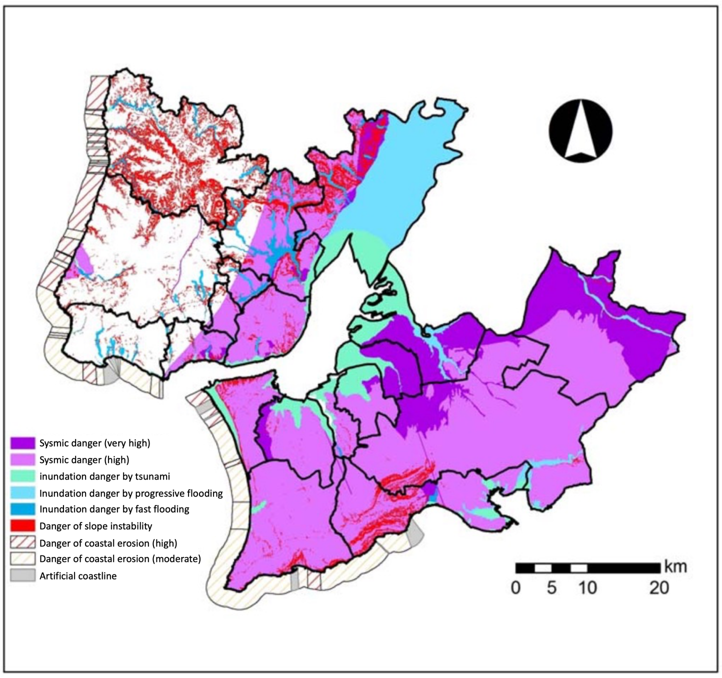

Figure 1.1: Lisbon Metropolitan Area natural hazard map, extracted and translated from Ramos et al. [1]

Since the Lisbon public transportation network is susceptible to these failures that can affect the daily commute of its users, a way to guarantee and improve the resilience of this component of our public services is crucial. To tackle this problem, we aim to understand how robust the Lisbon public transport network is. This assessment starts by quantitatively measuring robustness [17]. Since the Lisbon public transportation network is also complex, it is essential to look at how different stations

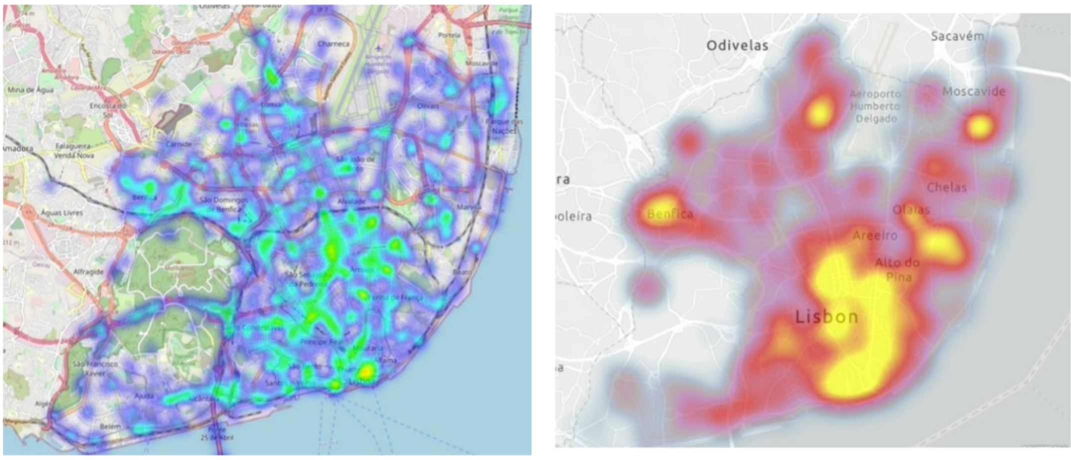

Figure 1.2: Distribution of incidents in the city of Lisbon from Elvas et al. 2021 [2]. On the right the occurrence of incidents and on the left their impact on pathways, i.e. number of roads affected.

and stops may have similar properties, bridging different lines (routes as linear road/rail/other mode infrastructures) and transportation modes. Topological attributes and concepts of network resilience, besides simulation, will play a role in this research study. A data driven approach is presupposed to improve our understanding of the usage of transportation system, hence understanding what kinds of behaviours we have in the system and what is the systems' response to this behaviour is a valuable contribution.

Moreover, urban mobility is continuously changing, so it is important to study the usage patterns such that transport demand and citizens' mobility needs can be answered through an effective supply. This is an area of focus on this study as well. The influence of the COVID-19 in the usage of transportation systems is not negligible [24]. This even poses a threat to the implementation of sustainable mobility, as the use of the resources is not adequate.

Summarizing, the current study aims to contribute to the literature with a more comprehensive review of how to objectively model multimodal transportation systems and quantitatively asses their resilience.

These concepts are applied to the Lisbon multimodal transport network in the context of the Integrative Learning from Urban data and the situational context for city mobility optimization (ILU) project. This project intends to contribute to a more efficient and sustainable transportation network in the Lisbon urban area. More information about this project can be found at `web.ist.utl.pt/rmch/ilu/`.

1.2 Problem formulation

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 [17]. 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 [25]. 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 is essential to provide knowledge to the public transportation's information systems, with the intent to increase its actionability. Since the currently available metrics do not allow for separately quantifying effects of each measure [26], we aim to propose a method to understand the changing patterns as well.

1.3 Objectives

This research aims to propose a method to assess the resilience of a multimodal transportation network. After comprehensively assessing topological resilience, we aim 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 multilayer 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.

1.4 Methodological approach and Research outputs

To achieve the afore mentioned research objectives, a design science research methodology [3, 27–30] was conducted. The following Figure 1.3 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.

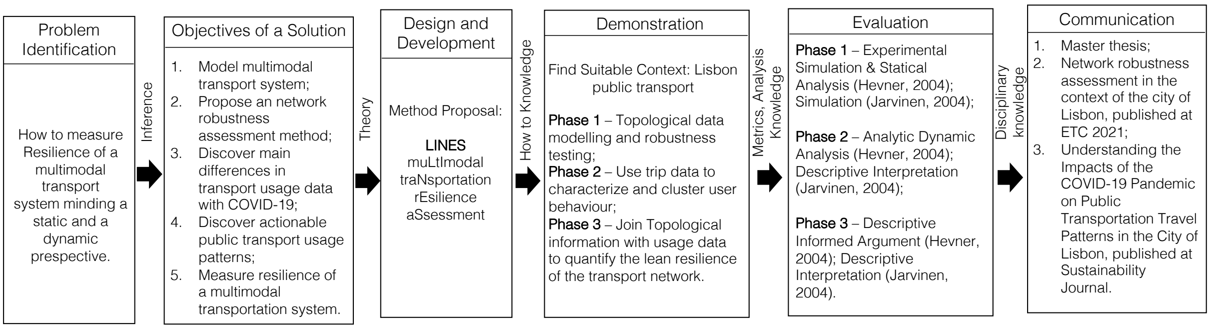

Figure 1.3: Methodological phases of the present research, based on Peffers et al [3] framework

To summarize the main contributions of the thesis, we present the March and Smith research output framework [28] with the main contributions of this research work of Table 1.1. These are mainly composed by design science research outputs.

	Design Science		**Natural Science**	
	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 1.1: Research outputs

1.5 Dissertation organisation

After identifying the guiding research questions and objectives in Chapter 1, Chapter 2 presents the context and essential concepts required to understand the proposed work. Chapter 3 surveys state-of-the-art contributions to urban transportation multimodality and the most relevant related studies regarding resilience assessment. Chapter 4 establishes guiding principles for addressing the target research goals. Chapter 5 presents the detailed process of modelling and results about the robustness analysis. Chapter 6 contains the analysis of transportation network usage behaviour. The network resilience analysis is presented in Chapter 7. Finally, concluding remarks and future works are synthesized in Chapter 8.

2

Background

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2.1 Urban mobility

The concept of multimodality is central to this research. Claudia Nobis [31] 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", according to Diana and Pirra [26]. 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 [32], 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 or research, as these dimensions are markedly present.

2.1.1 Sustainable Urban Mobility Planning

The focus of the analysis performed is a contribution to more sustainable mobility planning and management. Hence, defining it is important. This is a plan that has as its primary objective increasing urban accessibility and delivering high-quality, long-term mobility and transportation to, through, and within the city [33]. The more interconnected and diversified sustainable mobility alternatives are, the more efficient and resilient the transportation system as a whole will be [34].

2.1.2 Transport resilience

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 [35]. 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 [36,37] and connectivity [17], 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 [38] and weighted networks' [39] that result from these measurements may also characterize resilience in terms of functionality. Additionally, there is a stance firstly introduced by Bruneau et al. [4], where resilience is characterized by a curve based on the time to recover from a initial degradation event. Figure 2.1 shows an example of a curve (from the original study [4]) that characterizes resilience by measuring the size of the degradation in terms of infrastructure impact.

This stance originated the resilience triangle and the resilience index, later formalized by Reed et al. [40]. This resilience index in the context of a networked infrastructure can be calculated as

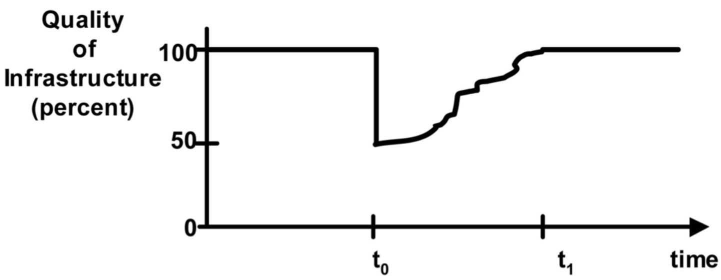

Figure 2.1: Conceptual definition of measure of seismic resilience by Bruneau et al. [4]

$$R = \frac{\int_{t_1}^{t_2} Q(t)dt}{t_2 - t_1}, \tag{2.1}$$

where $Q(t)$ 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 $Q(t)$ as the ratio between the transportation demand and supply.

2.2 Spatiotemporal data analysis

To understand the usage of multimodal behaviour on a particular level, computational approaches from pattern mining and network science are eligible candidates. In that sense, this section introduces the building blocks to understand the proposed analysis.

2.2.1 Event

An event is characterised by a variation of interest in a particular timestamp [41]. In the particular case of this analysis, we are also interested in the geographical information of such event, i. e. , where the event took place. This could be a particular station, for instance. Mathematically we can define an event as $E = (\mathbf{x_t}, s, t)$, where $\mathbf{x_t} = [x_{t1}, .., x_{tm}]$ is a selected set of observations (multivariate when $m > 1$), s is the geographic information of such observations and t is the timestamp of the event. In the context of public transport usage, it generally corresponds to the validation of a smart-card on the transport network.

2.2.2 Time series analysis

The data available for transport usage can be represented as a time series and corresponds to an aggregation of events in order. The most common view for monitoring transport use is in fact, to collect series from validation data, such as input and output validation volumes at stations, routes and public vehicles over time. These series are ordered sets of observations along time. We can also have observations of more than one variable along time, and these are called *multivariate* discrete time series. This could be, for instance, the volume of validations for different types of cards and user profiles.

Given n observations and m variables, with $n > 1, m > 1$,

$$X = \{\mathbf{x_1}, \cdots, \mathbf{x_n}\} \quad \text{and} \quad \mathbf{x_t} = [x_{t1}, \cdots, x_{tm}] \in \mathbb{R}^m,$$

where X is a multivariate time series.

According to Persons [42], time series are described by four elements: the trend, seasonal, cyclical, and irregular components. The trend describes a systematic change in the level of a series. The seasonal and cyclical components represent a repeating change over time, and the first is over a predefined period. The irregular component represents statistical noise. This can also be referred to as white noise when a correlation is not present [43]. Classic approaches to time series analysis model behaviour using auto-regression, difference and exponential smoothing operations, and more recent techniques consider recurrent networks.

2.2.3 Automatic Fare Collection data

Bus passengers' data for the public transport mode is generally based on title validation in the beginning of each trip (bus entry). It is characterised by the time of the validation, number of the vehicle fleet as well as the variant, number of the trip, direction of the trip, number of the card and code of the stop. These attributes allow us to know where traveller entered and is headed within that vehicle. This can further be mapped within this modality with other vehicles using the user id.

Validation of cards in the subway is usually done upon entry and exit as well. So it allows for an easier Origin-Destination (OD) mapping, but the path is not entirely clear as we do not have validations when the traveller enters each train. The more recent data available for this modality is characterised by the timestamp as well as the station, the card number and if the traveller was entering or exiting the station. However, before 2019, the METRO usage data available only describes the type of traveller cards and how many of each kind used the system at each timestamp, as well as how many travellers entered or exited each station of the network. These two types of validation can be joint, for instance, to understand how much the flow of travellers for each station has changed over time. In that case, instead of an event being a single validation and its properties, it would be the set of validations of a specific time span.

2.3 Hierarchical clustering

Hierarchical clustering is an algorithm that allows for a pairwise grouping of elements in a sequential way. This is done by using a metric to assess how distant element are from one another. In this context, the metrics are at the core of the study. Some of these metrics are explained bellow. The process of hierarchically clustering can be done in an agglomerative way by pairing all elements, using a certain linkage based on their similarity until a dendogram is generated. This allows for a new way to divide the generated clusters in accordance with the desired granularity of the analysis since we can have more or less clusters [44]. This family of clustering algorithms is a way to not exhaustively compute all the possible combinations of pairs [45]. Another way to compute a hierarchical cluster is by starting with one cluster and recursively dividing it into sub clusters using similar principles, in this case by maximizing the distance between subsets. This is, by contrast, called divisive hierarchical clustering. Hierarchical clustering has been used in the context of spatio-temporal data in the transportation sector [46] and particularly to analyse smart card data [47].

2.3.1 Distances

The Euclidean distance, also called L_2 distance, is defined as

$$L_2(a, b) = \sqrt{\sum_i (a_i - b_i)^2}, \tag{2.2}$$

where $\mathbf{a}, \mathbf{b}$ are multivariate observations.

The Manhattan distance also called L_1 distance is defined as

$$L_1(a, b) = \sum_i |a_i - b_i|\,, \tag{2.3}$$

where $\mathbf{a}, \mathbf{b}$ are multivariate observations.

Since, The above metrics 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. This has been used as a clustering metric for smart card data [8]. The idea is that the behaviour of two users may be the same but in different time-spans. Even though this may be interesting to cluster user behaviour, the lag between the pair of time-series should be relatively minimal since the profile of a midday and midnight travelers should be different as a means for better lean resilience. This distance was used and demonstrated for this purpose by Ghaemi et al. [44] and in can be defined as

$$CrossCorrelation(a, b, k) = \sqrt{\frac{(1 - \mathrm{Corr}(a, b, 0)^2)}{\sum_{k=1}^{K} (1 - \mathrm{Corr}(a, b, k)^2)}}, \tag{2.4}$$

where k is the lag and a, b are time-series.

2.3.2 Linkage criteria

The concept of linkage is core to hierarchical clustering since it is what determines the distance between sets of observations. The Complete linkage can be intuitively characterized by the farthest pair of neighbours within two clusters, this is

$$\max\{d(\mathbf{a}, \mathbf{b}) : \mathbf{a} \in A, \mathbf{b} \in B\}, \tag{2.5}$$

where A and B are the clusters containing each $\mathbf{a}$ and $\mathbf{b}$ respectively.

Single linkage on the other hand is the minimum distance between two elements of two clusters that is calculated by

$$\min\{d(\mathbf{a}, \mathbf{b}) : \mathbf{a} \in A, \mathbf{b} \in B\}. \tag{2.6}$$

The average linkage is defined by

$$\frac{1}{|A| \cdot |B|} \sum_{\mathbf{a} \in A} \sum_{\mathbf{b} \in B} d(\mathbf{a}, \mathbf{b}). \tag{2.7}$$

In this case the linkage is done by either maximizing or minimizing the average pairwise distance between all elements of two clusters.

The Ward linkage aims to minimize error of sum of squares, hence it effectively measures the increase in Euclidean distance between a pair of clusters A and B,

$$\sum_{i} d\left(\{A \cup B\}_i, \overline{\{A \cup B\}}\right) \tag{2.8}$$

, where the underlying idea is to minimize variance within each cluster.

2.3.3 Cluster Assessment

The silhouette score is a metric that measures both the cohesion within the clusters,

$$n(i) = \frac{1}{|C_i| - 1} \sum_{\mathbf{a} \in C_k, \mathbf{b} \neq \mathbf{a}} d(\mathbf{a}, \mathbf{b}), \tag{2.9}$$

as well as separation from other clusters,

$$m(i) = \min_{k \neq i} \frac{1}{|C_k|} \sum_{\mathbf{a} \in C_k} d(\mathbf{a}, \mathbf{b}), \tag{2.10}$$

where $\mathbf{a}$ and $\mathbf{b}$ are elemets, C_i and C_k are different clusters and d is the distance between elements, that can be measured according to the metrics proposed previously. The metric is then defined as,

$$silhouette(i) = \frac{m(i) - n(i)}{\max\{n(i), m(i)\}}, \text{ if } |C_i| > 1, \tag{2.11}$$

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 W,

$$W(K) = \left(\sum_{k=1}^{K} \sum_{C(j)=k} \|\mathbf{x_j} - \mathbf{x_k}\|^2 \right), \tag{2.12}$$

and between ,$B(K)$, the clusters,

$$B(K) = \left(\sum_{k=1}^{K} a_k \|\mathbf{x_k} - \bar{\mathbf{x}}\|^2 \right), \tag{2.13}$$

these are covariance measure that equating to a ratio, result in the index,

$$CH(K) = \frac{B(K)(N - K)}{W(K)(K - 1)}, \tag{2.14}$$

where, K and N are the number of clusters and total elements respectively, $\mathbf{x_k}$ is the centroid of each cluster, $\mathbf{x_j}$ is an element of a cluster, $\bar{\mathbf{x}}$ is the average value of all elements

The higher this value, the better the clusters are formed. Since the idea is to maximise variance between clusters and minimize within cluster variance. This is a particularly interesting metric to our work as we want to measure how well the average value for a particular cluster represents the set of elements within it.

2.4 Concepts in Network Modelling

In addition to dynamic data given by events based on validations we also use the topological properties of the transport network. In this work, multimodal networks are used to model all public transport modes in the city of Lisbon. However, 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 [48], multilayer networks are the optimal solution to represent this kind of metropolitan transportation systems as modalities should be represented in different layers, and they should also be kept separate to guarantee efficient coverage.

A simple network is characterised by $G = (V, E)$ where V is the set of nodes and E is the set of edges [49]. According to Tomasini [49], a multilayer network is characterised by a quadruple,

$$M = (V_M, E_M, V, L),$$

where:

- V is the set of nodes in the network.
- V_M is the set of the node-layer combinations, i.e. to which layers to nodes belong. These are the pairs of station-transportation modality.
- E_M is the set of intralayer and interlayer edges. These are the different paths that can be taken from a geographic place to another using the same transport modality and the possible modality changes with walkable distance.
- L is the set of layers in the network. In this specific case, each layer has only one aspect since edges of different types can connect the same geographic places. Hence the usage of a **Multiplex network** which is a particular type of a multilayer network.

With this definition, we can understand that a monoplex (single-layer) network is a type of network that has only one layer, and all the edges have the same nature. We can also understand that a multiplex network is a particular type of multilayer network where nodes can be connected to one another through multiple types of connections [50]. The use of the second is useful in multimodal transportation system modelling because we can connect the stations in the same geographical sites via different types of transport modalities. This relationship can be more easily understood with the example in Figure 2.2 by De Domenico et al. [51].

This type of representation allows us to define weights for modality changes and assess the robustness of the networks as well as understanding the geographic properties of multimodality patterns.

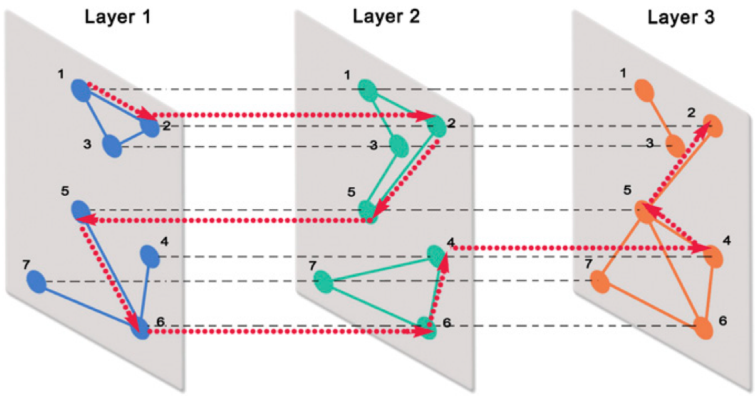

Figure 2.2: An example of navigation in a multiplex network. Several layers have different types of edges between the same geographic points. The red path shows the trajectory of an agent through intralayer and interlayer edges to reach the same geographic points in different layers.

Several metrics of the network can also help us understand the structure of the network. The simplest ones being the degree of a node, i. e. the number of edges connected to it.

