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THE RESILIENCE VALUE OF PUBLIC TRANSPORT DEVELOPMENT PLANS

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ABSTRACT

Investments in transport are increasingly motivated by the need to improve its resilience – the overall capability to maintain system integrity and functionality. Nonetheless, there is lack of knowledge on how to assess their impact on network resilience. This study investigates the resilience of alternative public transport networks by assessing the consequences of link failures on network performance. A full-scan disruption impact analysis is performed and its implications on travel times and network integrity are analyzed for a public transport expansion plan in Stockholm, Sweden. The results demonstrate that the extended network is considerably more resilient in terms of average performance deterioration as well as worst case scenario. Moreover, the critical links in each network are identified and impact disparity is investigated. The analysis method presented in this study can support the consideration of development plans impacts on network resilience in the planning process.

Keywords: Resilience, Public Transport, Link Failure, Network Design, Disruption

1. INTRODUCTION

Investments in transport are increasingly motivated by the need to improve reliability and resilience and not merely travel time savings under normal operations (Mackie et al. 2014). Transport systems are subject to recurrent disruptions that may carry substantial implications on network performance and society at large. Even though public transport systems are critical infrastructures in many urban and regional transport systems, only little is known about techniques and indicators to analyze the impacts of disruptions. For public transport services to be an attractive travel alternative, it needs to be efficient under normal operations as well as resilient in terms of its capability to withstand or quickly recover from disturbances. The impact of disruptions and risk perceptions may extend beyond the direct time losses due to their disproportional effect on travelers' decisions (Cox et al. 2011).

Disruptions in the public transport service could be caused by various reasons including mechanical and technical failures, planned maintenance works or targeted attacks. Depending on the type of disruption, the implications on the network could vary from local reduction in node or link capacity to a complete breakdown. Depending on network topology and operations, some nodes and links might be more critical for maintaining network performance and result in severe consequences in case of disturbance. For example, the impact of link failure depends not only on the number of travelers using this link but also on the availability and attractiveness of travel alternatives.

The resilience of public transport networks is defined by their capacity to absorb disturbances with a minimal impact on system performance. In the emerging research field of resilience studies, *Resilience* refers to the overall capability to maintain system integrity and functionality, while *Robustness* refers to system ability to withstand and recover from shocks (Reggiani 2013). Compared with car traffic, public transport networks are characterized by greater complexity due to limited connectivity and the importance of multi-modality and intermediate walking links. Urban rail-bound systems are particularly vulnerable to link failures because of their restricted capability to bypass link closures, and the low network density. Furthermore, these systems often consist of several separate railway systems which hinder operational flexibility.

Public transport networks vary in their capacity to absorb random and targeted attacks. Most studies on PTS vulnerability focused on network topology and how the degradation of physical links in a specific sub-network affects network connectivity (Angeloudis and Fisk 2006; Derrible and Kennedy, 2010; Zhang et al. 2011; von Ferber et al. 2012; Deng et al. 2013). Based on an investigation of 32 metro systems worldwide, Derrible and Kennedy (2010) postulated that network robustness is determined by the number of cyclic paths available in the network. The importance of circular and cross-radial lines in providing travel alternatives in case of disruptions was also emphasized by Rodriguez-Nunez and Garcia-Palomares (2014) and Jenelius and Cats (2014). Rodriguez-Nunez and Garcia-Palomares (2014) and De-Los-Santos et al. (2012) conducted a full network scan, while Jenelius and Cats (2014) performed a dynamic robustness analysis for a subset of critical links. Ash and Newth (2007) studied the optimal network design to withstand link closures. They developed an evolutionary algorithm that adds or removes links with the objective to improve network robustness and applied it on a synthetic grid network. The results suggested that high clustering, modularity and long path length characterized the most robust networks

While these studies provide insights on the general properties of robust public transport networks, there is lack of knowledge on how to assess the impact of alternative projects on overall network resilience. The evaluation of link failure impacts on alternative networks should consider also travel impedance, travel demand levels and network flows in order to estimate the delay associated with rerouting, the number of travelers affected and ultimately the societal costs attributed to a certain link failure.

This paper evaluates the impact of a development plan on the resilience of a multi-modal rapid urban rail network. The evaluation of the resilience value of a network extension plan consists of performing a full scan disruption impact analysis. A method to model and evaluate the impact of disruptions is first presented (Section 2) followed by its application to a public transport expansion plan that is currently underway in Stockholm, Sweden (Section 3). The results include an impact analysis of disruption scenarios on travel times, unsatisfied demand and link criticality (Section 4). This paper concludes with a discussion on the limitations and implications of this study (Section 5).

2. METHOD

A method to analyse the value of alternative public transport links by performing a full-scan of link failure scenarios is proposed. The analysis considers the change in total passenger travel times compared with the baseline undisrupted scenario as well as the share of passengers that are unable to perform their trip due to network (dis-)connectivity and the share of passengers that are delayed by the disruption.

