Joint Modelling and Robustness Analysis of Multimodal Transportation and Electricity Networks

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1 INTRODUCTION

In recent years, both individual and public transport sectors have increasingly electrified globally, aligning with the European Union's objectives set in October 2022 to cease sales of new combustion-powered vehicles by 2035. However, this massive electrification increases the electric power needs of urban infrastructures, intensifying and complexifying interactions between electricity and transport networks. Consequently, disruptions in one network can significantly impact the other. This emphasizes the need for a comprehensive study of these critical infrastructures, considered jointly rather than independently, which is an operational challenge due to the lack of interactions among system operators.

Resilience and robustness are widely discussed concepts in the scientific literature when it comes to assessing the performance of public transportation networks. Resilience refers to the network's ability to absorb and adapt to unexpected disruptions, as well as its capacity to recover quickly. This notion requires dynamic approaches and simulations to capture the network's response to disruptions. For example, in (Goldbeck et al., 2019), the authors study the resilience of London's interdependent metro and electricity networks, by dynamically redistributing passenger flows and deploying repair resources after a power breakdown. On the other hand, robustness is usually defined as the network's ability to maintain functionality in the face of failures. It is a narrower concept compared to resilience and it can be studied through static approaches. For instance, analyzing the topology of transport networks can provide valuable insights into their robustness, by measuring their resistance to disruptions or highlighting vulnerable elements.

However, transportation robustness studies rarely account for electricity networks in their model. Recent topological studies often focus on isolated properties of single-mode transportation networks and neglect their interconnectedness with power grids. For example, the robustness of rail networks in Paris and China was calculated in (Adjetey-Bahun et al., 2016) and (Fang et al., 2020) by using betweenness centrality, which is a metric that quantifies the proportion of the graph shortest paths between all pairs of nodes that run through a given node or link. (Cats, 2016) and (He et al., 2021) use metrics based on travel time delay caused by transit network disruptions to assess the robustness of the Stockholm's metro, commuter and light rail trains and the Netherlands' inland waterway, road and railway freight transport. The robustness of interdependent transport and power networks is thus a recent and complex area of study. The objective of this study is precisely to address this gap, by applying topological metrics to evaluate the robustness of a multimodal public transport network under various electric power breakdown scenarios. The methodology was applied to Lyon, France.

2 METHODOLOGY

2.1 Networks modeling

In our model, each public transport line T (metro, tramway, bus) is represented as a directed and weighted graph $G_T(V_T, E_T)$, with vertices $v_T \in V_T$ and edges $e_T \in E_T$, $E_T \subseteq (V_T \times V_T)$, respectively corresponding to transit stations and links between consecutive stations on the same line. The pedestrian graph $G_P(V_P, E_P)$ is constructed with a similar structure, where nodes denote points of interest such as street intersections, and edges represent walking paths. These two graphs are then unified into a final graph $G(V, E)$ by integrating intermediary edges $e_I \in E_I$, $E_I \subseteq (V_T \times V_P) \cup (V_P \times V_T)$, which connect each transit node to its nearest pedestrian node. In the end, $V = V_T \cup V_P$ and $E = E_T \cup E_P \cup E_I$.

Edges weights w correspond to travel times along edges and depend on the edge type. Weights of transit edges $w(e_T \in E_T)$ and pedestrian edges $w(e_P \in E_P)$ are equal to the in-vehicle travel time and the walking duration, respectively. As for intermediary edges, weights depend on their direction. When $e_I \in V_T \times V_P$, $w(e_I)$ is simply an estimation of the walking duration to leave a public transport vehicle and join the closest pedestrian node. Conversely, a waiting time is integrated in $w(e_I \in V_P \times V_T)$ to account for waiting at stations. Assuming proper transit line operation, this waiting time is calculated as half the average headway of the line. For instance, if a metro line operates at a frequency of one train every 6 minutes, the average waiting time equals 3 minutes.

The data related to G_T is publicly available and sourced from the General Transit Feed Specification, while G_P data is obtained from OpenStreetMap. Transit travel times and frequencies were calculated based on Tuesday the 24th of October 2023, between 7:00 and 9:00. We assume that this weekday morning during a peak-hour period is representative of the transit network operating at its full capacity.