2.4.1 Assortativity

Assortativity means the attachment preference of the nodes in a network to other similar nodes. Similarity in this case can be based in a set of characteristics. if we are talking about degree similarity we can also refer to this property as degree-degree correlation. Assortative mixing,

$$r = \frac{1}{\sigma_q^2}\left[\sum_{jk} jk\left(e_{j,k} - q(j)q(k)\right)\right], \tag{2.15}$$

was mathematically defined by Piraveenan et al. [52], where σ_q is the standard deviation of the degree distribution, $e_{j,k}$ is the joint probability distribution of the remaining degrees of two nodes, k is the degree of a node and

$$q(k) = \frac{(k+1)p(k+1)}{\sum_j jp(j)}, \tag{2.16}$$

is the relationship between the degree distribution $p(k)$ and the link distribution $e_{j,k}$.

In this case, assortative behaviour would correspond to stations with high degree link with other stations with high degree, and disassortative would correspond to stations with high degree link with others with low degree.

2.4.2 Average shortest path length

This metric is quite concise in that it informs us what it entails directly,

$$a = \sum_{s,t \in V} \frac{d(s,t)}{n(n-1)}, \tag{2.17}$$

a smaller value means that the nodes are more reachable to one another, on average. Where V is the set of nodes in the network, $d(s,t)$ is the shortest path from node s to mode t, and n is the number of nodes in the network.

2.4.3 Node centrality

The node centrality concept is important to define how important a node is. This can be calculated in different ways, that ultimately make up different types of centrality with distinct meanings. Betweenness centrality,

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t \mid v)}{\sigma(s,t)}, \tag{2.18}$$

measures how important a node is in connecting communities of nodes. V is the set of nodes in the network, $\sigma(s,t)$ is the number of shortest paths in a network and $\sigma(s,t \mid v)$ is the fraction that flow through the node v. A high betweenness centrality means that that node is an important bridge between communities, and literally, it means the percentage of shortest paths in the network flow through that node.

Closeness centrality measures how close a node is to every other, i. e.

$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)}, \tag{2.19}$$

the reciprocal of the average shortest path distance from any other node in the network to the node, u. Where, n is the number of nodes in the network and $d(v,u)$ is the distance between the nodes v and u.

2.4.4 Strongly connected component

In the context of directed graphs, a strongly connected component is a set of nodes such that there is a path from each node to every other node within that set. Figure 2.3 provides an example.

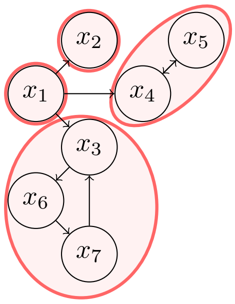

Figure 2.3: An example of a set of different types of a Strongly Connected Component (SCC) where we can see four SCC's $\{x_1\}, \{x_2\}, \{x_4, x_5\}$ and $\{x_3, x_6, x_7\}$

3

Related work

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3.1 Previous research within the ILU project

In the context of the ILU project, contributions have been recently proposed by the research team, to promote the sustainability of the Lisbon's mobility system. They projected as proposed both descriptive and predictive models for the integral analysis of traffic and situational context data in the Lisbon Metropolitan Area [53] in search of emerging mobility patterns [25] their interpretation based on historical data [54]. Multimodal mobility patterns [55] has also been proposed, offering a more structured view of the problems and opportunities for multimodal big data analysis and applied traditional metrics to measure multimodality. Complementing the previews analysis, autonomous methods for processing data from heterogeneous sensors present in traffic networks [56] have been developed, as well as the discovery of patterns inherent in such data. These studies have been conducted to use the data generated by the transport system to provide helpful suggestions on how to improve the system planning for a more sustainable usage outcome.

The combined effort of these publications has been implemented in a software that aims to improve the current information and decision making and boost mobility management towards a more data-centric approach. This allows for more objective, transparent and effective coordination between public transport operators for management purposes.

3.2 Modeling and study of multimodal transport networks

The modelling of multimodal transportation systems recurring to multilayer networks has been previously proposed to analyse urban transportation systems [57]. This modelling technique allowed for analysis of, for instance, the superlayer interdependence. Multilayer networks are also used to model air transportation networks. These networks can, for instance, be used to study how the degree–degree correlations of a network affects the spreading of an epidemic [58]. The modelling of different types of multimodal transport networks have been done in the context of different empirical studies as shown in Table 3.1 authored by Zhan et al. [10]. Note that air travel can be seen as a multimodal transport problem as different air travel companies constitute different layers of a network.

Different authors have modelled and assessed these types of networks: Bogart [59] addressed the evolution along time using historical data. Tavasszy et al. [60] developed a method for choosing different routes in shipment according to demand. Derudder et al. [61] studied connectedness in India using community membership and betweenness centrality. Varga [62] applied a weighted multiplex to air traffic to then make a network analysis with metrics such as average degree and assortativity. Du et al. [63] modeled an air traffic network in layers based on flight frequency and concluded that is less redundant in the Chinese network than the worldwide network. De Arruda et al. [58] modeled an air traffic network

Authors	Networks	Area	Basis
Bogart [59]	Road, canal, port	England	Transport mode
Tavasszy et al. [60]	Maritime, road	World	Transport mode
Derudder et al. [61]	Rail, road, air	South Asian	Transport mode
Varga [62]	Air	Europe	Country
Du et al. [63]	Air	China	City
de Arruda et al. [58]	Air	Europe	Company
Aleta et al. [57]	Tram, metro, buses	Spain	Transport mode
Ding et al. [64]	Rail, road	Malaysia	Transport mode
Liu et al. [65]	Bus, metro	China	Transport mode

Table 3.1: Empirical studies of multilayer transportation networks, by Zhan et al. [10]

and assessed assortativity and rich club effect (nodes with high degree connect to nodes with high degree) in international flights. Aleta et al. [57] modelled the Madrid urban transport network, measured overlap between different modes and transfers and time from one station to another. Ding et al. [64] studied how the topology of the network affected the formation of communities and how betweenness centrality and closeness centrality affect growth. Liu et al. [65] created a methodology to assess the spatial accessibility of public transportation network using a case study in Shanghai, China.

Using Open Street Maps data, Orozco et al. [5] 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. The study of overlap is fairly interesting in this context, to understand what is in fact the role of overlap in network resilience. Are urban multimodal networks in fact more resilient if they exhibit high levels of overlap between different modal layers?

User location data can be useful to classify the transportation mode being used. This idea has been explored [66] and can be used for further enhancing the current information we have on the usage of the system. Improving existing recommendation systems for multimodal transportation [67]. The deployment of such systems promotes an increased usage of multimodality by recommending users to use it in their daily transportation.

Given the disaggregated nature of the transport usage data, there have been efforts to make an Origin–Destination mapping over different transportation modalities [68]. Moreover, the integration of such public transport modalities with Park-and-Ride systems has also been subject to study. This is a very useful solution to avoid out of the city traffic to inflow into the city traffic. [69]

The analysis of network-based spatial data and particularly network event data has been explored in the context of the development of the `pysal/spaghetti` python library. [70] However, this does not include the exploration of multilayered networks, nor multimodal data nor the temporal dimension of the data.

To understand the multimodality behaviours, M. Diana and M. Pirra [26] proposed the use of indices

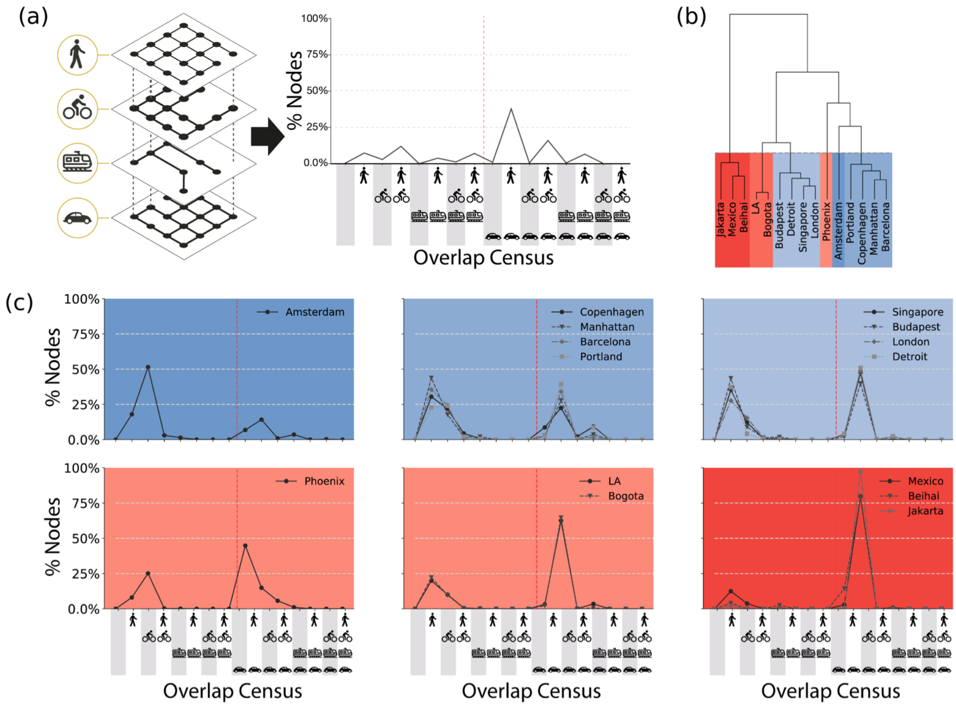

Figure 3.1: Orozco's [5] study shows how different layers overlap with one another, in the context of different urban transportation networks, including pedestrian paths, rail and tram lines, bicycle paths, and motorways. This study clustered different cities according to their overlap similarity (c).

from other disciplines to quantitatively measure the usage within different transportation modalities, *e.g.* bus, metro, train. All of these measures help us understand the overall behaviour of the travellers in terms of how unequal is the usage of different modalities, the Herfindahl–Hirschman index, or the equity of distribution of public facilities, Gini coefficient, or the uncertainty of the usage of the travel means, Shannon Entropy, or how travel means have different usages intensities, the Dalton Index. However, the values of such indices alone may not be enough to reach actionable conclusions, as specific information on multimodality per mode and station is crucial to adapt the supply.

In terms of network structural metrics, Aleta et al. [57] reference the average number of mode transfers in a trip as a metric to assess multimodality as well as overlapping degree. This metric is fairly simple to calculate and brings useful actionable information without user data. However as they noted, the highest overlapping degree nodes are not the ones with the most activity. So user data is also very important to clarify common misconceptions. In terms of metrics that require user data, they look at waiting time and walking distance between transfers of user trips as well as the number of transfers within each trip and fraction of users using each line. These can be very insightful to promote actionability, since historic values of such variables help us determine the worst preforming stations service wise. However they only present distributions instead of values associated per station, which would be even more helpful for actionability.

3.3 Passenger flow analysis

The concept of network resilience is inherently linked to the passenger flow and demand patterns within a transport network [71]. Since the vulnerabilities of such a network are not only dependent of topological features and 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 key stakeholder behaviour can be considered to design systems that can withstand stronger specific vulnerabilities [72]. Ivanov [71] 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), since the COVID and post-COVID changes are felt abruptly in the world of transportation [73]. 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, Rad et al. [73], here we define public transportation lean resilience as a measurement regarding resilience comprehending passenger flow and transportation supply with continuous adaptability. In this document we operationalize this conceptual construct through the artifact proposed in chapter 4, which refers to the method proposal as solution (the artifact: muLtImodal traNsportation rEsilience aSsessment (LINES) Process).

Recent studies have approached the passenger demand change understanding by identifying different usage profiles using different clustering techniques. This is the case since individual travel patterns provide higher detailed description than zonal commuting behaviour analysis [74, 75], since we can detail what kinds of users are coming from where. Additionally, Ma et al. [76] 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 [77] 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 ones available in the city of Lisbon. Distinctively, Kung et al. explored the usage patterns based on mobile phone location data [78]. Ma et al. [6] 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 very large number of Non-commuters given the strong assumption that there were only three profiles of commuters. Nevertheless the distribution of departure times (Figure 3.2) showed fair results. As we can see in Figure 3.2, there is a clear distinction of the 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

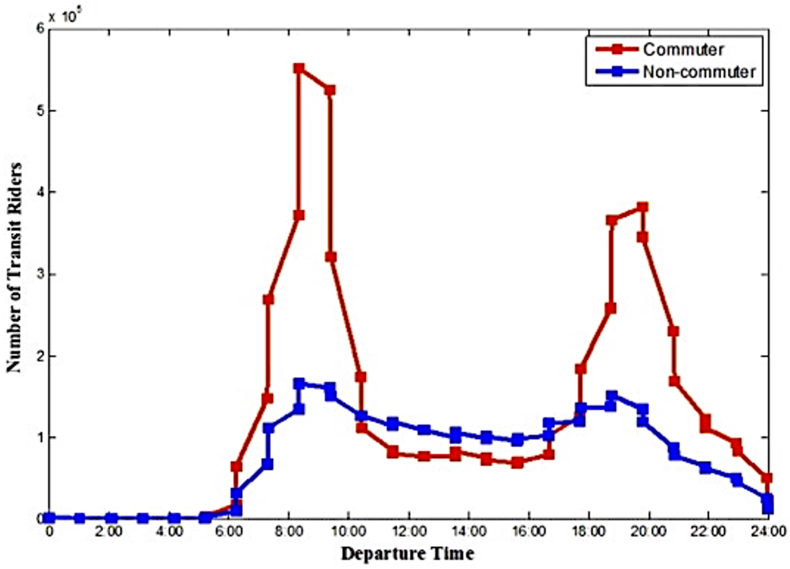

Figure 3.2: Distribution of departure times of public transport commuters and non-commuters by Ma et al. [6]

distance between two curves Dynamic Time Wrapping (DTW) comes to mind. However, He et al. [7] 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. We can clearly see this difference in Figure 3.3. 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. [79] used an hourly observation granularity and calculated clusters of users based on k-means and the hamming distance. Agard [80] 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. [44] 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. Figure 3.4, shows the output from their experiment that totaled 11 detailed clusters and 2 main user types. This allows for a more or less granular approach depending on the goal. There is a very clear distinction of the cluster profiles, yielding that this technique contributes to better describe user profiles, as a means to understand the user journey. This is relevant since the perception about demand of users reinforces the lean resilience. For example, if there is a clear understanding about the routes of the user types we can clearly adapt the supply of transportation to the demand of each type of user, according to their needs, turning the transportation more resilient in a lean way.

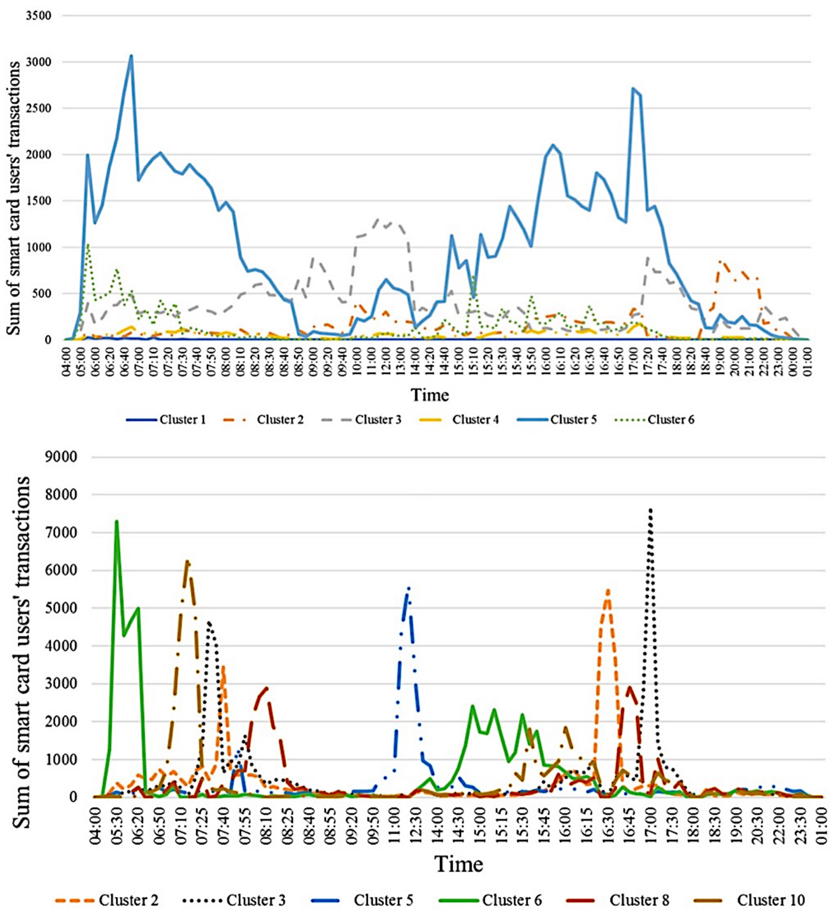

Figure 3.3: Sum of transaction time of users, above using Dynamic Time Warping (DTW) and bellow using Cross Correlation Distance (CCD), extracted from He et al. [7] On the DTW graph cluster 5 agglomerates most of the usage time signatures and other clusters are residual and have non homogeneous groups.

3.4 Measuring resilience in transport networks

To answer the need for measuring resilience of networks, Klau and Weiskircher [81] 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. [82] 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. [83] 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 [84].

These studies were a very much related with the earlier study of reliability done by Chen et al. [85], where they measured the reliability of networks given the demand change based on models of route

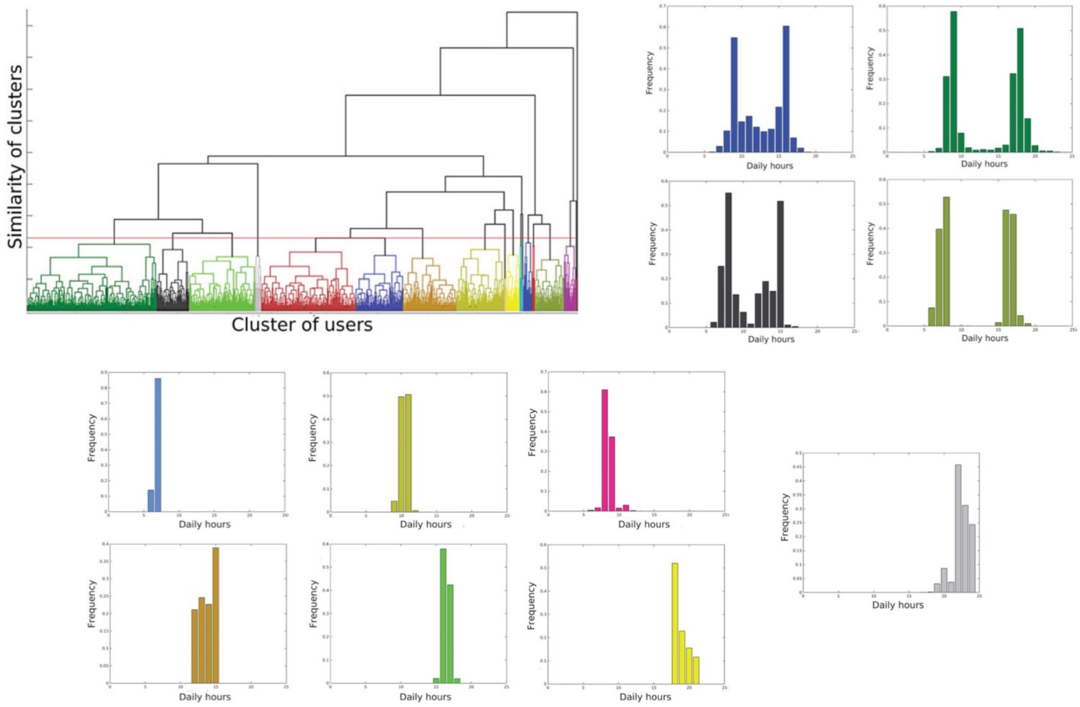

Figure 3.4: Hierarchical clustering of users extracted from Ghaemi et al. [8] On the top left corner the dendogram outputted from the hierarchical clustering. On the top right the regular users and bellow the single trip users.

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 [86] 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 is usually measured the interruption of service. Resilience, on the other hand, measures the ability to recover from such interruption in service [87]. 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 [88] 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.

Another view on resilience measurement on multimodal transport networks is given by Bocewicz [89] who postulates that a whirlpool network structure on a multimodal transport network leads to a cyclic steady state unlike a tree structure. A whirlpool state is one that points towards another and the following states recursively point to the following until it completes a circle. Then measurement of robustness is given by the ration of states in a whirlpool structure and the total number of states in the multimodal transport network.

Besides a simpler network structure resilience test, a dynamic measurement of such property has also been studied in multimodal urban transport. Stamos et al. [90] studied resilience to Extreme Weather Event (EWE) in several European cities by measuring the percentage change during the EWE. Then claimed this could be used for prediction tasks by using past rail, air and road usage data. However this method lacked in terms of actionable information, because prevention is only attainable if we know where to act. Later on, Cats et al. [9] defined a framework to assess robustness ilustrated in Figure 3.5. This helped the description of robustness assessment as an economic problem. This kind of assessment is very relevant for this study because it provides a baseline for understanding the impact of different disruption scenarios in specific links, quantifying the criticality Fig 3.6. This is a type of assessment that provides specific enough data to be actionable in the real world.