2.1 Network Representation

The public transport network is represented by a variant of a L-space graph, a directed and weighted graph $G(S,E)$, where the node set S represents stops and rail stations (all called stops here for simplicity), and the link set $E \subseteq S \times S$ represents road or track segments between stops. The graph is fully specified by: (1) an adjacency matrix A where cell a_{ij} equals one if nodes $i,j \in S$ are connected and zero if not; (2) a vector of weights associated with each link $e \in E$ reflecting the travel impedance, t_e, considered deterministic at the strategic planning evaluation. Similarly to the representation used by Derrible and Kenedy (2010), only transfer stations (served by more than a single line, except for intermediate stations on a common corridor) and terminals are included in the node set. Intermediate stations without transfer possibilities are discarded in this analysis as the exact location of the disruption between interchange stations will not influence passenger route alternatives.

Travel demand is assigned using the all-or-nothing approach for a given network and disruption scenario, similarly to Rodriguez-Nunez and Garcia-Palomares (2014). For each pair of stops the shortest path is calculated and the respective travel demand given by an OD matrix, f_{ij} $(i,j \in S)$, is assigned. Let δ_e^{ij} take the value one if link e is on the shortest path between nodes i and j and zero otherwise. The number of travellers traversing each link is obtained by superimposing the flows assigned for all OD pairs,

$$v_e = \sum_{i \in S} \sum_{j \in S} \delta_e^{ij} f_{ij} \tag{1}$$

The resilience value of alternative network design is assessed by comparing network performance to the base case network, n_0. The resilience analysis consists of assessing the impacts of a disruption occurring on each of the network elements. A full-scan approach is taken in this study where each scenario corresponds to the closure of a single link in the network, independently. A scenario involving the failure of link e in network n is denoted by (n,e).

The impact of the failure of link e is assessed by comparing the vector of performance metrics, Y, of scenario $\sigma = (n,e)$ to the base case non-disrupted scenario of the respective network

$$\Delta Y(e|n) = Y(n,e) - Y(n,0) \tag{2}$$

This vector od changes in network performance reflects *link criticality*. When this vector is reduced to change in travel times, it becomes equivalent to the network robustness index proposed by Scott et al. (2006) for evaluating the criticality of highway segments.

The robustness value of a certain network alternative with respect to the failure of link e is defined by comparing the impacts of this disruption to the impacts of this disruption for the base case network

$$\Delta Y(n|e) = Y(n,e) - Y(n_0,e) \tag{3}$$

2.2 Performance Metrics

The impact of disruptions depends on the number of travellers delayed by the incident and the detours invoked by the disruption. The travel impedance of travellers travelling between stops i and j under scenario $\sigma$is

$$t_{ij}(\sigma) = \sum_e \delta_e^{ij}(\sigma) \cdot t_e \tag{4}$$

Whereas the *total travel impedance* experienced by travellers for scenario σ is

$$tt(\sigma) = \sum_{i\in S}\sum_{j\in S} f_{ij} \cdot \left(\sum_e \delta_e^{ij}(\sigma) \cdot t_e\right) \tag{5}$$

Note that different disruptions may result with similar total travel time effect but vary in terms of the number of travellers delayed and the extent of their impact per passenger. For example, a disruption may have large negative consequences for few travellers or induce relatively minor detours to a large number of passengers. The magnitude of the impact of a disruption could thus be measured also in terms of the *share of passengers that experience delays*, as follows

$$q(\sigma) = \frac{\sum_{i\in S}\sum_{j\in S} f_{ij} \cdot \varphi^{ij}}{\sum_{i\in S}\sum_{j\in S} f_{ij}} \tag{6}$$

Where φ^{ij} equals one if $t_{ij}(n,e) - t_{ij}(n,0) > 0$ and is zero otherwise.

Certain disruptions may result with unsatisfied demand due to the partitioning of the network. The impact of network disintegration on incomplete trips could be reflected by assigning as infinite or big M travel time values. However, this will make the comparison of $q(\sigma)$ for such scenarios meaningless. A non-compensatory approach is instead adopted in this study. This implies considering a vector of performance metrics by formulating additional measures that explicitly account for unsatisfied demand and then recalculating travel time impact for completed trips only.

The *share of unsatisfied demand* that results from scenario σ is

$$z(\sigma) = \frac{\sum_{i\in S}\sum_{j\in S} f_{ij} \cdot \omega^{ij}(\sigma)}{\sum_{i\in S}\sum_{j\in S} f_{ij}} \tag{7}$$

Where $\omega^{ij}(\sigma)$ equals one if $\delta_e^{ij}(\sigma) = 0 \ \ \forall e$ and is zero otherwise.