2.2 Electricity network disruptions

In addition to the modelling assumptions previously discussed, public transport operators were interviewed in order to integrate valuable information in the proposed methodology, such as the number of electricity substations supplying each transit line or the consequences of power grid failures on the transit lines operation. Moreover, these discussions led to the assumption that an electric breakdown affects a line entirely and not only a portion of it, thus excluding the application of traditional network attack strategies such as single node/edge removal to assess the robustness of the coupled system.

In this study, each transit line is described by a functional state that relies on power supply:

- s_0 : "normal operation", the line functions properly;
- s_1 : "partial operation", the frequency of the line is reduced by half, thus doubling waiting time;
- s_2 : "anticipated disrupted operation", the line is replaced by a shuttle operating in road traffic;
- s_3 : "unforeseen disrupted operation", the line is entirely removed;

Figure 1 illustrates the differences among these functional states. The impact of state s_1 is relatively low since it only affects waiting times $w(e_I \in V_P \times V_T)$. In state s_2, $w(e_T \in E_T)$ increases significantly because the replacement shuttle is slowed by traffic jams and traffic lights. State s_3 is the most extreme scenario, in which the entire line is removed. It is worth noting that quicker alternative paths connecting origin and destination points can exist when a line is degraded, using bus lines or walking.

2.3 Robustness evaluation

Two metrics are employed in this robustness analysis: Average Travel Time (ATT) and Node Betweenness Centrality (NBC). ATT is a global measure that represents the average duration of the shortest paths connecting all pairs of transit nodes within the graph. Meanwhile, NBC is a local measure that quantifies the total number of times a node is crossed by the shortest path between any two transit nodes. Both metrics provide valuable insights into the efficiency of the transportation network. Betweenness centrality was also applied to edges and the results provided identical insights.

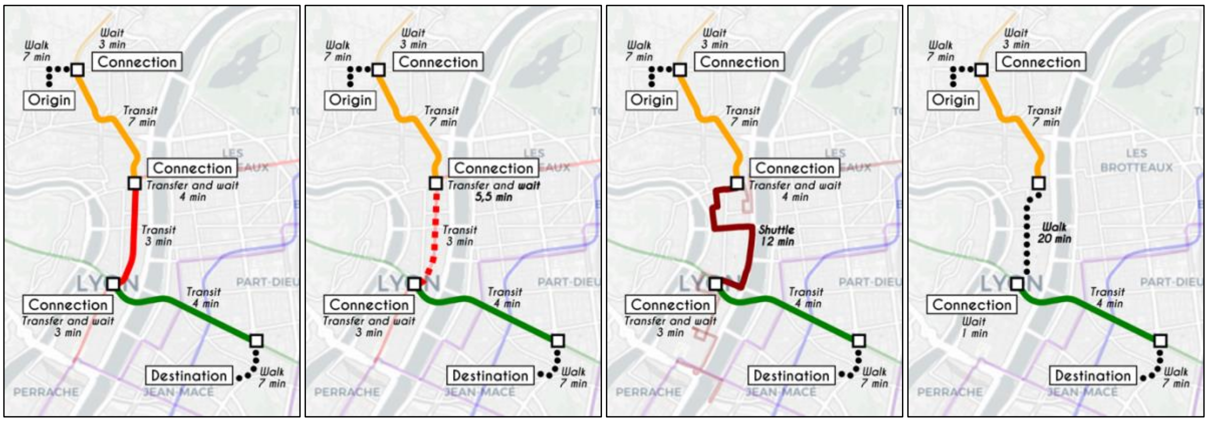

Figure 1 – *Description of each functional state, with a trip example visiting 3 metro lines (a) All lines in state s_0. (b) Red line in state s_1. (c) Red line in state s_2. (d) Red line in state s_3.*

2.4 Disruption scenarios

Based on the aforementioned methodology, various electrical failure scenarios were simulated to identify weaknesses in the transit network. The reference scenario assumes that all transit lines operate at state s_0. This provides a baseline for comparison with disruption scenarios. In degraded scenarios 1, 2, and 3, one transit line operates in the degraded state s_1, s_2, and s_3, respectively, while all the others operate properly. Hence, each failure scenario is associated with multiple graphs, each representing the disruption of a single transit line. The failure scenarios can then be investigated to identify the most vulnerable lines, by comparing the ATT values of the disrupted graphs with that from the reference graph. A significant deviation indicates a substantial impact on passenger travel time.