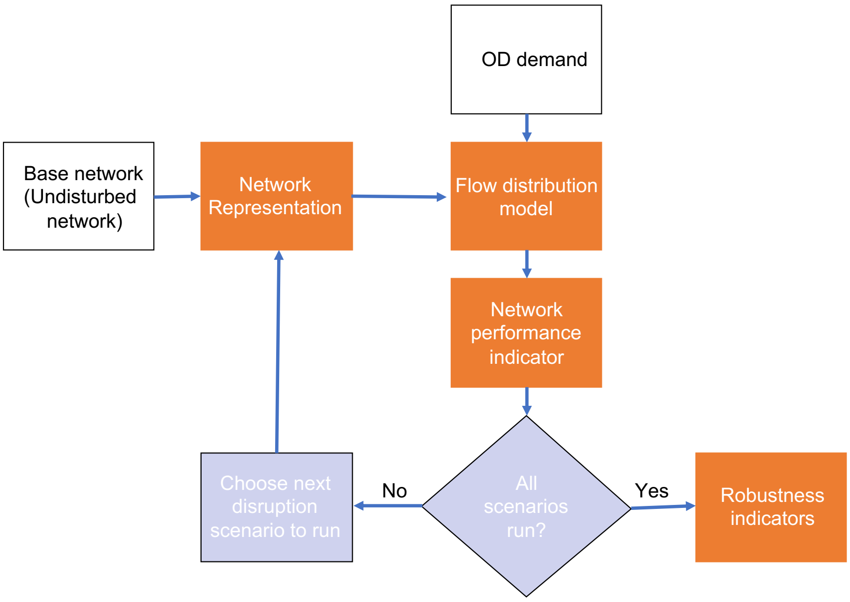

Figure 3.5: Cats et al. [9] robustness assessment modelling framework.

Figure 3.6: Link criticality indicator in Cats et al. [9] robustness assessment during a disruption scenario.

Part II

Proposal

4

Solution

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With this work, 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 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 4.1 presents a Work Breakdown Structure (WBS) diagram with the main activities of the muLtImodal traNsportation rEsilience aSsessment (LINES) Process.

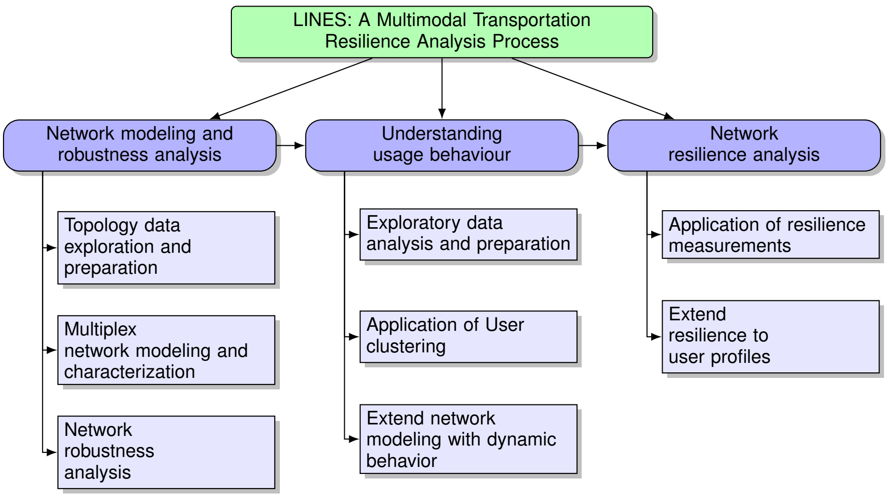

Figure 4.1: Interconnectivity of each activity of the proposal using a WBS diagram, integrating the methodology for assessing the resilience of a multimodal transportation system. The modelling and assessment phases have an impact on finding actionable patterns.

4.1 Network modeling and robustness analysis

To understand the structure of the multimodal transport network and how robust it is, a first methodological set of activities related to network science are proposed:

1. Topology data exploration and preparation. This step involves the network topology inference

based on the network data. This includes calculating distances between stations and how the different layers connect to one another;

2. Multiplex network modelling. Using the data prepared in the previous step, we can build the computational representation of the network. This will allow us to further understand how the network is structured. This step also includes for a meaningful data exploration of the public transport topological data, displaying a network map and network statistics. In this step, we understand the key features of the network.

3. Network resilience testing and assessment. In this step, we test different attack strategies described in previous literature. In this section, we subdivide the interpretation of the resilience tests it into the following questions:

   - What is the role of **degree-degree correlations**?
   - How do different attack strategies affect the **connectedness** of the network?
   - How does node, and edge targeting affects the **average path length**?
   - How many nodes do we have to delete to fragment the network into **isolated components**?
   - What is the impact of removing **edges vs nodes**?
   - Should we **recalculate** the degree and betweenness after each attack?
   - What is the impact of **cascading failures**?

   Additionally, the study of how network resilience plays a role in the flow dynamics of the network is of interest in this step.

4.2 Understanding usage behaviour

Having understood the topological features of the data, we move on to the other main focus of this work, discovering patterns inherent to the flow of the travellers in the public transportation network. It is subdivided into the following steps:

1. Exploratory data analysis and preparation. This step involves the exploration of the set of validations we have for CARRIS and METRO and possibly other transportation modalities. This is where we make key decisions involving missing data imputation and apply data mappings and feature extraction for a more conducive pattern analysis in the subsequent steps. By the end of this stage, we have developed a further understanding of the data we have to extract patterns and also have mitigated different problems inherent to the data.

2. Application of user clustering, focused on a hierarchical approach. Former variants of hierarchical clustering algorithms have been developed in the context of public transport data to understand user behaviour. However, the profiling of usage behaviour in the context of the Lisbon public transportation network is, in fact, a novelty. The types of usage discovered along this stage will be discussed with experts. Here we aim to understand how the travelers use the network in aims to understand what kind of demand could be expected depending on user type.

3. Extend network modeling to capture dynamic behavior. Taking advantage of the network modeling in a previous step, we apply the spatial distribution of user types. This allows a better understanding of the spatio-temporal nature of the data being described.

4.3 Network resilience analysis

Given the nature of the associated research project, the applicability of the results is key. In this context, the understanding of how resilience is measured and how it is connected to the previous steps is of high importance. As such, we propose the following steps:

1. Application of resilience measurements. In this step, we extend the previous results to include resilience analysis and the characterization of the transportation network in terms of its vulnerabilities in a dynamic way.

2. Extending resilience to user profiles to further aid actionability. Having applied and explained the usage patterns inherent to the pubic transport data, minding the network topology, the knowledge transfer is crucial to bring more relevance to this work. By integrating an explanation of the practical impact of this study, we can assist the decision-making process.

4.4 Assessment methodology

4.4.1 Evaluation of network resilience

4.4.1.A Network attack strategies

A way to assess the 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. [91] 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. This precision technique allows us to attack the most important nodes according to each metric. We used the six following attack strategies for nodes and edges:

1. Random removal,
2. Initial Degree removal (ID)
3. Initial Betweenness removal (IB)
4. Recalculate Degree removal (RD)
5. Recalculate Betweenness removal (RB)
6. Multimodal Hubs removal

Strategies with 'initial' only calculate target metrics and do not update them after removing nodes; these are much less time-consuming. Recalculate strategies, on the other hand, recalculate removals per removal or set of removals. Recalculating for each set of removals is a strategy used to run the algorithms faster. We selected two main network metrics for targeting removals. The first metric is the node degree. As nodes with the highest degree are considered important nodes, removing them may have a higher impact. Strategies that apply this principle are ID and RD. On the other hand, another critical attribute is the centrality of a node. There are a few types of centrality, but the betweenness centrality is crucial since it represents the nodes with edges that unify communities/groups inside the network. These nodes are an ideal location to increase the damage of the attack since it disconnects the communities of the network. Strategies that apply this are IB and RB.

A multimodal public transportation network is a multilayer. Thus we also wanted to test if removing nodes that connect the graph layers destroys the network faster. We call these nodes *multimodal hubs* [1] and this attack strategy is *Multimodal Hubs removal*. Some notes about implementation and expected results are provided in Appendix.

4.4.1.B Cascading attack strategies.

We understand that single nodes fail, but more catastrophic events can happen in the network, bringing the notion of cascading effect. For the *cascading effects*, we described and implemented two attack strategies:

1. *Line Failure*, crashes an entire transportation line in the network. In our case, it could happen with a landslide or obstacles on the line interrupting the connectivity of a set of connected stations, thus making the whole line stop and creating a Line Failure. We simulate this by removing all the

[1] For example, two multimodal hubs are *Alameda*, that connects METRO and CARRIS , and *Gare do Oriente*, that connects CARRIS , METRO and Comboios de Portugal (CP).

nodes that have the attribute of that line. Some nodes may belong to more than one line, even from different modalities.

2. *Neighbours Failure*, simulates the crashing of several layers of the neighbours of a failed node. One example of this is a recursive failing of transports in the same area. When a station fails, the neighbour stations experience overflows and potentially fail as well. To simulate this type of cascading effects, we collect several layers of the node's neighbours, and then, remove all these nodes at the same time.

To assess the impact of each strategy, we will graph the evolution of different metrics for each removal. To understand how connectedness is affected, we will measure the average path length (also known as average geodesic distance), average degree, number of isolated components, and the giant strongly connected component size. To understand how the average path length progresses, we only average out the shortest paths that still exist in the network. This approach allows us not to calculate the inverse path length, l^{-1}.

4.4.2 Evaluation of cluster quality

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 Aslam et al. [92] and Tang et al. [93] 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.

4.4.3 Evaluation of resilience

When the transport can recover from the over demand 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 as defined by Reed et al. [40]. We measure R as the ratio between the demand and the supply ($Q(t)$) for transportation in a defined time period ($t_2 - t_1$), 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.

4.4.4 Expert evaluation

This study is done in a partnership composed by Instituto de Engenharia de Sistemas e Computadores - Investigação e Desenvolvimento (INESC-ID), Laboratório Nacional de Engenharia Civil (LNEC), Câmara Municipal de Lisboa (CML) and public transport operators. So, along with computer scientists, we have access to experts in the field of transport systems, mobility, and planning. With their knowledge and previous experience, they provided valuable insight into the importance of the found patterns and how actionable they are.

Part III

Empirical Studies

5

Network modelling and assessment

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This chapter 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 [94].

5.1 Data extraction and preprocessing

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.

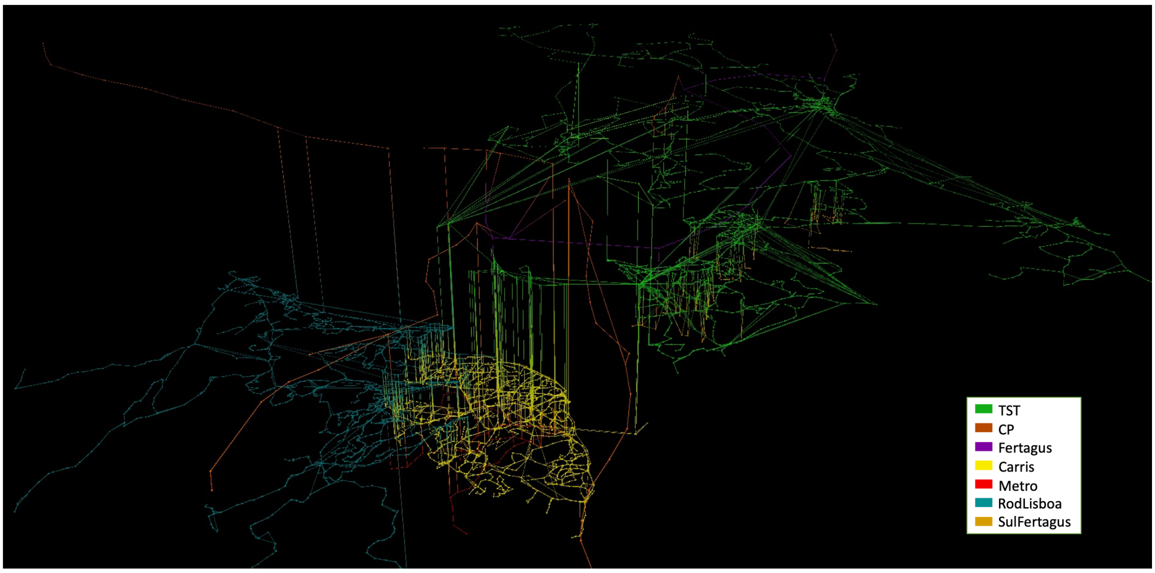

Figure 5.1: Multilayer Lisbon transport network topology on a Three Dimensions (3D) representation with all the layers

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. The distribution of the distances selected account for a very small amount (about 0,0040%) of the distances calculated. They exhibit an exciting feature as can be seen in Figure 5.2.

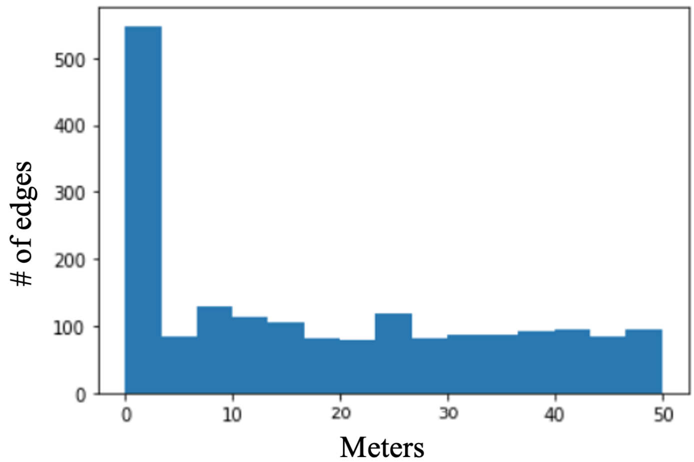

Figure 5.2: The distribution of distances from stations selected (about 1878) have a very high cardinality of distances close to 0 meters. This represents the stations/stops that simultaneously belong to both layers

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 5.1 for more detail. This network is composed of 8 layers, 7,972 nodes and 11,892 edges. The full network required the computation of 46,399,492 distances to join all the layers with the multimodal connections.

5.2 Network Analysis

The distribution of nodes and edges respectively per each layer is in the Table 5.1. So, it is clear that the distribution of the station is not equitable in terms of layers. Additionally, there were added 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.

Carrier	Nodes	Edges
CARRIS	2144	2894
CP	58	125
FERTAGUS	13	25
METRO	49	105
RODLISBOA	2210	2752
SULFERTAGUS	110	187
TRANSTEJO	8	12
TST	3372	4281

Table 5.1: Number of edges and nodes for each transport operator. Here we can clearly see that the distribution of the station is not equitable in terms of layers, as carriers have a very high variance in the number of stations.

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 CP have only bidirectional relationships between nodes. An example that would cause a higher number of SCC's would be for instance an set of isolating line from the rest of the network by eliminating a critical station. Lines that are naturaly isolated within the present topology happen in the Transportes Sul do Tejo (TST) Sesimbra line and the RODLISBOA Vila nova line. The remaining small SCC's in the multilayer network are single stations where the flow is unidirectional. 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.

5.3 How many stations are connected with each station?

In this multilayered network, we can examine the kind of degree distribution we have, shown in Figure 5.3. We can see a high tendency of having both the in-degree and out-degree equal to one (part of a line) and two to four (stations that have intersections of lines of one or more modes). We can also see some nodes with an out-degree of 0. These are start and end stations respectively that have no reciprocal edges on the opposite direction. Stations with in-degree and out-degree equal to one can be caused by a significant amount of stations that flow only in one direction, or career end stops have different identifiers depending on orientation. This fact is also explaining the high number of low distances in the figure above. The in-degree is always very close to the out-degree. Since we are looking at a transportation network, this tells us that the majority of the connections between stations flow both ways, forming what is known as a *chain* (or a line), even though there are apparent exceptions (stations that connect with many stations) as we can see on the tail of the plot with a log scale.

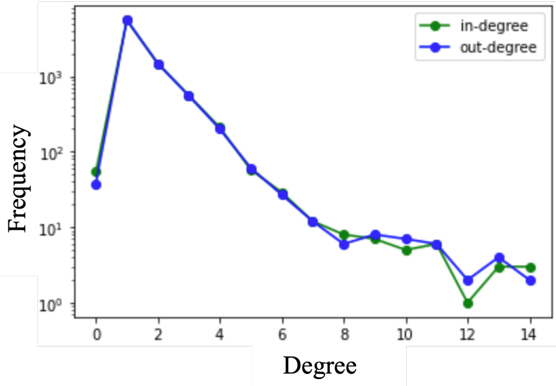

Figure 5.3: Degree distribution of the network: Like all of the nodes belong to a specific line, we can see a high tendency of having both the in-degree and out-degree equal to one. There are also some intersections of lines, that is why we see a fairly high prominence of in and out-degree equal to two.

5.3.1 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.

5.3.2 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 (See Figure 5.4), these are mostly from TST , this may be a sign that TST is kind of bridging layer in some zones. Some examples of such bridging stations are Lisboa Gare do Oriente (0,2529), Setúbal Ciprestes (0,1639), Lisboa Alcântra (0,1592) at TST . METRO also has three stations with exceptionally high betweenness centrality; these are Campo Grande (0,1813), Oriente (0,1504) and Cidade Unversitária (0,1480). Rodoviária de Lisboa (RodLisboa) also has a station with a very high betweenness centrality, Lisboa Campo Grande (0,1879). With this simple analysis, we can see that both Lisboa Campo Grande and Lisboa Oriente are multimodality hubs that bridge across different layers.

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 [9].

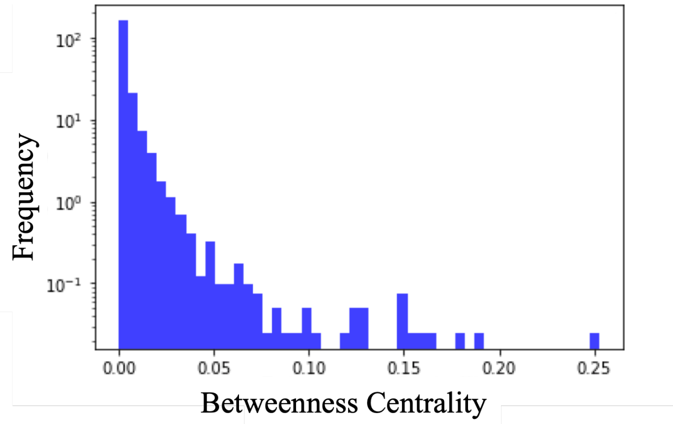

Figure 5.4: Betweenness centrality distribution: In the graph we can clearly see a few nodes with very high centrality, these are the nodes that represent the stations mentioned above.

5.4 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 similarity of connected nodes concerning their degree. Arruda et al. [58] noted that in multilayer networks, degree-degree correlations should be measured system-wide. In that same study, he generalizes this concept for these types of networks and applies it to an airport transportation multilayer network. There he notes that the rich-club effect is, in fact, present in such networks, masked due to the high number of peripheral nodes that connect the hubs. However, intralayer, the networks tend to be disassortative as they focus on one specific region.

Studying this network, we expect to see similar behaviour given some geographical similarities of the reality being represented. We calculated the assortativity for the multilayer network and for each layer, and we observed the same results. In Figure 5.5, we see the same pattern described by Arruda et. al.. This is reasonably simple to understand since the assortativity is influenced by the high number of multimodal hubs that connect to one another. Analogous to the properties found in past case studies, we may find a kind of a rich-club effect, that may be harder to detect due to many peripheral nodes. Since this is not the focus of this work, it will be left for future studies.

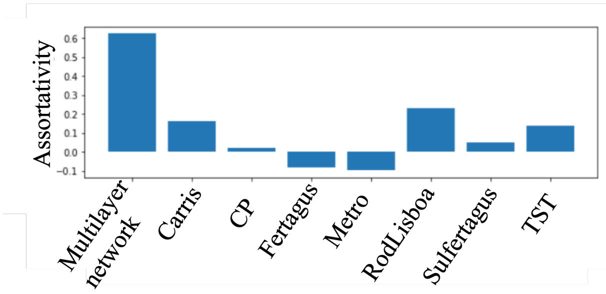

Figure 5.5: Assortativity distribution of each layer and the multilayer network. We can see a much higher assortativity in the multilayer network than in any of the single layers.

5.5 How do different attack strategies affect the connectedness of the network?

In this section, 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 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 Area Under Curve (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:

$$AUC_{Normalized} = \sum_{i=0}^{\chi} \frac{\tau_i}{V} \cdot \frac{100}{\chi}, \tag{5.1}$$

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 5.2, the most resilient layer is FERTAGUS , and the least resilient layer is RODLISBOA .

Looking at the table 5.2, 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 5.6. 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 ID strategy has a

Network	Strategy				
	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 5.2: 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.

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.