The *average travel impedance per passenger*, $\bar{t}$, is then calculated only for satisfied demand

$$\bar{t}(\sigma) = \frac{tt}{(1 - z(\sigma)) \cdot \sum_{i\in S}\sum_{j\in S} f_{ij}} \tag{8}$$

The abovementioned performance metrics enable to assess the criticality of each link for maintaining network functionality and integrity. It has long been recognized that the ability of transport networks to withstand degradations has clear connections to the structure of the network. In particular, central links, in the sense that many paths between pairs of nodes must cross those links, are often also critical in case of disruptions (Freeman et al. 1991). At the same time, different disruption scenarios also result with different network topology and hence link centrality. The impact of various scenarios on link centrality is examined in this study through the betweenness centrality measure. The latter is a network science indicator that corresponds to the share of shortest paths that traverse through a certain link. Let $g_{i,j}(e)$ denotes the fraction of shortest paths between stop i and stop j that contain link e. The *relative betweenness centrality* of link e in the public transport network is then defined as

$$b_e = \frac{1}{|S|(|S|-1)} \sum_{i\in S}\sum_{j\in S\setminus s_1} g_{i,j}(e) \tag{9}$$

This is a standardized indicator that corresponds to the average share of shortest paths that traverse through a certain link when averaged over all origin-destination pairs. This simple network measure has a number of limitations which may reduce its relevance for identifying central links in real-world public transport network. In particular, it assumes that all node pairs are equally important for the centrality of a link. A *weighted relative link betweenness centrality* measure is instead used in this study

$$\widehat{b_e} = \frac{1}{\sum_{i\in S}\sum_{j\in S} f_{ij}} \sum_{i\in S}\sum_{j\in S\backslash s_1} g_{i,j}(e)\, f_{ij} \tag{10}$$

Although the betweenness measures are relative, they do not necessarily sum up to one as paths consist of multiply links. The next section presents the case study public transport network and development plan for which this analysis method was applied.

3. APPLICATION

The analysis method was applied to the rapid rail-bound transport system of Stockholm, Sweden, which consists of metro, commuter train and light rail train (Figure 1). This network includes 176 stations served by 12 lines and constitutes the backbone of the public transport system in Stockholm with more than 1.5 million passenger trips per day.

Stockholm is famous for its long-term monocentric planning with a dominant central core and the planning of relatively dense satellite rail-bound towns (Cevero 1995). The inseparable urban and transport planning in Stockholm are a prime example of a radial public transport system which is primarily oriented towards suburb to center commuting. The metro network is designed to provide regional accessibility rather than local coverage (Derrible and Kenedy 2010, Börjesson et al. 2013) and the commuter train further extends to neighboring communities in Stockholm County and beyond. Since the turn of the century there has been a noticeable shift towards developing sub-centers, promoting a more balanced distribution of activities (Schmitt et al. 2013). An orbital light rail line was therefore constructed to allow passengers to travel between the southern and western parts of Stockholm without going through the oversaturated city center line segments and transfer hubs (Jenelius and Cats 2014).

While radial commuting patterns still dominate passenger flows, a more polycentric structure is promoted and supported by the development of a corresponding transport infrastructure. These developments include further extensions of the cross-radial light rail train, several extensions of the metro system and increasing the capacity of the commuter train system which are designed to support a stronger network of strategic nodes in Greater Stockholm (Stockholm City 2011). A political decision to extend this system substantially with 23 new stations and 35km of new tracks was recently undertaken (Figure 1).

The investment plan includes the following expansions:

a. A 6 km long new north-south commuter train tunnel (known as '*Citybanan*') underneath Stockholm inner-city (dashed blue line in Figure 1). The project will double the capacity compared with 2014. The construction also involves two new commuter train stations: *Odenplan* and *Stockholm City*.

b. The metro network will be extended in three locations (dashed green lines). First, Line 11 will be extended in the northward direction with two additional stations and will terminate at *Barkarby station*. Second, Lines 10 and 11 will be extended from their current end station at *Kungsträdgården* across the Baltic sea to serve the south-eastern area of *Sofia*, *Sickla* and further to *Nacka Forum*, its new end station. This extension also includes a connection to other metro lines by connection the new station at *Sofia* to the existing *Gullmarsplan* transfer station. Third, one of the metro lines will be extended from *Odenplan* north of the inner-city with two additional stations, terminating at a new station in *Arenastaden*. All of these extensions will serve areas that are undergoing significant transformation with the development of new housing and offices.

c. The light rail line is undergoing several developments including an extension towards the northern suburbs which provides connections to the commuter train and additional metro lines (dashed yellow lines). The expansion plan includes the extension of the line to *Solna station* as well as the construction of a new branch towards *Helenelund*. Finally, the southwest end of the line is extended to *Sickla*, to enable transfers to the planned metro station.

The development plan was partially motivated by the potential value of the proposed extensions to reduce the impact of service disruptions. Nonetheless, this potential effect was neither assessed systematically nor quantified. Network vulnerability is evaluated in this study in terms of the capability of the *Extended* network to withstand link failures as compared with the base case *DoNothing* where the network maintains its current form as of spring 2014. A directional graph of rail tracks and walking links in transfer facilities was used for representing the network and enabling the analysis of link failure disruptions.