3 RESULTS

3.1 Case study

The model was applied to the metro, tramway, bus and pedestrian networks of Lyon, with 4 metro lines, 7 tramway lines and 153 bus lines. The associated graph contains approximately 145.000 vertices and 417.000 edges, 97% of which correspond to the pedestrian graph. Discussions with power grid experts from the public transport operator Keolis Lyon led to the assumption, for the purposes of this study, that only metro and tramway lines would be subject to power outages. Indeed, power grid failures affect bus lines differently based on their diverse power sources, including battery-powered, motor-based, and trolleybus capabilities, and will be the focus of future investigation. In this work, they are consistently assigned the operational state s_0. Still, including bus and pedestrian networks in the graph is crucial since it ensures that connectivity is maintained even when metro and tramway lines are disrupted.

3.2 Average travel time

Figure 2 displays the ATT values obtained in the reference case and the three failure scenarios. Firstly, when focusing on Scenario 1, it is notable that considering any line in state s_1, while others operate properly, does not markedly penalize the overall travel time. Conversely, Scenarios 2 and 3 can significantly increase travel times across the shortest paths of the transit network, particularly for metro lines D, B and A, as well as tramway T3, indicating their importance in maintaining efficient mobility.

3.3 Betweenness centrality

Betweenness centrality was computed on the reference graph only. Table 1 lists the ten more central stations and displays the associated number of times it is crossed by the shortest paths between all pairs of transit stations. These results highlight the pivotal role of the lines D and T4 in network centrality.

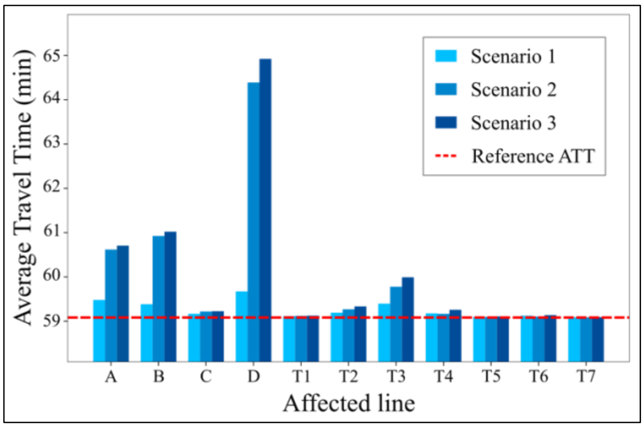

Figure 2 – *Average Travel Time of the reference and three disruption scenarios*

	Node description	NBC
T4	Manufacture Montluc	18764
T4	Lycée Colbert	17062
D	Saxe - Gambetta	16300
T4	Archives Depart.	16191
T4	Jet d'Eau - M. France	15707
T4	Gare Part-Dieu Villette	15644
D	Guillotière Gabriel Péri	15320
D	Bellecour	15204
T4	Lycée Lumière	14144
D	Vieux Lyon	13711

Table 1 – *Transit stations with the highest betweenness centrality values*

4 DISCUSSION

The ATT and NBC metrics offer complementary insights into transit network robustness. While ATT provides a global view of line efficiency, NBC measures station importance individually. By pinpointing the lines and stations that are most vulnerable, infrastructure operators can enhance disruption preparedness and response strategies. Here, line D appears to be the one where maintenance efforts should be focused on. A notable outlier arises with tramway T4, highly central yet minimally impacting travel time when disrupted, unlike metro D. The main reason is that line T4 overlaps on many sections with other tram lines, making it easily replaceable when disrupted. More generally, ATT and NBC are worth being investigated separately precisely because they do not necessarily coincide. Consider for example a hypothetical line D' serving the same stations than metro D, but slightly slower. Line D would retain highly central, but its disruption would have little impact on travel times.

It is important to highlight this study faces limitations currently under investigation. For instance, we plan to model the impact of power failures on electric bus operation and integrate a power grid graph, whose topology will enable us to assess geographical vulnerabilities, vital for natural event responses. Moreover, the current methodology is agnostic to travel demand, which provides crucial information on the actual usage of each public transport line. Also, we are currently working on analyzing the quantitative correlation between the two presented metrics ATT and NBC. Finally, we conducted a similar analysis for the public transport network of Stockholm; the comparison of these two case studies will facilitate the development of a generalized approach applicable to various transit networks.

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