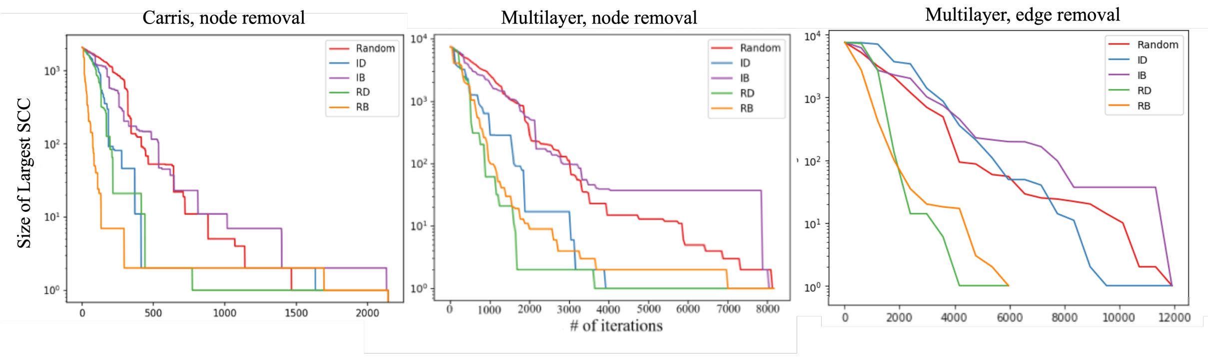

Figure 5.6: Evolution of SCC size along node attack strategies for a single layer, CARRIS (left) all layers (middle) and edge removal in multilayer network (right). The RD strategy yields a faster decrease, this checks out with the Normalized AUC with a lowest value. In the right graph we observe that we still need many more edge removals to get a similarly large SCC, as in node strategies.

5.6 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 5.8, the RD is the best strategy. This means that removing the stops with the highest degree has the highest impact on the length of stations one can reach. Note that may change with alternative routes and redundancy techniques. The remaining strategies have about the same efficiency, with RB being slightly ahead towards the end of the simulation. This result is not unanimous, as we can see in Figure 5.7. As we see, RB can either be the best or the worst strategy, depending on the network. This can be due to nodes with high betweenness centrality being part of paths that do not have alternatives. RB providing an efficient strategy indicates a lower network robustness. This is the case because it is a topological fragility to have most of the shortest paths within a network going through a single station. In the multimodal network with all the layers (Figure 5.8) we see that RB is a strategy that promotes a fast decrease the APL. This indicates a lower network robustness. In the multimodal network we see that many shortest paths go through the intermodal hubs, allowing parts of the city that have a single mode to be connected with the rest of the city. We can see that the APL decreases much faster in the RB than in the RD for the multilayer, unlike in the CARRIS network. We can also see a slight increase at the beginning of the simulation (only for other extraction strategies), this is due to the removal of less critical stations. The number of removals needed to get the same APL is much higher for edge strategies, meaning node removal is more effective for decreasing APL.

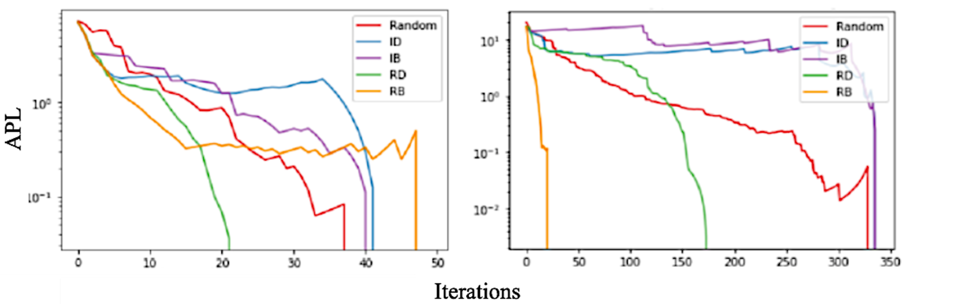

Figure 5.7: Evolution of APL along node attack strategies for METRO (left) and SULFERTAGUS (right). As we see, RB can either be the best or the worst strategy, depending on the network. This can be due to nodes with high betweenness centrality being part of paths that do not have alternatives. RB provides an efficient strategy for robustness analysis indicating a lower tolerance in the multilayer network.

5.7 How many nodes or edges do we have to delete to fragment the network into isolated components?

An *isolated component* is when a node loses all its edges. Since our graph is directed, when we talk about all the edges, we are mentioning both the in and out edges. To be able to answer this question,

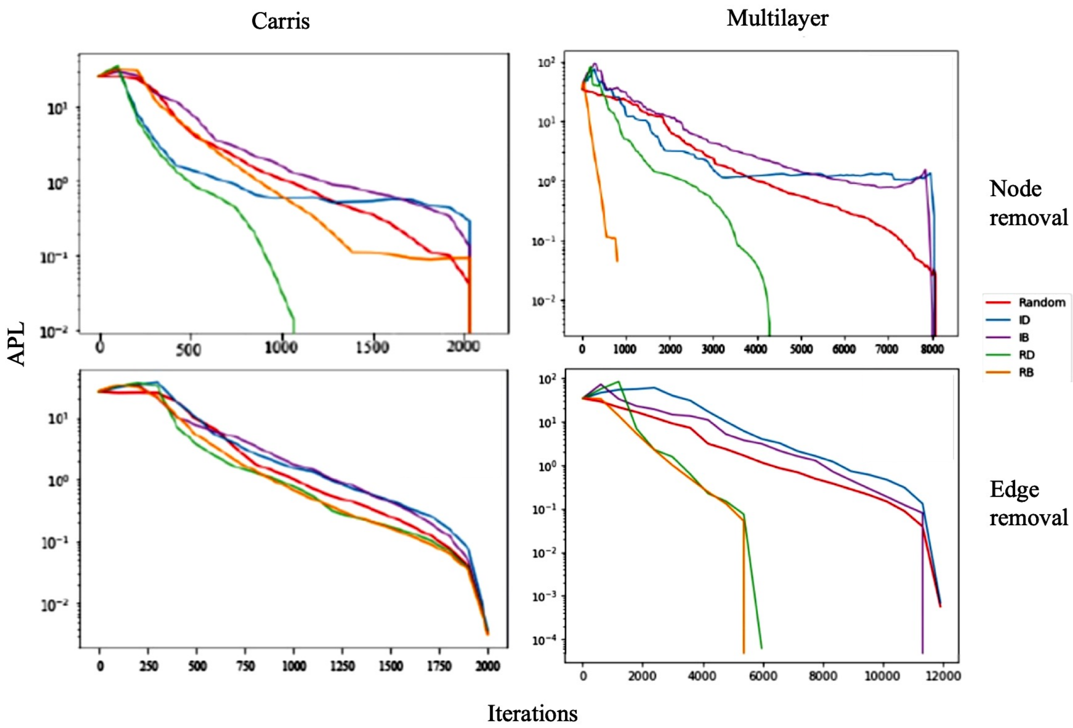

Figure 5.8: Evolution of APL along node (above) and edge (bellow) attack strategies for the CARRIS and the Multilayer network. We can see that the APL decreases much faster in the RB than in the RD for the multilayer, unlike in the CARRIS network. We can also see a slight increase at the beginning of the simulation (only for other attack strategies), this is due to redundancy of paths. The number of removals needed to get the same APL is much higher for edge strategies, meaning node removal is more effective for decreasing APL.

we used the extraction strategies proposed on the methods and evaluate the evolution of the network by showing the distribution of the isolated components. To accurately understand the extraction strategies, we ran them across every layer in isolation and then in the complete network, except for multimodal hub removal on isolated layers because there are no multimodal hubs in isolated layers. Figure 5.9 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.

We also find that all extraction strategies, except RD, increase and then decrease the number of isolated components (Figure 5.9). This means that after we reach the maximum number of Isolated Component (IC)'s, we are only removing isolated nodes. This means that the lower the maximum and the later its reached, the less effective at measuring the robustness to isolation of different parts of the city the strategy is. Halfway through RB, we start to see rapid growth. This is because after removing the main bridges from communities, there still are redundancy paths. Once these paths start to be removed, it is simpler to disconnect each community individually. It should be noted that it is likely that a node with a high degree also has a high betweenness centrality since multimodal hubs are often points that connect communities. However, this is not the case the other way around since less connected stations may be very important at connecting different parts of the city. The IB extraction is the worst because we are dividing the problem infinitely. This is virtually dividing the path from A to B into 2 recursively. In summation, the only effective strategy to measure the vulnerability of disconnecting the network from different parts of the city is RD.

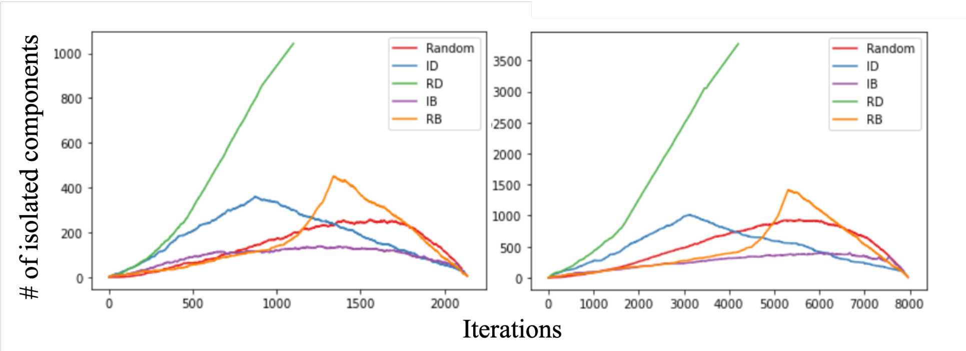

Figure 5.9: Evolution of the Isolated components (IC) in the CARRIS layer (left) and Multi-modality network (right) for node removal. In this graphs we can clearly see the that RD had the best results, this is the only one that stopped before the end of the simulation, because there are only isolated components when it stops.

So, to answer the highlighted question in this section, we look at the number of iterations when RD ends the simulation. This is the number of nodes that have been removed when all the remaining nodes are isolated. The higher the percentage of nodes that need to be removed from the total of nodes in this network, the more robust the network is, see Figure 5.10. We can see that the robustness across all networks using this metric is about the same.

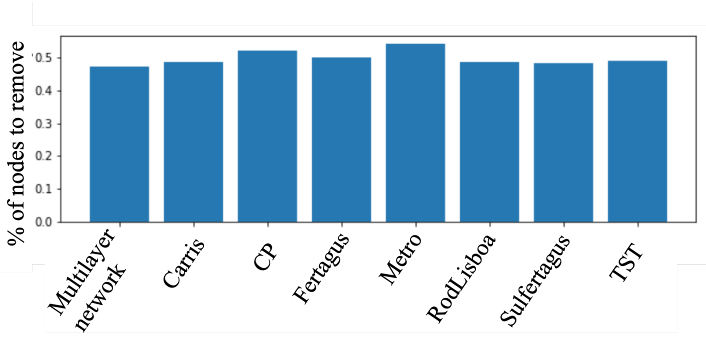

Figure 5.10: Minimum percentage of nodes that need to be removed to separate the network into only isolated components, using targeted attacks. The lower this value the less resilient is this network. We can see that the resilience across all networks using this metric is about the same.

To understand the multimodal hub removal, we preformed another simulation, see Figure 5.11. As the graph reaches a pique and then decreases, we can see that we do not need to remove all the multimodal nodes to get isolated layers. As we can also see, there is a slight variation when some nodes are removed. This means that removing specific nodes has more impact on the interlayer connections

(Figure 5.11). We can see that node removal is much better than edge removal, that makes sense since in edges we only separate in at most 8 IC's (single layers). This is not directly comparable with other strategies, as it only encompasses the removal of about 10% of the nodes. However, from what we can assess, in the beginning, the growth in the number of isolated components follows approximately a linear function, which is slower than RD. However, we can safely conclude that redundancy of intermodal hubs is the best way to ensure connectedness in this multimodal network, since not all layers are redundant in all areas of the city. Redundancy on all areas of the city would be much more costly and may even cause other issues like consuming space of the already established routes.

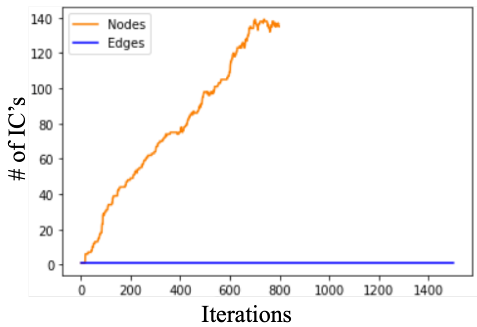

Figure 5.11: Evolution of the isolated components using the *Multimodal Hubs removal strategy*, we can see that node removal is much better than edge removal, that makes sense since in edges we only separate in at most 8 IC's (single layers)

On the other hand, there are edge extractions. In this case, it is expected that we have to remove all the edges to have all nodes isolated, Figure 5.12 shows exactly that. The behaviour of extraction per layer and in the multilayer network is identical as can be seen in both graphs of Figure 5.12. Contrary to node targeting, the worst strategy is RD, and the best strategy is IB. The RD is always the worst strategy, this is the case because we are removing edges from nodes with high degree. We can conclude that the betweenness centrality is a more adequate metric for edge targeting and node degree is better for node targeting. This means that removing single pathways that are in many shortest paths has a higher impact than removing single pathways that lead to high degree stations. However, deactivation or failure of high degree stations have the highest impact. High degree stations are the ones that are usually more central geographically and have a more critical role in connecting different modes of transport.

5.8 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 the previous Figures (5.6, 5.8 and 5.11) show, it takes much more iterations to destroy a network by attacking the edges. This happens for various reasons. Trivially there are more edges than nodes, so more iterations

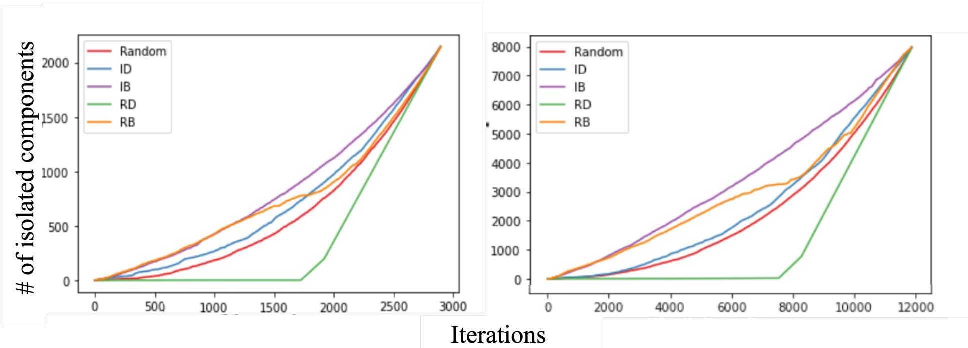

Figure 5.12: Evolution of isolated components along edge attack strategies for CARRIS (left) and for the multilayer network (right). The RD is always the worst strategy, this is the case because we are removing edges from nodes with high degree.

are needed to create the same impact. Another important reason is that when we remove a node, we also are removing all the edges of that specific node while removing an edge, does not remove the nodes that are connected. This makes the node removal more efficient on harming the network.

On the SCC and the APL evaluation, we also see that edges attacks are very similar to each other and also less efficient at destroying the network than nodes removal. We can conclude that the network has various redundant paths. So, when removing edges, we can go to the same destination by going through other network paths.

It is also important to note that in the IC evaluation, the ID and RD removal attacks on the edges are not as efficient as in the nodes and has a slow impact. Slow impact means that we need to remove more edges, to create the same damage as the node removal. This happens because, when we base the attack on the edge degree, we are attacking edges of hub nodes (nodes with higher degree). This means that we are removing edges from nodes with lots of edges and so it does not show the effect at first.

5.9 Should we recalculate the degree and betweenness after each attack?

The random strategy was found to be better than the strategies which do not recalculate the new metrics of the new graph (IB, and ID). On the other hand, RB and RD removal strategies can be very effective, yet not so computationally efficient. They take much more computational power to compute metrics, especially the RB. As can be seen in previous sections, recalculating degree after each node removal has proven to be beneficial, but recalculating betweenness centrality has yielded relatively stable result for IC's and wildly variable results in APL evolution. Intuitively this could probably be explained by the lack of redundant paths in some networks, which is a fair way to assess its robustness. Both RB and RD strategies have the same similar results across layers and being the best ones to reduce the SCC.

For the edge removing strategies, in the case of the goal being generating more isolated components, recalculating the betweenness centrality yields worst results. These results are curious as they are quite different from the ones proposed by [91], “suggesting that the network structure changes as important vertices or edges are removed”.

Despite the RD and RB strategy overall having better results for nodes attacks, in massive graphs seems unfeasible to calculate the betweenness centrality per each iteration, maybe choosing a slightly worst strategy is not such an issue. Another possible strategy is, instead of calculating per each iteration, i.e., each node removal, we calculate per each percentage of nodes. This way, we are avoiding the complexity, with the trade-off of disrupting a little of the result.

5.10 What is the impact of cascading failures?

The cascading failures are a complex topic, and we have only scratched the surface. On cascading failures, we used two removal strategies: entirely deleting a transportation line (e.g. route) and removing the neighbours of a given node (e.g. station). For the first removal, we simulated the crash of each line separately, that is, one line at a time, and measured the number of ICs, then repeat the process for each line after resetting the network to its initial condition. We were able to get the maximum number of 6 separated components from a single line by doing this assessment. This line/route connects *Pontinha* and *Campo Grande*, operated by RODLISBOA (bus road operator). It's mainly a commuting route that connects passengers living in *Pontinha* (county within LMA) with the Lisbon city, mainly for home-work purposes.

In our second simulation, we applied the failure removal approach of a neighbour. Line Failure was used as a model for the simulation. We estimated the neighbours of each node, eliminated them, and gathered the metric of the isolated component. We chose three layers of a node's neighbours since the average number was closer to the average number of each line when comparing the two. *Odivelas* was discovered to be the key point in this method, with a maximum number of isolated components of ten. We can see that the nodes that connect the Lisbon city with other counties within LMA are critical to the organisation of the city's public transportation system. Nonetheless, this Neighbour Failure technique has much more devastating effects than the Line Failure strategy, with nearly double the network damage (6 vs. 10), but this is based on a small sample. These results tell us that the impact of a localised failure that deactivates that spot in several layers has a higher impact than a line failure in this topology. However, this result may vary depending on the region, since localized failures in remote areas have a lower relative impact.

A future study could be done with this cascading events attack strategy. For example, fail more than one line at the time and also not crash lines randomly and use a specific metric to decide what lines to crash, analogous to what we have done with the degree and betweenness centrality. The second attack could be further explored by testing a different number of layers of neighbours, with more depth. The archetype of these could be joining these two methods, trying to fail lines that are near other lines by using the information of the neighbours of each node. This alone is an extensive study on the cascading effects area.

6

Understanding usage behaviour

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In this section we discuss the process of understanding the transport usage data and grouping different behaviours. Since this research is focused on a multimodal prospective we focus on two main public transportation modes of transportation, CARRIS and METRO , the largest public transport operators in the Lisbon metropolitan area. This next 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 [11] that assesses the main differences in terms of multimodal public transport demand pre and post COVID-19 (below are some of the key figures and graphs that show the differences). Aditionaly in later sections of this chapter we aim to discover actionable public transport usage patterns. The target individual trip record data was made available by the two major carriers in the Lisbon metropolitan area, CARRIS (the tramway and major bus operator) and METRO (the subway operator).

6.1 Exploratory data analysis and preparation

The information gathered from this section is derived from the smart card usage data. Table 6.1 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 6.1: Sample of smart card validation data. From Aparicio, Arsénio Henriques [11]

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[1]. 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 6.1. From this kind of data we can extract usage patterns that are more detailed than the trivial kind of pattern we see for instance in Figure 6.1. This shows us that there is a clear weekly pattern in the amount of users that use the Alameda METRO station and CARRIS stop.

Figure 6.2 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

[1] The Lisbon city was in strict quarantine throughout all days of May of 2020. The Portuguese government changed quarantine restrictions at two moments, the 2nd of and the 18th of May.