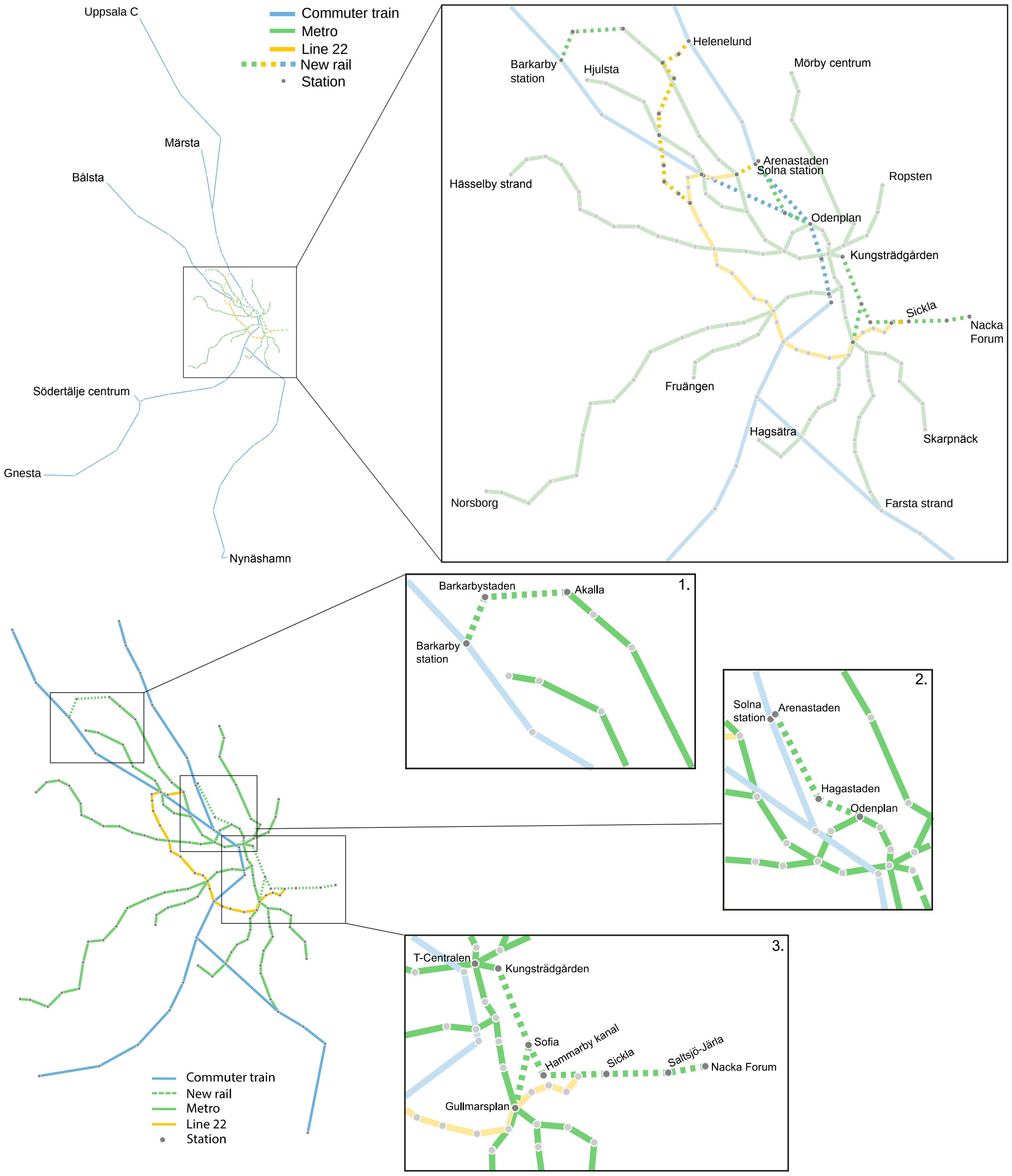

Figure 1. Planned extensions of the Stockholm rapid rail-bound network (above) and zooming-in on the metro extensions (below)

The planned expansion plan will increase the number of interchange stations or end terminals from the current number of 49 to 62. Moreover, the number of network links, which correspond to a direct connection between interchange stations which may include a number of intermediate stations – is set to increase from 92 to 126. The extensions will result with additional cross-radial connections, increase network connectivity and the number of cyclic paths. The Extended network yields an increase in network connectivity (gamma index, share of links out of complete graph) from 0.440 to 0.467. Furthermore, network meshedness (alpha index, share of cycles out of maximum possible) will increase by almost 30%, from 0.151 to 0.196 in comparison to the DoNothing case (Barthelemy 2010). This will in turn increase the number of transfer opportunities and route alternatives in general and in the case of service disruptions in particular.