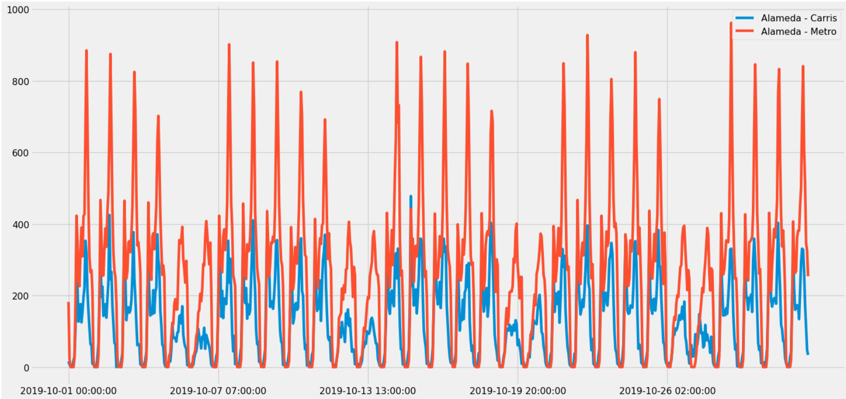

Figure 6.1: Example of validation data across different modes CARRIS and METRO at the Alameda stops and stations

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 [95], 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

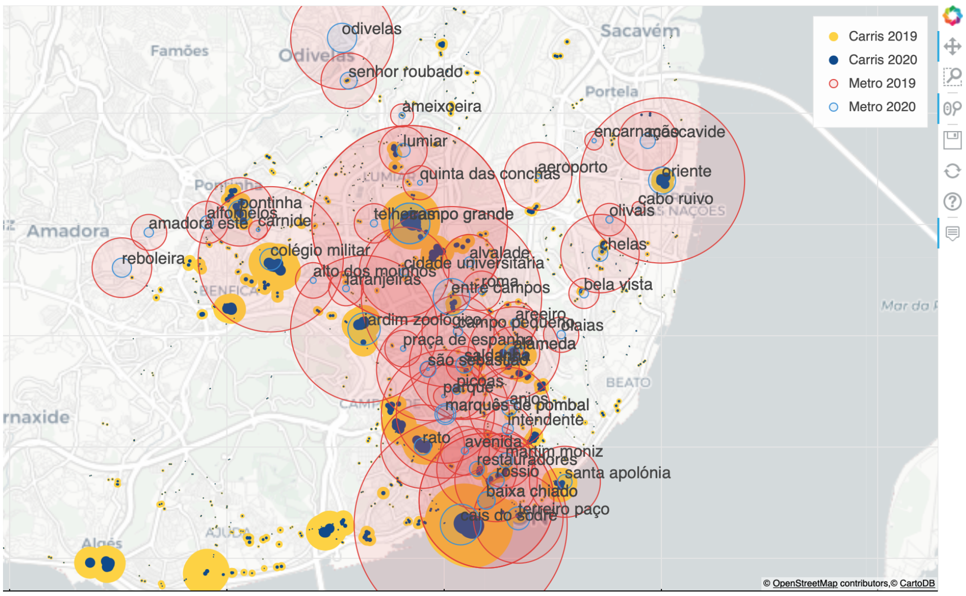

Figure 6.2: City view of demand variations (2019 vs 2020) along METRO and CARRIS stations

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 6.3 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. This analysis underlines the statistically significant nature of the observed differences, and further shows the routes along the city that were subjected to a higher contraction in demand. Generally, the higher the number of stations in the city periphery, the lower the demand contraction.

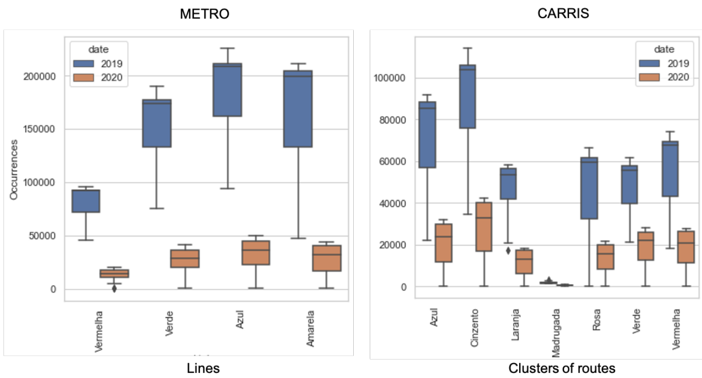

Figure 6.3: Daily validations along the four lines of the METRO network and the seven clusters of routes of the CARRIS network for 2019 versus 2020.

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 6.4) 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. Although the mandatory quarantine was already lifted by May 2020, this result reveals the conservative usage of the public transport propelled by safety and fear considerations. Demand consistently decreased between approximately ten to thirty percent points. 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.

The changes in demand observed along the CARRIS bus-tramway network reveals a considerably different reality (see Figure 6.5). 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

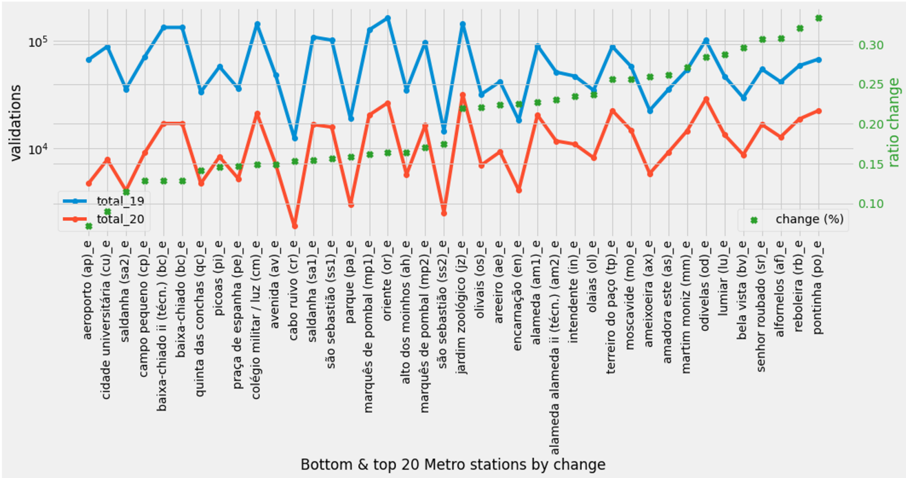

Figure 6.4: Demand for METRO stations in 2019 versus 2020 and ratio, top and bottom 20 stations

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. The R. Castelo Branco Saraiva stop recorded more than 2.5 times the number of validations in 2020 than in 2019. The closest subway station from this stop, Anjos station, suffered a considerable decrease, yielding less than 20% of the demand observed in the previous year.

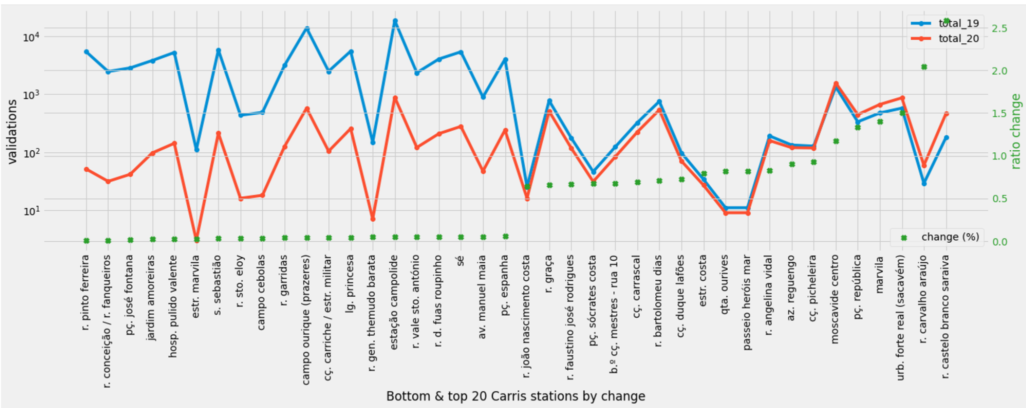

Figure 6.5: Demand for CARRIS stations in 2019 versus 2020 and ratio, top and bottom 20 stations

Figures 6.6 and 6.7 assess the average hourly demand for METRO and CARRIS networks throughout typical working days (top) and weekends (bottom) for the stations with the highest and lowest demand variation from 2019 to 2020. The presented heatmaps have a logarithmic demand scale to foster interpretability and softening differences of high magnitude.

Considering the subway demand (Figure 6.6), we identify clear demand peaks from 7AM to 10 AM and 4 PM to 8PM corresponding to rush hours. Morning demand distribution approaches a normal hourly distribution, while the hourly demand distribution in the afternoon shows a skew towards earlier hours. Most of the stations on the top 10 (highest change in demand) are stations within the city center. The contraction in demand along these stations is possibly explained by a decrease in tourism activity and on-site commutes to business districts and schools. On the bottom of each heatmap we find the stations with least change – Ameixoeira, Amadora Este, Martim Moniz, Odivelas, Lumiar, Bela Vista, Senhor Roubado, Alfornelos, Reboleira and Pontinha – mainly residential areas. Along these stations, we observe an understandable symmetric pattern, a higher demand for entries during the morning period than the afternoon.

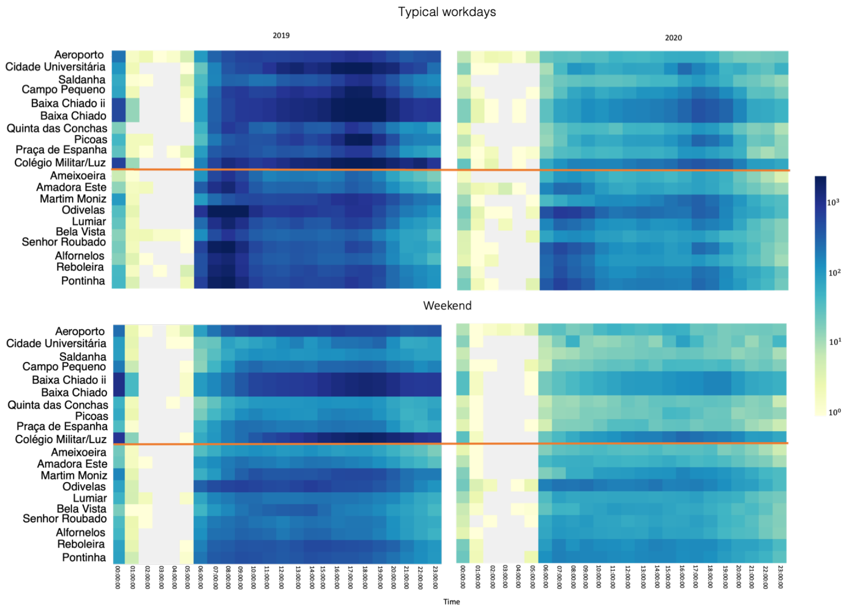

Figure 6.6: Demand for METRO stations during Tuesdays, Wednesdays and Thursdays (above) Weekend (below) by hour, top and bottom 10 stations by change from 2019 to 2020

The corresponding results for the bus-tram network are provided in Figure 6.7. There is a considerable difference in terms of average values through all the stops in the weekdays versus weekend. This can be noticed by looking at the scale of both heatmaps. The demand changes along the CARRIS stops follows a less delineate distribution, with no clear rush hours. We can observe an almost desertification effect on five of the top ten stops with most demand change. Different factors may cause this decrease, ranging from remote working and scholar programs to less-trivial factors, including decreased hospital visits and patient's mode preferences (Hosp. Pulido Valente stop serves a nearby hospital), and non-essential commerce (R. Conceição/ R. Fanqueiros stop is known to serve a commercial zone in downtown Lisbon). Considering the stations with less diminishing effect, Moscavide Centro stop shows an actual increase (compensating the significant decrease on the Moscavide subway station on the other side of the street). We can also observe delineate increases in demand over the early morning and afternoon peak hours, reinforcing the idea that the users using similar stops are usual daily commuters going and coming from the workplace. Other distinct features of each stop, including the properties of the associated routes and the surrounding area, may also play a pivotal role.

Figures 6.8 and 6.9 provide a zoom over Figure 6.2, capturing the demand changes along the routes serving major city centres – Baixa (downtown), Marquês do Pombal, Saldanha, Sete Rios, Campo Grande, Oriente and Benfica.

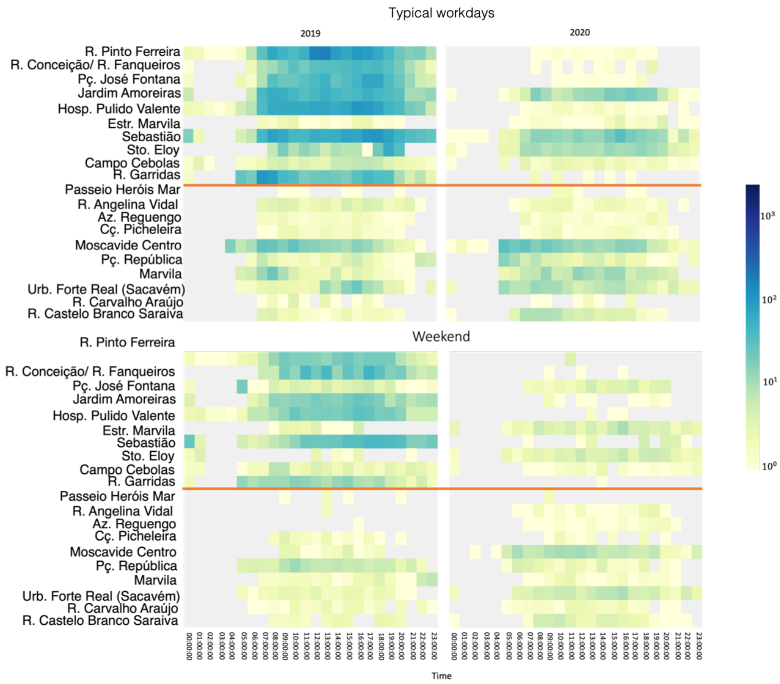

Figure 6.7: Demand for CARRIS stations during Tuesdays Wednesdays and Thursdays (above) Weekend (below) by hour, top and bottom 10 stations by change from 2019 to 2020

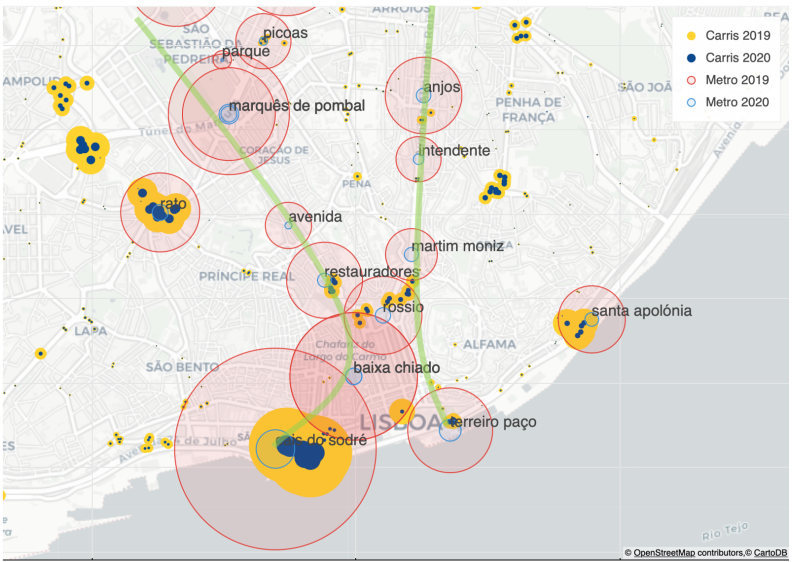

Figure 6.8: Station demand variation for 2019 vs 2020 along Marques de Pombal to Baixa route.

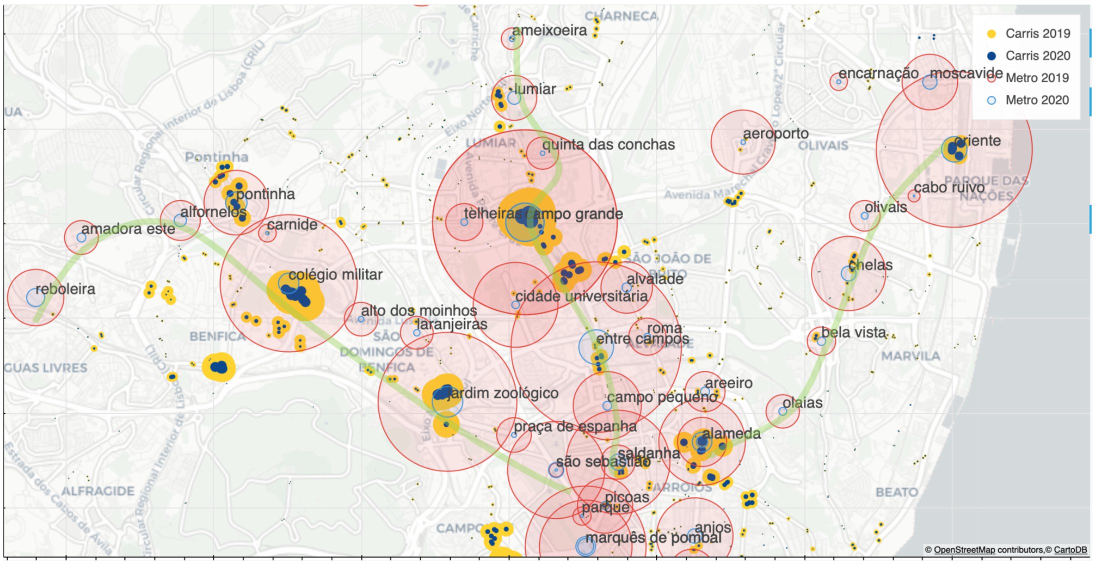

Figure 6.9: Station demand variation for 2019 vs 2020 along three major routes from Marques de Pombal to Campo Grande, Benfica and Oriente routes.

6.2 Application of user clustering

Now based on the differences seen in the previous section, 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, this section aims to define a baseline of usage patterns in the public transportation system. To do this 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 (section 3). To preform the clustering, we used aggregated smart card validations per hour for each user along periods of 24 hours. Effectively the result of this operation is a time-series with length of 24, disclosing the number of validations per user. To be able to compute the different clusters and test each method, we randomly sub sampled a 1000 users. Due to extension and time constraints and ease of interpretability in a smaller network, we opted to perform this analysis in the METRO network. However the methods applied in this section are applicable to any other one of the remaining transportation modes.

To represent the usage profiles we use the average of the time-series that belong to a specific cluster as the usage profile for a particular cluster. To further explain the representation let there be a pair of agents, A and B that use the transport mode. If A validates a trip at 9AM and another at 5PM and B validates a trip at 8AM and another at 5PM the user profile generated from a cluster that includes both users is a series with values 0.5 at 8AM and 9AM, 1 at 5PM and 0 on the remaining time-spans.

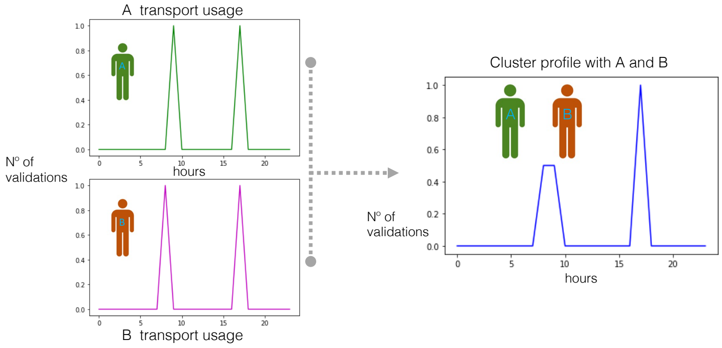

Figure 6.10: Hypothetical usage cluster profile generation with transport users A and B.

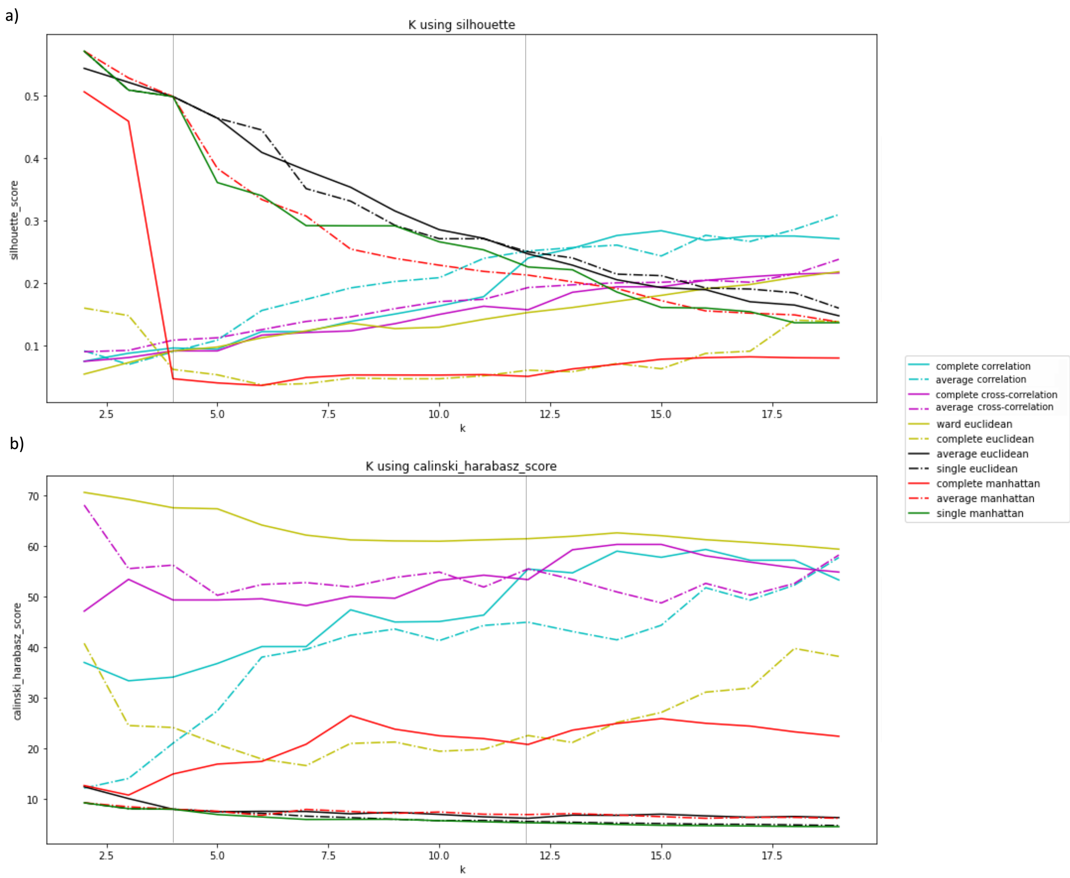

Figure 6.11: Cluster performance using Silhouette Score (above) and the Calinski Harabaz Index (Below)

The Figure 6.11 shows the performance of the clustering solutions for a varying number of clusters. This is a crucial analysis to understand what may be the best number of user behaviour profiles. The Silhouette Score is measured based on each clustering metric. The Ward linkage was only used for Euclidean distances because it assumes the presence of an Euclidean space. The single linkage for correlation metrics was not able to devise clusters, this not acceptable at this point.

We see that the Manhattan distance has a good silhouette score, however the distribution of user behaviour per cluster is highly unbalanced. For instance, where we have four clusters, three of them have only single user. 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 6.11 a).

On the Figure 6.11 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, however we cannot conclude that yet. 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.

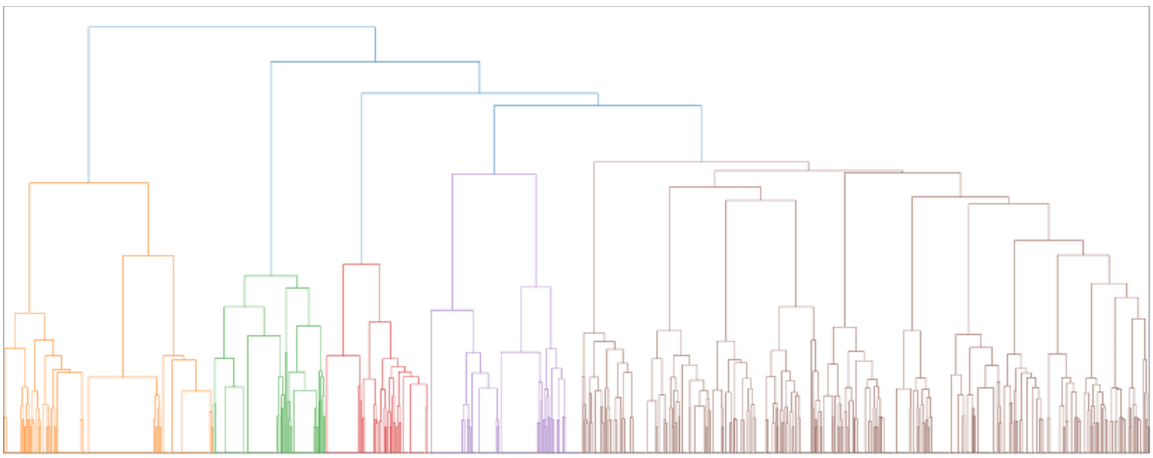

Figure 6.12: Dendogram generated by Euclidean Ward

First looking at the Ward Euclidean, the dendogram (Figure 6.12) shows that a clear cutting point would be at 5 or 14 clusters, this can also be seen in a small increase in the Calinski Harabaz score plot. 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.

After cutting the dendogram at both 5 and 14 clusters, we analysed where the validations were taking place, what was the cluster profile and what was the balance between clusters. Figure 6.13 shows that for the 5 clusters the cardinality of the users per cluster is very inbalanced, the cluster profiles, represented by the average values per cluster are very similar and that cluster 0 has no clear profile. This is not an ideal solution since the average values of the users within the cluster per hour were all about the same every hour and with low values, this means that they were not similar. The 14 cluster solution shows a more balanced distribution. However, many clusters have the same problem as cluster 0 from the 5 cluster-cut: grouping users that are not similar and getting low average values.

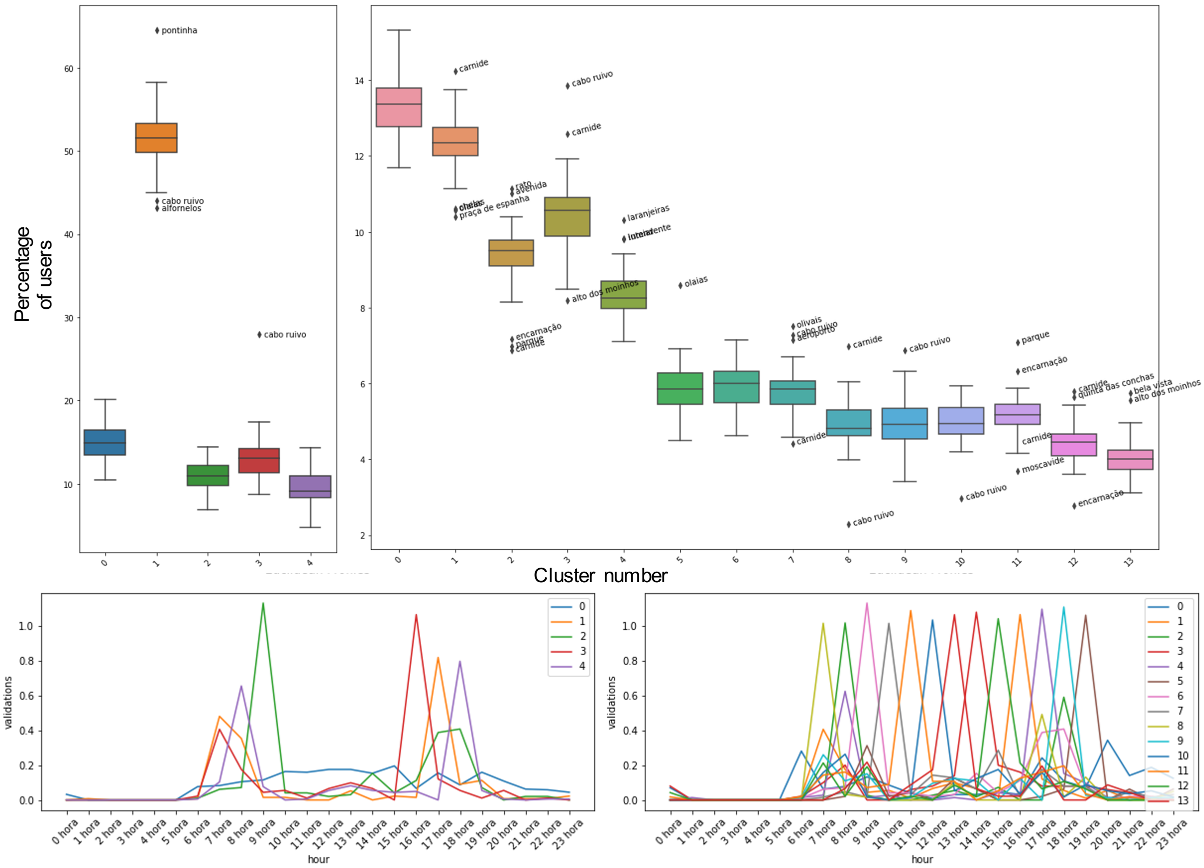

Figure 6.13: Clusters generated by Euclidean Ward clustering solution with 4 clusters versus 14. Above we see the distribution of cluster per station and bellow we see the cluster profiles.

On the box plots in Figure 6.13, we also see the names of station with particularly high or low percentages of each user types. This may be used as an actionable information to develop the system supply according to user types. So for instance if we see that Pontinha has a particularly high number of commuters that mainly use the transport at 7AM, 8AM and 5PM , (through the cluster profile bellow) the priority in transport supply is in those particular hours. Additionally, other incentives may be made available to incentivize users to ride on off peak hours to level the users distribution over other profiles. This analysis can be integrated in a dynamic dashboard as a monitoring tool.

Nevertheless, 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. [8] Below we look further into cluster formation to understand the generated clusters and how they can be useful. Figure 6.14 shows the dendogram generated for this method. 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).

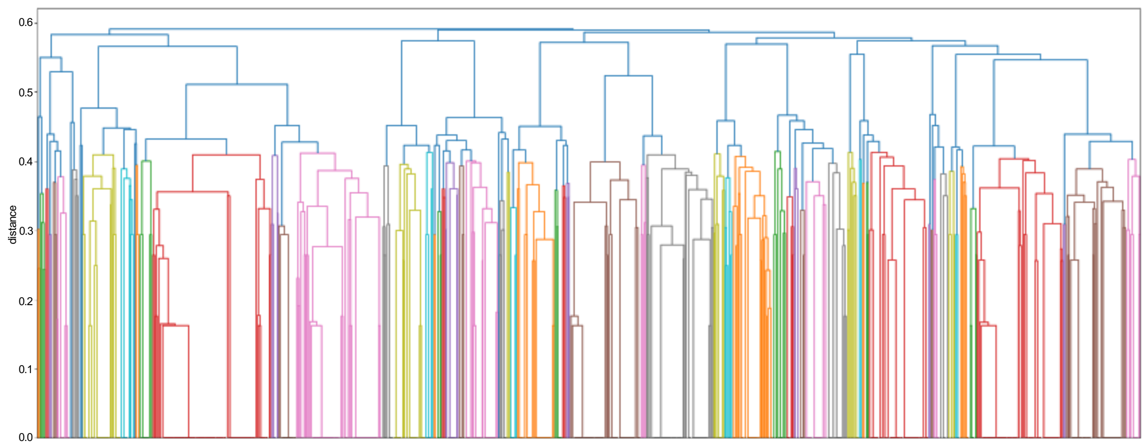

Figure 6.14: Dendogram generated by Average Cross-correlation

As expected the clusters formed from the Average Cross-correlation method are not particularly useful, see Figure 6.15. Yet again we see an inbalanced cluster size and many clusters with low average values per hour. This means that they are not very similar.

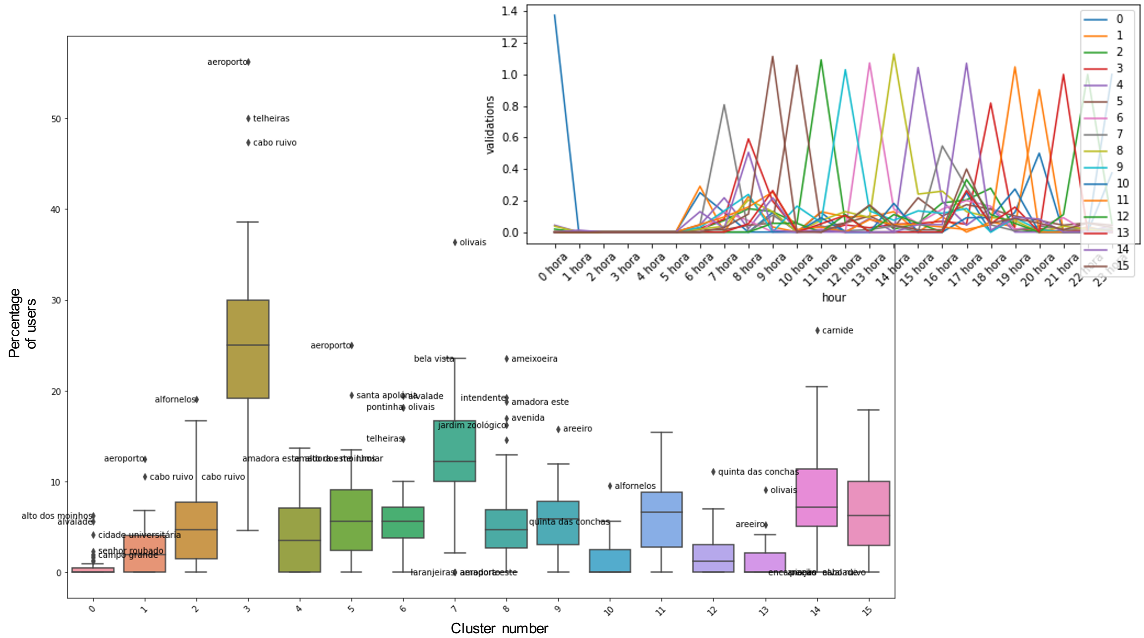

Figure 6.15: Clusters generated by Average Cross-correlation

This leaves us to wonder if in fact the complete cross-correlation actually yelded better results, so we test that. In Figure 6.16 we see the dendogram resulting from that method. There is a clear cutting point at 2 clusters. Notwithstanding, we would like a more detailed information. So, we consider 4 and 6 cluster which are also clear cutting points.

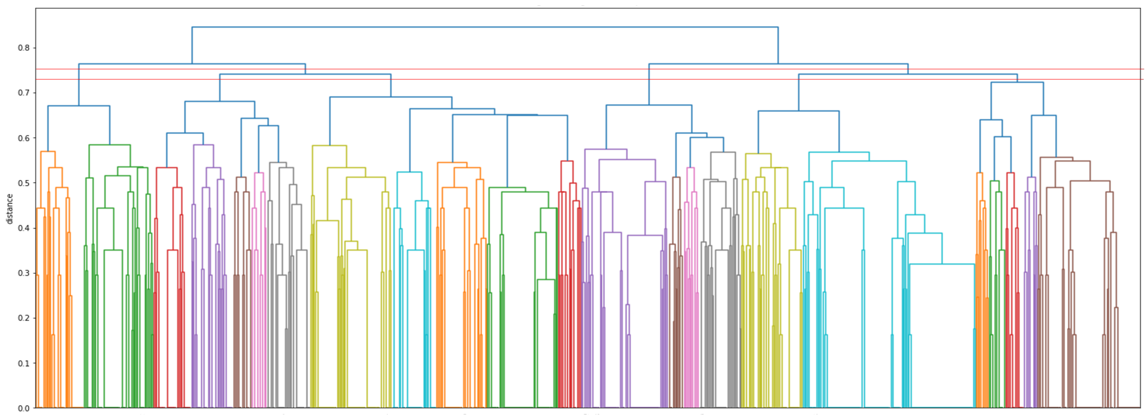

Figure 6.16: Dendogram generated by Complete Cross-correlation

A more balanced number of users per cluster in both cutting points (Figure 6.17). Even though, the 6 cluster formation has a better balance, the average values per cluster for the 4 cluster solution 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.

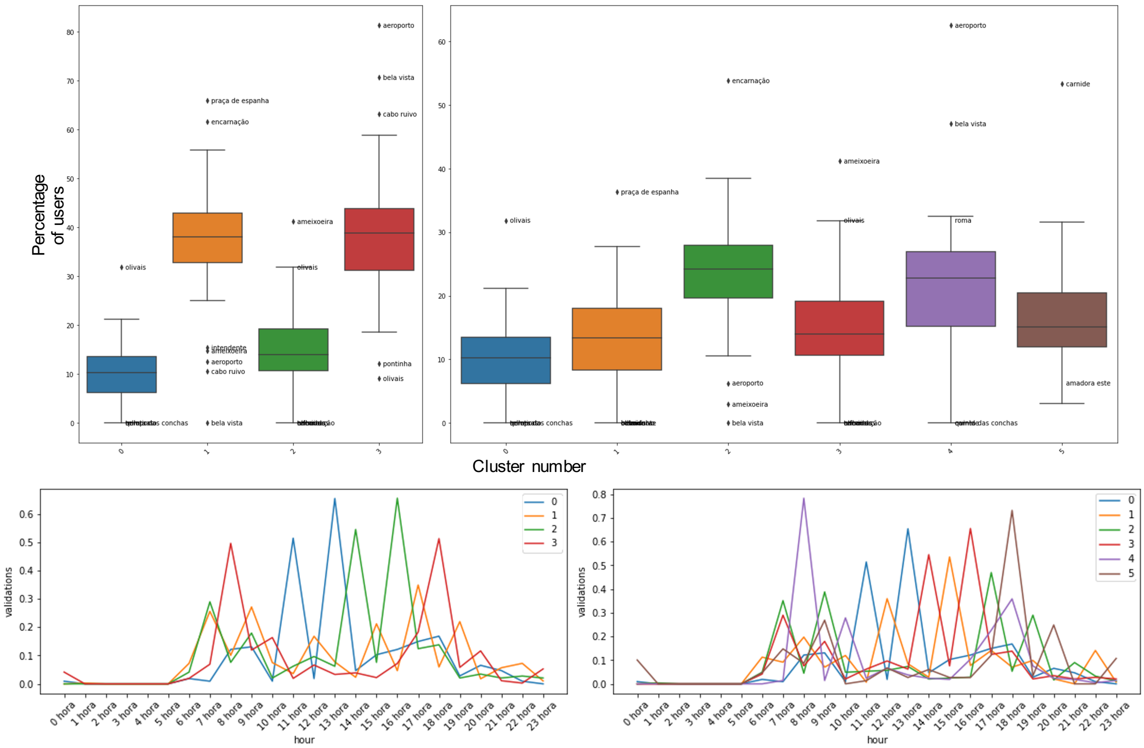

Figure 6.17: Clusters generated by Complete Cross-correlation

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 6.18 we see the user profiles generated. Starting from cluster 3 (top left) we see that most of the validations were done at 8AM and 6PM (18h) with a few temporal misalignments. This leads us to believe that this profile has the average commuter performing a 9-to-5 job. The time misalignment may be explained by the presence of some late workers in the morning. In the afternoon, the effect may be from workers leaving late from work. Cluster 2 (bottom left) has a shorter commuter pattern that groups users that may have an earlier start and finish of the work period, these may be part-time workers for example. There is also a much higher average value for afternoon validations, which may indicate that these people are using other modes of transportation in the morning. Cluster 1 has a fairly spiky pattern, this may indicate either a very generic cluster or several groups of users that have similar behavior a few hours apart. The second is a very plausible possibility given that the cluster resulted from cross-correlation. The interpretation of this could be commuters at 7AM and 5PM (17h) or at 9AM and 7PM (19h) or later and some of the users commute during lunchtime. Cluster 0 shows a very prominent number of average validations at 11AM and 1PM (13h) which points to users that use the transportation exclusively at lunchtime. However, a low number of these users may resort to METRO at other times in the late morning and the afternoon.

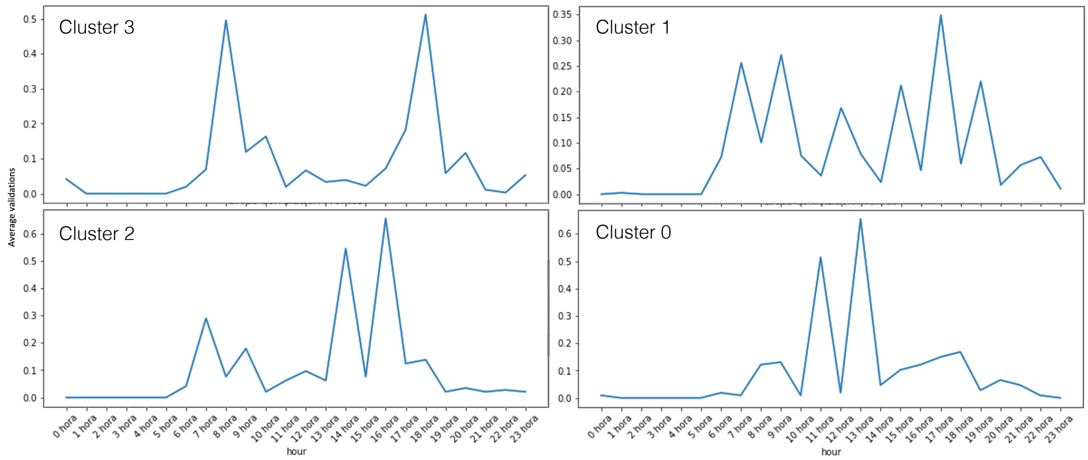

Figure 6.18: METRO User Profiles generated by Average Cross-correlation

Now that we have explored the user journey based on the usage 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 6.17, we see the outliers identified for exceptionally high and low percentage of a certain user profile. In the Olivais station more than 30% of the users are ”Lunchtime commuters”, as well as the lowest 9-to-5 commuter profile with less than 10%. Bela Vista on the other hand has an exceptionally high percentage of these commuters and a very low percentage of cluster 1. This trend is shared with the Aeroporto and Bela Vista stations. This kind of analysis is interesting to understand what kinds of users uses a particular station. However, this is not enough in terms of actionable information to foster network resilience. So, naturally, the next step is to understand where do users travel.

6.3 Extend network modelling with dynamic behaviour

In this section we extend the network modelled in the previous Chapter 4 to with the usage data described in the previous section. Based on the Origin-Destination (OD) mapping developed by Cerqueira et al. [96], 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 and CARRIS networks with the number of users that go through each pathway (or edge of the graph) at every hour of the day.