An origin-destination demand matrix for 2025 was generated based on the regional travel demand model. It is expected that more than 350 000 passenger trips will be generated and distributed over the case study network during the morning peak period (6:00-9:00) on an average weekday. In order to allow the comparison of disruption effects, travel demand is considered fix and is assigned to the closest equivalent node. For example, the demand for the metro line that is extended to *Nacka* (Figure 1) in the Extended network is distributed over transfer hubs that serve as access station to the metro system in the DoNothing scenario (primarily *Slussen* and to a lesser extent *Gullmarsplan*) based on VISUM model assignment results for the DoNothing network that were available for this study.

As described in the methodology section, passenger demand is assigned based on an all-or-nothing assignment to the shortest path. Travel impedance was based on planned travel time in this case study and were extracted from timetables and detailed line plans. The assignment and the calculation of performance metrics were performed in a specially tailored MATLAB code whereas Gephi was used for calculating network indicators and visualization purposes.

4. RESULTS

4.1 Disruption Impact on Passengers

The performance of the existing network versus the network planned for 2025 upon completion of the planned expansion was analysed. For each network, DoNothing and Extended, a failure on each of the network links was simulated along with the non-disrupted case. This amounts to a total of 93 scenarios for the DoNothing network and 127 scenarios for the Extended network. For each scenario, the total passenger travel time and the share of travel demand that cannot reach its destination due to network disintegration were calculated. In addition, the share of travel demand that experienced delays (longer travel times than under the non-disrupted scenario) out of those trips that could be completed was obtained. These results are presented in Table 1 for the undisrupted networks and the average, standard deviation and maximum values calculated over the respective link failure scenarios.

Table 1. Summary of performance metrics

Performance metric	**DoNothing**		**Extended**	
	Undisrupted	Disrupted	Undisrupted	Disrupted
Total travel time [min] tt	9 993 785	Avg. 9 891 921 Std. 345 050 Max. 10 529 403	9 403 674	Avg. 9 346 689 Std. 266 764 Max. 9 931260
Share of unsatisfied demand [%] z	0	Avg. 1.33 Std. 0.025 Max. 14.86	0	Avg. 0.79 Std. 0.020 Max. 14.77
Share of delayed passengers [%] q	0	Avg. 3.18 Std. 0.046 Max. 22.43	0	Avg. 1.49 Std. 0.023 Max. 15.83

The Extended network will reduce total passenger travel time by more than 9 800 passenger hours on a single peak morning period compared with the DoNothing network. This time saving amounts to shortening travel times by 6% or 1 minute and 40 seconds shorter per passenger trip in the undisrupted case.

On average, a link failure in the DoNothing scenario cuts off 1.33% of the travel demand which corresponds to 4 762 travellers. These travellers have no path alternative to the path that contains the disrupted link and their origins and destinations are positioned on two unlinked networks that are generated by the disintegration of the connected network. In contrast, only 0.77% (2 829) of the travellers are strained on average when a disruption occurs. This reflects a reduction of more than 40% compared with the previous level. The overall variation among disruption scenarios is low for both networks (i.e. due to the high share of link closures that do not lead to network disintegration). Notwithstanding, much higher shares of the travellers are not able to reach their destinations under certain disruptions. Every seventh traveller or more than 52 000 travellers, are unable to perform his or her trip in the worst case scenario.

In addition to those travellers that cannot execute their trip, another segment of the travel demand is subject to delays because the disruption occurred on their shortest path but rerouting is still possible albeit with a longer travel time. The average share of passengers experiencing delays is more than halved in the Extended network compared with the DoNothing network, 1.49% vs. 3.18%, respectively. Moreover, the worst case scenario in the DoNothing network inflicts longer travel time to 22.43% of the passengers that can carry out their trip which corresponds to more than 83 000 passengers in the analysis period. The network extensions embedded in the Extended scenario yields longer travel times to less than 15.83% or 56 679 passengers.

The abovementioned differences in the shares of unsatisfied demand, z, and delayed passengers, q, between the DoNothing and Extended networks are further investigated by plotting their cumulative distribution function in Figure 2. More than 40% of all link failure scenarios result with unsatisfied demand in the DoNothing network, whereas less than 30% result with network disintegration in the Extended network (dashed lines). Furthermore, those disruptions that result with unsatisfied demand in the Extended network involve fewer strained passengers than is the case of DoNothing. The pattern emerging for the share of delayed passengers is considerably different (solid lines). The share of disruptions that does not result with any passenger delay is higher for DoNothing than in the case of Extended. This result may seem counterintuitive at first but this is explained by those disruptions that result with unsatisfied demand rather than travel time increase. Thereafter, the Extended network shows better resilience with 90% of link failures causing delays to less than 15 000 passengers compared with the corresponding value of 37 500 passengers when the DoNothing network is in place.