In Figure 6.19, 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. The high flux of users are going towards stations such as Marquês de Pombal, Picoas,

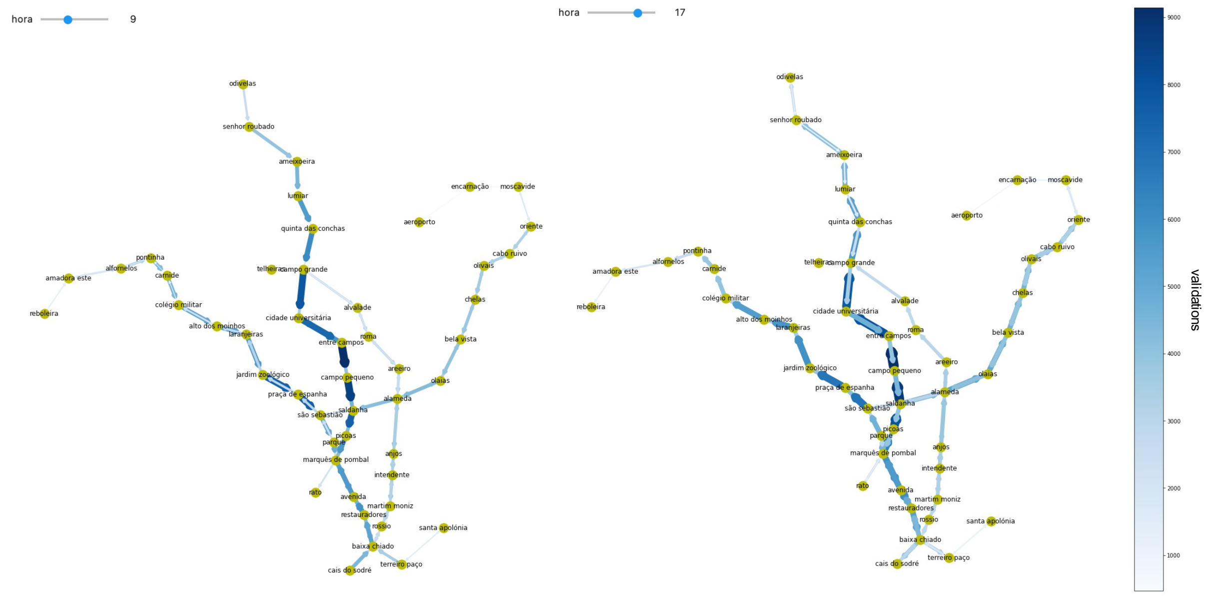

Figure 6.19: METRO user demand throughout the network in the 10th of October of 2019 at 9AM on the left and 5PM on the right.

Saldana and São Sebastião. There is a clear cumulative effect that happens within the line that causes congestion of users within some regions of the network, from Campo Grande to Picoas for example. On the extremities of the network we see a much lower flux of users and in some cases we see a fairly balanced number of users flowing both ways, like the Alameda Martim Moniz pathway and the Oriente Chelas pathway. 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.

This method may be extended with average or median values through the month. Yet, the goal here is to understand a flow of users in a single day, so we can later understand how the network is able to handle the users in a particular day. This is important since not all days have the same service levels and the variation may have a high impact on the information we perceive.

Now looking at the geographic distribution of the users by profile (Figure 6.20), we see that the line occupation of these users is very similar within this network. This is understandable since time series distancing does not explicitly capture the spatial extent of the network usage. But, this might be effect of this occupation similar in terms of effect in service resilience? We will see in the next chapter.

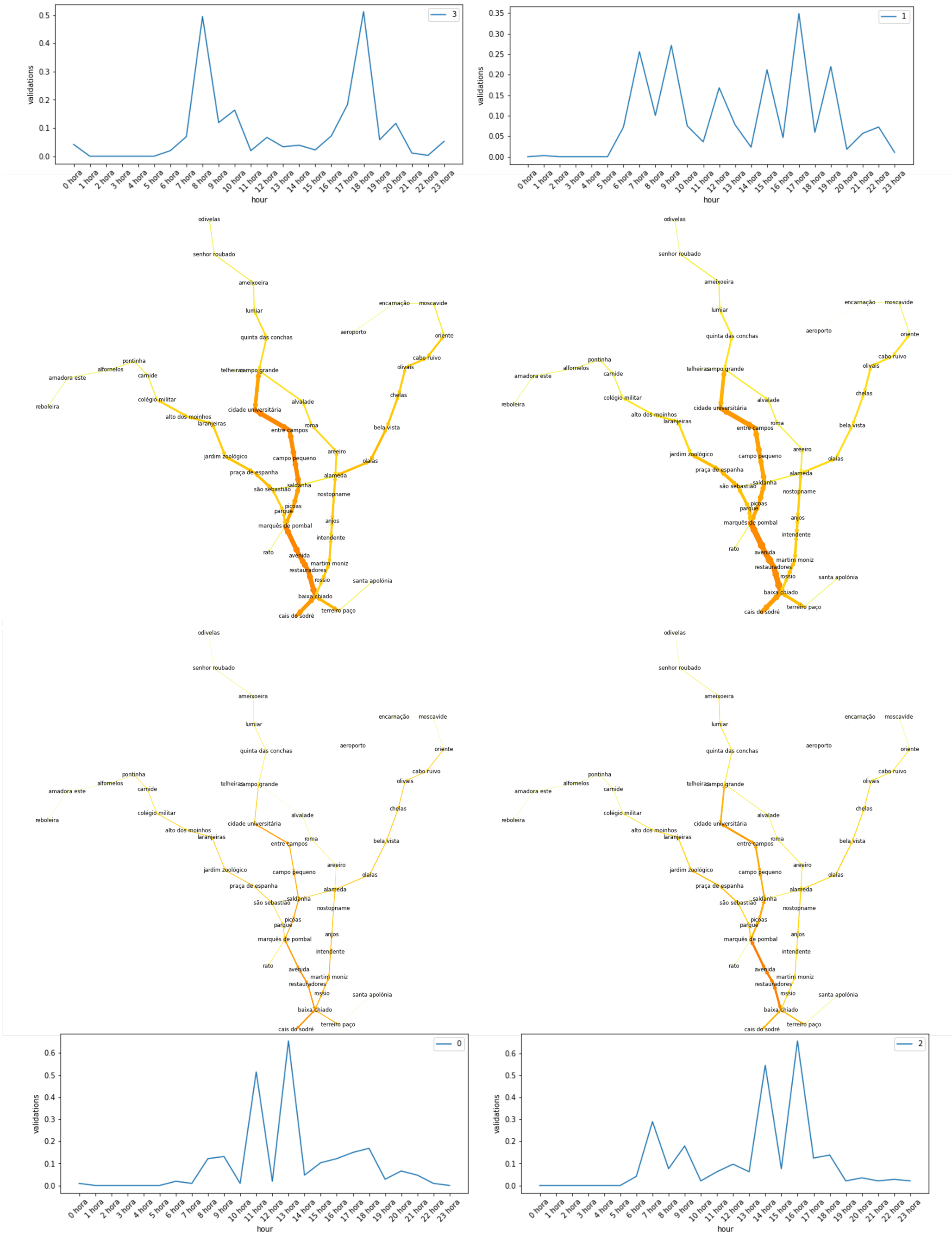

Figure 6.20: METRO user demand, according to profile throughout the network in the 10th of October at 9AM on the left and 9PM on the right.

In terms of CARRIS usage (Figure 6.21), we find a much more complex network with loads of nuances in terms of passenger traffic flows differences between 9AM and 5PM . In a higher level analysis, we can see that the southern river front lines have the highest flows and the magnitude of variation of user occupation is much higher in this mode, even though the total occupation per pathway is much lower. This is perceivable, since METRO carriages can hold more people than CARRIS buses.

Figure 6.21: CARRIS user demand throughout the network in the 10th of October of 2019 at 9AM on the left and 5PM on the right.

In this chapter we used clustering to devise user profiles. This solution is far from perfect at the task at hand however it offers insight into the typical usage of user groups, not discriminating by age of type of social class for instance. The fact that this is an unsupervised solution, means that it is more prone to error. However the results yielded are interpretable, which contributes to a better understand of the transport user journey. This data may be used to predict hours with peak usage in particular stations at particular times, by using the percentage of users per station and the cluster profile. Moreover it can be used to devise incentives for off peak usage. Since we can understand the stations of users using the network at what time, this may be an important step towards a sustainable and resilient transport system.

It is important to note that since these models may cluster fairly heterogeneous groups of users, using this kind of model for restrictive policies regarding riding times can be dangerous, and is not advised. Additionally, the method used a sub-sample of the users available for the present analysis, due to high computation time. At this moment, it is not feasible to apply these algorithms in real time. Sub-sampling may also be prone to bias and false generalizations in this case. It is also important to note that transport usage of a single agent may change along time and so, the cluster solutions must evolve continuously.

7

Network resilience analysis

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In the previous, section we have extended the dynamic passenger behaviour and its spatial distribution along the network structure created. With the generated data we were able to better understand the flow of users on the network throughout the day. 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.

7.1 Application of resilience measurements

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. These schedules are highly complex and may include several passenger vehicles in each route with various delays. Fortunately, this schedule is available as open data is updated regularly. For the case of CARRIS (bus and tram network), this is divided into several data files regarding the calendar of the bus routes, the dates and days of the week where each particular route is not functional and where it has slightly different schedules, eg. weekends. It is also specified the list of temporary buses that were on the predefined routes and at what hour did each bus stop in each station.

Having the schedule, we used the CARRIS official website for information regarding the fleet that is being used. The calculations were made based on the standard MAN 18.310 HOCL-NL bus, since we had no further information regarding the bus type distribution. This is the most common bus type and is about the average in terms of capacity, with a maximum occupancy of 76 passengers. Being the highest occupancy possible 155 passengers on the articulated kind and the lowest 27 on the mini buses. Nevertheless the occupancy numbers may vary greatly depending on safety measures imposed by COVID-19 restrictions. In this case we used the schedule values for 2019 since the 2020 occupancy values are not representative of a typical year due to the lockdown and the civil emergency state [11]. Figure 7.1 depicts the CARRIS 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 route (or line in the case of METRO) 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.

Now looking at the supply levels for CARRIS (Figure 7.1), we see clearly higher supply levels for 5PM than 9AM. Most of the pathways support 100 passenger or less (per hour) this may be due to traffic constraints, however these segments may be more susceptible to variations in demand. However the planning seems to be congruent to the demand in particular cases. For instance, the city center inward flow from Ponte 25 de Abril is prioritized in the morning and the outward flow in the afternoon.

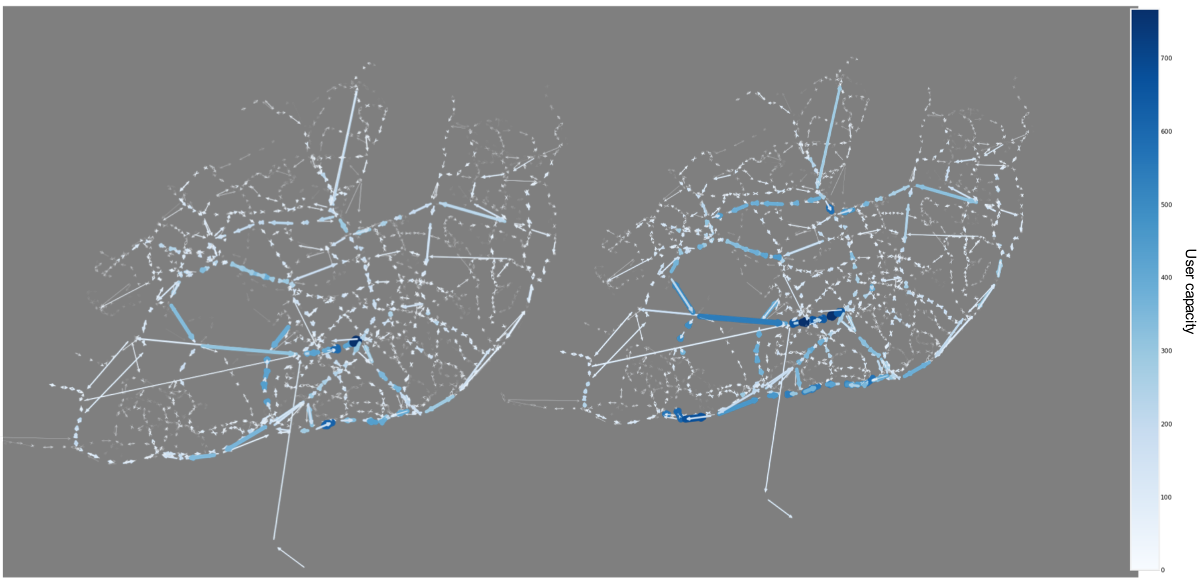

Figure 7.1: CARRIS supply in the 10th of October at 9AM on the left and 5PM on the right.

Figure 7.2 shows us resilience levels that are between 0 and 2 in most line segments. However, in some particular segments, the demand is 8 times higher than the supply. We can see examples of this between the stations marquês de pombal and av. duque de loulé, as well as pina manique and cruz das oliveiras. This may be due to low tolerance to variance due to low bus frequency. However, the model used presupposes, the usage of standard buses, and these segments may be supplied with high capacity buses.

Figure 7.2: CARRIS lean resilience using supply and demand in the 10th of October at 9AM on the left and 5PM on the right.

We applied an analogous 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 [97]. We also presupposed a length of 3 carriages, totaling a 510 of maximum occupancy. These assumptions are made since we were unable to get more detailed data.

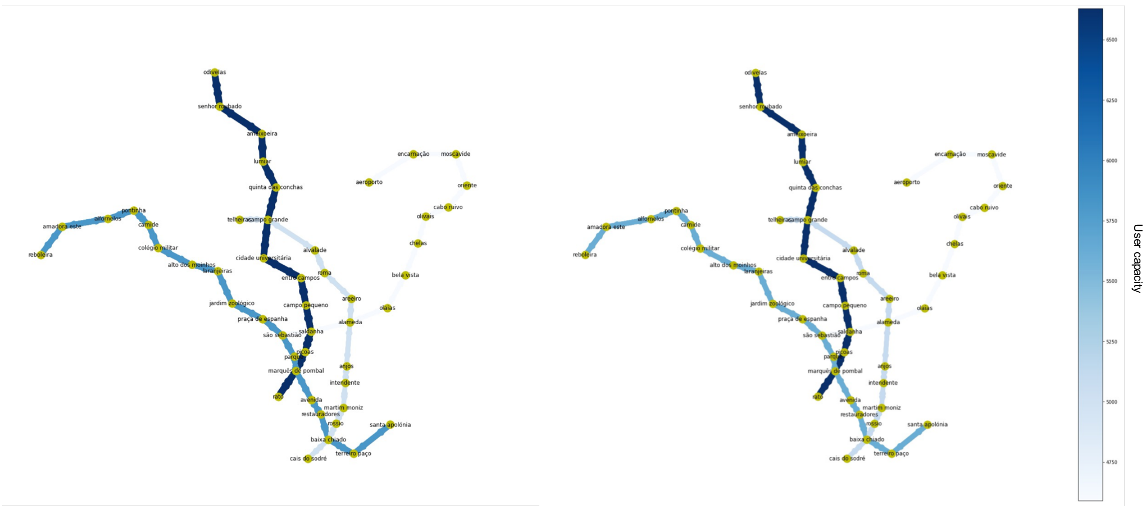

Figure 7.3: METRO supply in the 10th of October of 2019 at 9AM on the left and 5PM on the right.

The METRO supply levels 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. The red line, Aeroporto to São Sebastião also seems to have an exceptionally low level of service.

October 15th was selected as the day for this analysis due to the fact that it has perturbations reported by the metro users in all lines at 9 AM along with a train breakdown. Below, Figure 7.4, shows the reports from `perturbacoes.pt` [98]. This is important since it can give us a better understanding on where the failures may impact the transport users.

Figure 7.4: METRO line incidents allong all four lines: Yellow (Amarela), Blue (Azul), Red (Vermelha) and Green (Verde)

For the METRO lean resilience, Figure 7.5 discloses the ratio of user demand per service supply. So, the value of 1 means that the system has reached its full capacity in that particular segment of the network. The left plot for 9AM shows us that the service inwards to the city center is being overcrowded in particular segments, such as Entrecampos-Picoas and Jardim Zoologico-São Sebastião. Interestingly, the red line (Aeroporto to São Sebastião) has a high occupancy between Cabo Ruivo and Saldanha. However, the flow of users is fairly low on this line, which may be explained by the perturbation and the lowest level of service in METRO . The 9PM service levels on the other hand have even higher vulnerability levels than in the morning, nevertheless there are no reported incidents for this hour and day. This means that even with incidents in the morning in all lines, the afternoon demand supply equilibrium is worse in the afternoon normal operation. This means that the levels of service need to be reinforced even in normal conditions. 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 7.5, which highlights the low resilience links. This would bring further actionable information.

Figure 7.5: METRO lean resilience using supply and demand in the 15th of October of 2019 at 9AM on the left and 5PM on the right.

7.2 Extend resilience to user profiles

In the previous chapter, we identified clusters that group METRO passengers into different behaviours. These have different impacts in the network depending on the hours each user uses the network and where. This means that even if there are few users of a particular type, the network may be less resilient to that particular demand. Below, we look at the different profiles and the lean resilience for each cluster of users. To produce these representations we calculate the paths each user in each cluster (based on shortest the path minding the preexisting routes), and weighted the edges of the network based on the accumulated demand supply ratio over an hourly basis. 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.

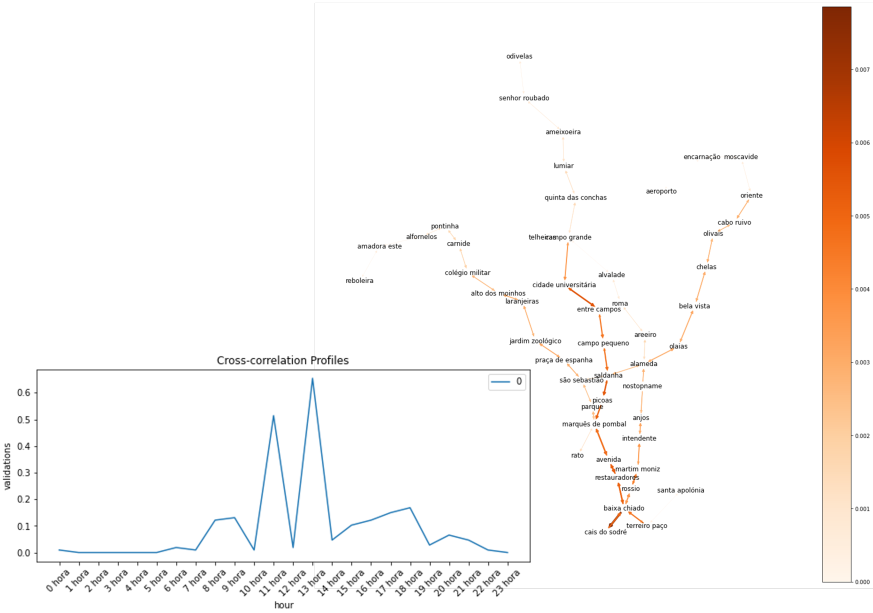

Figure 7.6: METRO lean resilience to users cluster 0 - Lunch time commuters

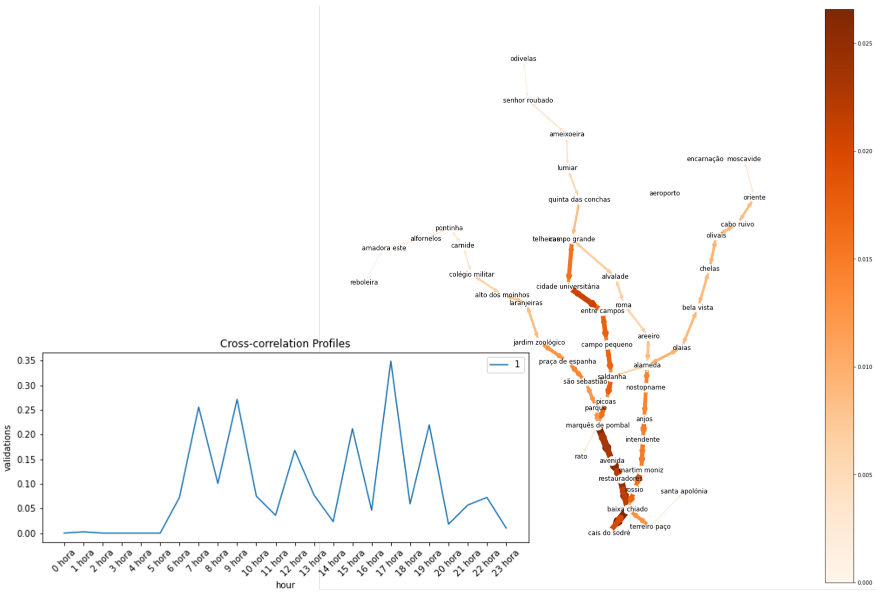

Figure 7.7: METRO lean resilience to users cluster 1 - Long workday commuters

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.