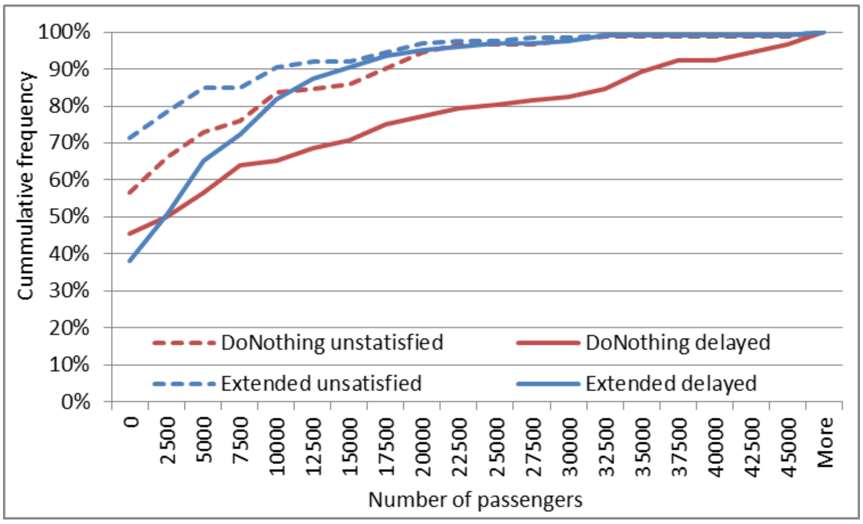

Figure 2. Cumulative density function of link failure scenarios that result with a certain number of delayed passengers and unsatisfied demand for DoNothing and Extended networks

Total passenger travel time is lower on the average disrupted scenario than in the undisrupted case due to those trips that cannot reach their destination (Table 1). This is an inherent difficulty in assessing network vulnerability. The average travel time, $\bar{t}$, was therefore calculated for each disruption scenario. Figure 3 presents the histogram of this performance metric over all link failure scenarios for each network. It is evident that the average travel time is significantly shorter in the case of the Extended network. In fact, only 2 of Extended network scenarios obtain an average travel time that is higher than any DoNothing scenarios. In other words, there is almost no overlap in the range of values obtained by the two networks where the worst performers of the Extended network are similar to the best performers of the DoNothing network. As we have seen in Figure 2, the share of unsatisfied demand is consistently higher in the DoNothing network and therefore does not undermine these results (i.e. those that are disconnected from the network tend to be located in the network fringes and therefore induce longer travel times) .

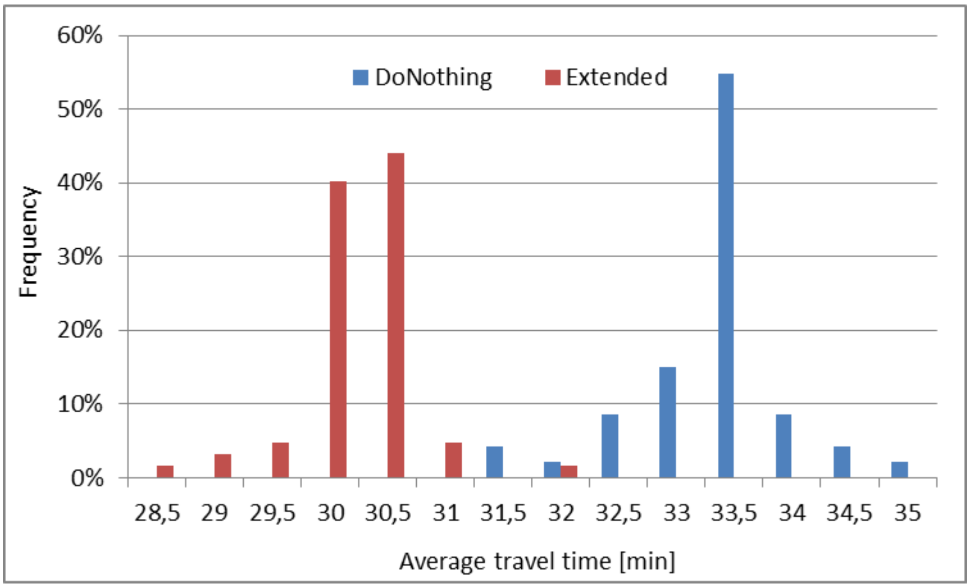

Figure 3: Distribution of average travel time over link failure scenarios

The delay caused by a service disruption may be distributed unevenly among travellers depending on the availability and characteristics of rerouting alternatives (Jenelius 2009). The distribution of delays over travellers population was further investigated by examining the share of travellers that experienced different magnitudes of increases in travel times. The differences between the DoNothing and Extended networks are evident in Figure 4. Each curve in these figures correspond to a single link failure scenario and the graphs show that share of travellers experiencing a delay of one minute, two minutes and so forth. While some disruptions impose a small delay for many travellers, others result with long delays for few travellers. Hence, the impact of two disruptions with similar societal costs may be manifested very differently across the population, even among the minority of travellers that experience some delay due to link failure. In some rare cases, detours due to link failures prolong travel times by more than 30 minutes, showing significant disparities in the impact of disruptions. The results suggest that the robustness value associated with the Extended network is mostly yield by reducing the number of passengers that experience relatively short delays while long delays remain largely unchanged.