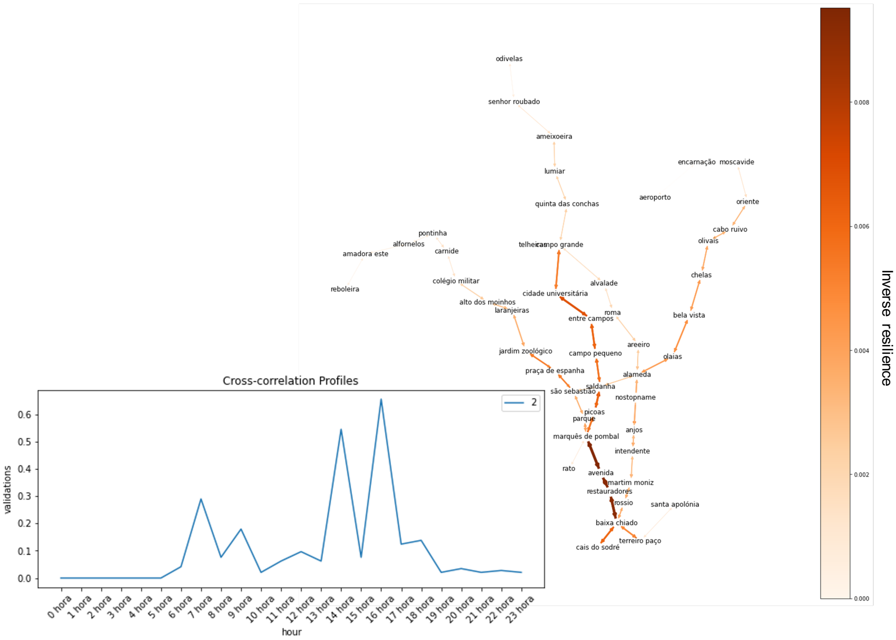

Figure 7.8: METRO lean resilience to users cluster 2 - part-time workday commuters

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 could be either be done by vehicles with higher capacity, higher frequency or even a mixture of both. Another solution could be based on incentivizing the flow of users towards off-peak hours. This later strategy can be achieved by implementing a gamification system that attributes usable points for good behavior like in other smart city gamification systems [99]. This could also be integratively solved with the aid of alternative modes of transportation. It is important to note that if incentives for adoption of

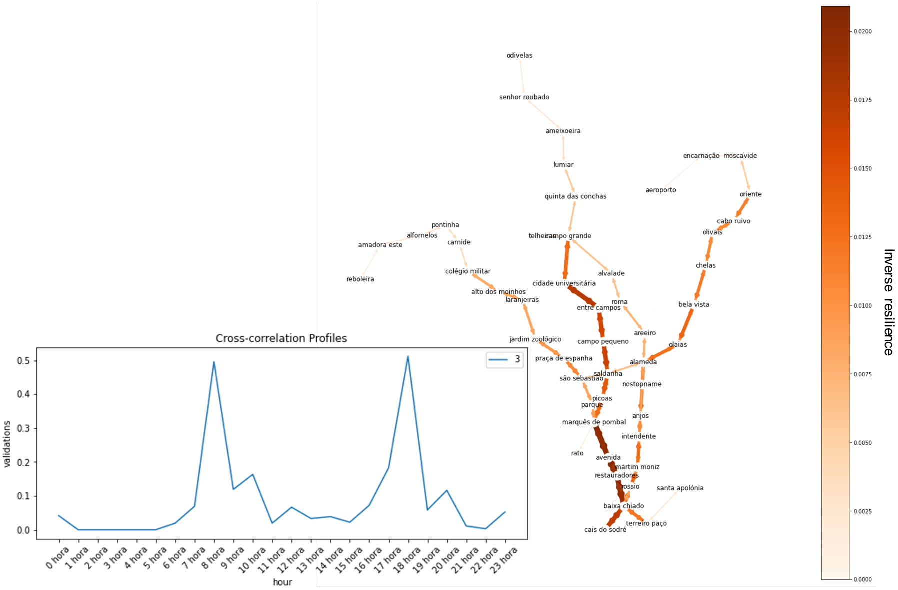

Figure 7.9: METRO lean resilience to users cluster 3 - 9-to-5 Workday commuters

other transport modes is a desired solution, note that the strain of the target modes must be considered. Using a multimodal approach to transportation we could induce transport users to shift to less used modes by attributing points as incentives to change mode that could be used for monthly fare discounts, for instance. The use of past and current data could be used to generate agent based systems to decide under those circumstances [100]. The study of these incentives and the implementation of similar techniques to the ones used in this research could yield extremely interesting results. These studies could answer questions such as: What incentives may be qualified as worthy? Can we model agents based on a data driven behaviour? Did the usage profiles change? Did the pathways became less strained after incentives?

To understand the fragility of the METRO and CARRIS networks, 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 Figures 7.11 and 7.10). 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. Although most of the pathways that exceeded user capacity do not have a particularly high betweeness, there seems to be a positive relationship in the southwest part of the city in CARRIS (Figure 7.11). In METRO (Figure 7.10) this relationship is fairly evident in parts of the blue and red lines: São Sebastião to Alto dos Moinhos and Alameda to Boa Vista. Nevertheless, we see that the resilience is mainly caused by the dynamic usage features, it happens not only because of topology and cumulative effects but also because of a lack of equilibrium between supply and demand in particular time frames, i.e. low lean resilience. A good example of this is the yellow line (Odivelas to Rato) and the southern part of the blue line (Marquês de Pombal - Baixa Chiado) that have no station with particularly high betweeness centrality, but have low resilience, according to usage intensity. Still it is important to note that edges with very low betweeness centrality have high levels of lean resilience, since they are not subject to the cumulative effect of the demand variation from other parts on the network.

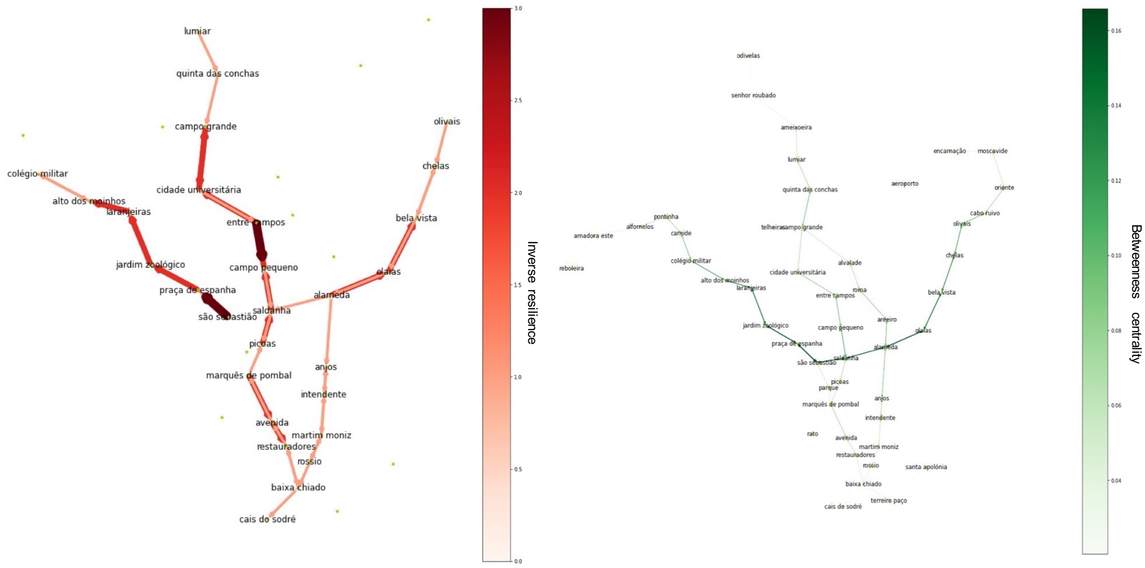

Figure 7.10: METRO low resilience links in accordance with demand supply dynamics on the left and Topological criticality on the right in accordance with betweeness centrality

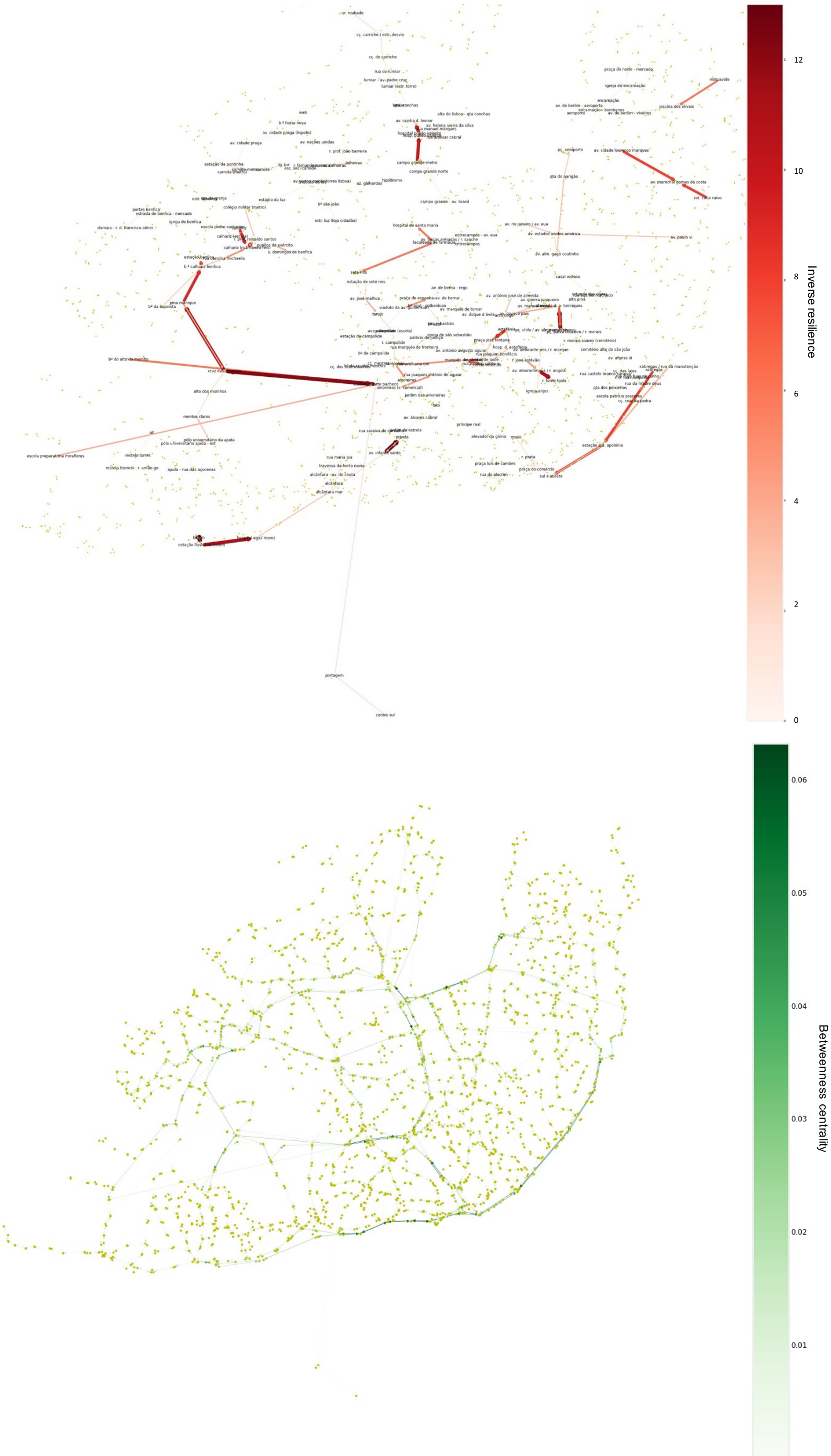

Figure 7.11: CARRIS low resilience links on the left and Topological criticality on the right

Part IV

Conclusions and Future Work

8

Conclusions

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8.1 Conclusions

In this work, we introduced the need to objectively measure the resilience of multimodal networks, both dynamic and topological as a means to achieve a sustainable transport system. To further characterize the proposed solution, towards 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. Knowing what had been done to address the research problem, we proposed a multiplex network modeling and its assessment, the pattern exploration in this network using dynamic weights based on demand-supply ratios; the aglomerative hierarchical clustering of passengers for further understanding specific multimodal behaviours; along with metrics to describe the generated solution. The assessment of the described solution is based on network metrics and cluster cohesion and separation indices.

The structure of the Lisbon's public transport network is modelled and analysed to measure its robustness according to a multimodal stance. Results allow us to understand the geographic information inherent to the multiplex network by programming a 3D plotting method. After calculating and interpreting some of the network metrics, results indicate that multimodal coordination can help diminish the number of stops in a pathway. After identifying stations that work as bridges between different layers and communities, we then analysed different extraction strategies based on previous work. This is an important step to guide the assessment of classic robustness metrics in the context of multimodal transport networks. The target metrics include the size of the largest SCC (strongly connected components), APL (average path length) and IC's (isolated components), as well as a proposed normalised AUC (area under curve). Hence, we observed that the selection of metrics should be constrained to the goal and type of removal (edge vs node).

Results show that the strategies that depend on recalculating metrics are generally more effective, with the exception of a particular case of edge removal using betweenness centrality to maximise IC's, which counter-intuitively had better results for the IB (initial betweenness) strategy. Even though we were able to postulate on this phenomena, further research needs to be done to understand it. We also showed that the resilience tests needed to remove about half the nodes of the network to leave all the remaining nodes wholly disconnected. This is a phenomenon that happens in all layers and the multilayer network as well, suggesting that betweenness targeting is the best way to measure robustness across the different strategies. We also verified higher assortativity phenomena in multilayered networks, in contrast to single layers, highlighting the importance of inter-modal hub redundancy.

Based on the robustness tests we were able to conclude 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. This means that the number of pathways to a station is less important than how many shortest paths go through that station in a multimodal scenario when completely disconnecting the network. 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 actually RB. This means that 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.

Using a normalised variant of AUC, we were able to compare, side by side, the robustness of each transport operator-specific network, regardless their size. CARRIS , RodLisboa, SULFERTAGUS and TST show inferior robustness than the remaining networks. The two most robust networks were FERTAGUS and TRANSTEJO . Nevertheless, this result may be due to inflation on smaller sizes, pinpointing the need for non-uniform scaling factors for the AUC normalization. The multilayer network was more resilient than one-half of the layers but less than the other.

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 point out 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. Results of this study allow practitioners and urban transportation policy makers to tackle the impact of negative disruption in multimodal transportation networks.

On a dynamic perspective, which has in part been published [11], the research revealed that the impact of COVID-19 on public transportation demand were considerably lower in those stations located in areas outside of Lisbon municipality and in zones with lower incomes. A possible interpretation is the need experienced by some daily commuters to continue relying on public transport modes to travel to work. The observed relationship between the demand impact and average income is cohesive with the arguments for inequality. In this context, public transportation reveals to be key to address mobility needs during disruption and, hence, provision of safe services is a means to contribute to social equity goals. On the other hand, patterns and stations registering the highest decrease in demand are mostly located in specific areas in the city of Lisbon (higher price of housing per square meter) which seem to indicate that residents could adapt their working status and change it to digital forms. Overall, impacts of COVID-19 on public transportation highlighted the socioeconomic disparities of users across different areas and corridors.

The analysis of the changing mobility dynamics along the major city arteries (Figures 6.8 and 6.9) show that stations serving the downtown district (Cais do Sodré, Rossio and Terreiro do Paço) and the central business district (Saldanha and Marques de Pombal) suffered a heightened demand contraction after the pandemic, altering the pre-pandemic established demand effects of those classic traffic attracting poles. Upper regions of the Avenida Almirante Reis also entailed higher changes when compared with stations lower in the same avenue, for both modes of transportation. On the Marques de Pombal to Campo Grande route, we observe a greater impact on the demand for METRO stations over bus stops, particular those stations serving large commercial and sports poles, such as Benfica and Campo Grande.

Further on the user dynamics, we applied aglomerative hierarchical clustering to the temporal usage data and created different usage profiles. This was done by using different metrics for cluster cohesion and aglomerative clustering metrics. We concluded that the cross-correlation using a complete linkage was the metric that generated the best clusters and we devised four profiles based on the average usage within 4 clusters. We also characterized the percentage of each user profiles per station which is usually imbalanced. The spatial description of the user types was further applied by using a weighted graph to assign users to pathways within the METRO network. The spatial location of these users varied slightly.This spatio-temporal characterization was achieved using the average usage at each hour of the day.

The description of overall user demand regardless of cluster profiles was introduced using weighted graphs in two time periods of the day for CARRIS and METRO . This allowed for an integrated view of the demand that showed clear inward and outward patterns, as well as flow of users through the network.

The notion of transport supply was also introduced and modelled on a weighted network based on schedule and data pertaining to the vehicles used by the two transportation layers. This allowed for a better understanding of the transport levels during all periods of the day.

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 but a data driven approach is essential as well to understand the user behaviour. 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 discussed principles involve gamification techniques, however these are yet to be tested in the city of Lisbon. The generated resilience graphs for the public transport of the city of Lisbon aim to improve the lean resilience of the transport towards demand variation using real-time data. These are able to reproduce accurate representations regarding the absorbability of users in the system, hence the resilience measurement.

8.2 System Limitations and Future Work

In the analysis of the lean resilience, a future direction may be the analysis of the resilience of inter-modal pathways (or links). Nevertheless, we have contributed to the 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 betweeness 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 the redundancy of high degree stations. This was also the first study on the subject matter in the context of the city if Lisbon.

Cascading effects on network topology and lean resilience are an alternative focal topic that may be covered in the future. They can further reveal perspectives on the resilience of the network to to demand relocation scenarios throughout the multimodal network. On a topological level, the concept of percolation may be applied to connected segments of the network, either in route (simulating vehicle failure or a casualty on the pathway) or in surrounding nodes in the same geographic zone (simulating a natural disaster).

The profiles devised from this analysis may be used to further understand how different targeting strategies affect the network usage and distribution, contributing with useful insights for managing multimodal mobility.

The analysis of the post COVID-19 pandemic transport usage in Lisbon is a natural secession of the work here present. It might be extremely relevant to understand to impact of a wide adoption of remote work on the transportation demand, as well as the tendencies for private vehicle use as well as micromobility adoption.

The static analysis of the network robustness might have a strong impact on a further study regarding network accidents and their impact on the transport accessibility, as well as the impact on usage dynamics. The dynamic analysis may also be extended for a prescriptive analysis of long term patterns and pattern change. A contextual analysis of the current analysis might also be extremely useful. The study of causality of events on demand changes in the network segments and how that estimation may be done with heterogeneous data sources.

Lastly, from a practical point of view, the resilience improvement of the Lisbon public transport network will also require a closer coordination between all the transport operators and the availability of data from diverse sources. Thus, this work also serves as an objective data-centric ground to to motivate the local authorities and transport operators to develop an integrated plan for a more resilient network.

8.3 Scientific communication

The following contributions of the dissertation have been published in peer-reviewed scientific Journals and conferences. Namely, the contributions regarding the impact of COVID-19 pandemic on transport demand change in Lisbon published in the Sustainability Journal [11] (Q1 in Geography, Planning and Development according to Scimago Journal rankings). The contributions regarding the network robustness assessment in the context of the city of Lisbon are published in the European Transport Conference 2021 [94] (a B rank conference according to Excellence in Research for Australia (ERA) and the 6th best ranked transport conference worldwide according to conferenceranks.com). Additional publications were done previously and during the present research work period, more information is available at my Google Scholar page.

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Assessment remarks

It is expected that the random removal strategy may not maximize the damage to the network. Still, it can be a reasonably realistic approach since the Lisbon public transport network usually has failures in random stations due to unpredictable and unexpected events. We can expect that the more specific attacks should be more harmful than the random failures. Concerning the nodes vs edges, we believe that there should be a small difference between these attacks, but this is hard to predict. Degree based strategies should split the network into many subgraphs of vertices with low degrees. Betweenness centrality strategies should create clusters that are highly connected since they tend to destroy the bridges that connect communities first.

It is worth noting that the Multimodal Hubs removal attack strategy only makes sense when evaluating the multilayer network. When evaluating each modality, this strategy is invalid because there are no multimodal hubs.

Removing nodes from this network may correspond to a stop being destroyed or being in constructions. In contrast, removing edges may correspond to cutting roads or accidents preventing any vehicle from passing through. *Edges* can also fail. All our node attack strategies can be applied to edges with a few modifications. For example, how can we get the degree of an edge? The edge degree depends on the nodes that are connected by it. Following the study of Holme et al. [91], where they concluded that method $k_e = k_v * k_w$ was the best fit to the majority of the network types they studied. Where k_e is the edge degree and k_v and k_w are the degree of the nodes that are connect by the edge e. Since our network is directed, use v as the source and w as the destination node of the edge. Other possible methods to calculate edge degreecould be:

1. $k_e = k_v * k_w$
2. $k_e = k_v + k_w$
3. $k_e = min(k_v, k_w)$
4. $k_e = max(k_v, k_w)$

ID and RD removal are *local strategies* because when a node is removed, it only changes the degree of the neighbours of that node. Thus, only these local nodes need to be updated. On the other hand, IB and RB removal are *global strategies* since by removing a node, we need to recalculate the betweenness centrality globally, i.e., of all nodes.

Every calculation of the betweenness centrality of the network costs around 5 minutes. To apply the RB removal strategy, we would need at least 15 days. Because of that, we decided only to recalculate the betweenness centrality when batches of 5% of the nodes were removed. Being *N the number of Nodes* and *E the number of Edges*, the ID algorithm is *O(N+E)*, the RD is *O(N(N+E))*, the IB is *O(NE)* (using a faster algorithm for betweenness centrality created by Brandes [101]) and the RB is *O(N^2E)*. To calculate the betweenness centrality of an edge, we also used the Brandes [101] O(NE) algorithm.