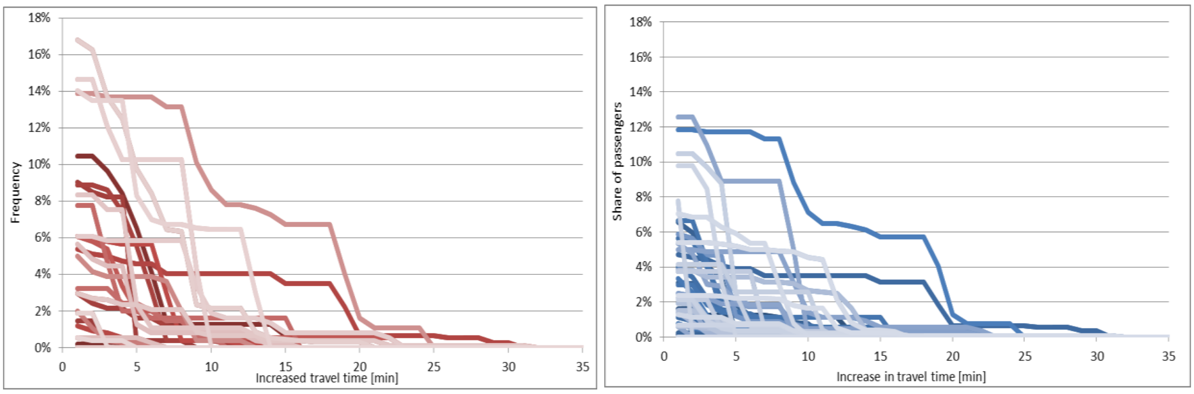

Figure 4: Share of passengers experiencing a certain increase in travel time under link failure scenarios in the DoNothing network (left) vs. Extended network (right)

4.2 Link Criticality

The analysis above suggests that the Extended network can withstand link closure disruptions better than the DoNothing network does. This improved resilience is attributed to the routing possibilities enabled by increasing network connectivity. Figure 5 shows the cumulative distribution of the weighted link betweenness centrality $\widehat{b_e}$ for both networks. The value of this indicator corresponds to the share of travel demand that traverse through a certain link when travelling along its shortest path. In both networks the majority of network links are on the shortest path of less than 1% of travel demand. Moreover, the distribution of betweeness centrality, and hence travel demand, is more evenly distributed in the Extended network than in the DoNothing scenario. Approximately 9% of links in DoNothing scenario carry 3-4% of the travel demand, which corresponds to passenger loads of 10,000-14,000, approaching link capacity. The more balanced distribution of passengers in the Extended network under normal conditions makes the network less vulnerable to link failures, whereas the performance of the DoNothing network is more dependent on few critical links.

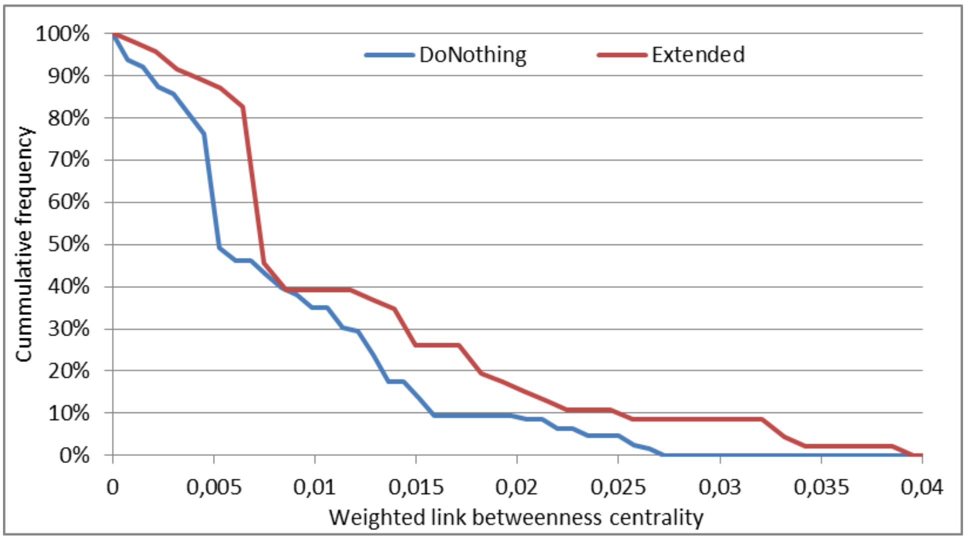

Figure 5: Distribution of weighted relative link betweenness centrality for the DoNothing and Extended networks

The alteration in network topology changes the impacts of various link failures on network performance. It is important for transport planners and operators to identify the most critical links in the network in order to prioritize investments and allocate resources to mitigate the impacts of disruptions on these links. Table 2 lists the five most critical links for each network based on changes in performance indicators, $\Delta Y(e|n)$.

While some links that are critical in the current network remain so in the Expended network, there are also considerable changes in the identification of the most critical links. The connection between *T-Centralen – Östermalmstorg* is critical for maintaining network integrity since the metro line branches out from *Östermalmstorg* and there are no rail-bound alternatives in this north-east section (Figure 1). Hence, all travel demand between the rest of the network and this section (or vice-versa) cannot be performed in case this link (or the opposite direction) becomes dysfunctional. The high-demand metro branch *Solna Centurm – Akalla* becomes less susceptible in the Extended network because of the availability of a new transfer connections to the commuter and light rail lines.

The redistribution of travel demand results with significant changes in link criticality in terms of the share of delayed passengers. The most critical links in the DoNothing network are also the most heavily loaded links in the core of the network – the metro and commuter links that lead inbound and outbound of *T-Centralen* and *Central Station*, respectively. This changes in the *Extended* network where the most critical links are those connected to *Årstaberg*, south of the inner-city. The new station in *Odenplan* creates an attractive north-south travel alternative to the existing metro alternatives. Consequently, disruptions on the links leading to and from *Årstaberg* induce significant delays in the Extended network compared with the undisrupted case.

Table 2. Top 5 most critical links by performance indicator

Based on	**DoNothing**	**Extended**
Share of unsatisfied demand, z	*T-Centralen - Östermalmstorg* *Östermalmstorg – T-Centralen* *Bålsta - Sundbyberg Station* *Östermalmstorg - Ropsten* *Solna Centurm - Akalla*	*T-Centralen - Östermalmstorg* *Östermalmstorg – T-Centralen* *Bålsta – Barkarby Station* *Östermalmstorg - Ropsten* *Hässelby Strand - Alvik*
Share of delayed passengers, q	*Årstaberg - Central Station* *Fridhmesplan – T-Centralen* *T-Centralen - Fridhemsplan* *Karlberg - Central Station* *Slussen – T-Centralen*	*Årstaberg - Central Station* *Liljeholmen – Årstaberg* *Central Station – Årstaberg* *Årstaberg – Liljeholmen* *Älvsjö - Årstaberg*
Average travel time, $\bar{t}$	*Älvsjö – Årstaberg* *Årstaberg – Älvsjö* *Karlberg - Central Station* *Central Station - Karlberg* *Årstaberg - Central Station*	*Älvsjö – Årstaberg* *Årstaberg – Älvsjö* *Årstaberg - Central Station* *Central Station - Årstaberg* *Skärmarbrink - Gullmarsplan*

The most devastating scenarios in terms of average passenger travel time are also listed in Table 2. These are also the links that their closure result with highest increase in total passenger travel time and where all demand can be satisfied. The worst case scenario corresponds to the same link failure (*Älvsjö – Årstaberg*) for both networks, with an increase of more than 5% in total travel costs, approximately 1 million SEK for a disruption during the peak morning period based on the Swedish value-of-time. A targeted attack may therefore induce these costs. The resilience effect of the new metro connection between *T-Centralen* and *Gullmarsplan* (Figure 1) is especially remarkable when a disruption on the segment connecting *Gullmarsplan* to *Slussen* occurs. This disruption scenario results with an average travel time of 33.4 in DoNothing network, an increase of 1.22% compared with normal disruptions, whereas the same disruption results with an average travel time of 30.0 min in the Extended network, an increase of 0.05% compared with the normal operations of the respective network.

5. CONCLUSION

This study investigated the resilience of alternative public transport networks by assessing the impact of link failures on network performance. A full-scan of network links was performed and the impacts of each disruption were analyzed in terms of the capability of the network to maintain its integrity and guarantee that travelers can reach their destinations. In addition, the travel time consequences of each disruption were estimated by performing an all-or-nothing assignment which enabled the assessment of total passenger delay and comparing the share of travelers that are subject to delays.

The systematic vulnerability analysis was applied to the rapid rail-bound network in Stockholm. This network will undergo significant investments in the coming decade. The resilience of the extended network is quantitatively evaluated against the resilience of the existing network when assigning the travel demand projected for 2025. The results demonstrate that the extended network is considerably more resilient in terms of average performance deterioration as well as the worst case scenario. Moreover, the critical links in each network were identified and the equity implications were analyzed in terms of how delays are distributed over travelers' population. The analysis performed in this study facilitates the consideration of expansion plans impacts on network resilience effects in the decision making and planning processes. However, the incorporation of such effects into project appraisal require making assumptions on link failure probabilities. Even in the lack of risk estimations, alternative networks can be compared and prioritized based on their performance metrics in order to support transport planners in designing resilient development plans.

The evaluation framework used in this study has several limitations. Most importantly, the assignment model could be enhanced by considering probabilistic assignment principles. Moreover, travel impedance could include other travel attributes such as waiting time and transfers, although this will require a substantially more complex graph representation. Notwithstanding, Ramli et al. (2014) compared the results obtained by the assignment approached applied in this study to ridership data of the rapid transit system in Singapore and concluded that it results with reasonably accurate predictions. While static assignment models can reasonably be used to estimate the impact of link failure on passengers' redistribution, a dynamic non-equilibrium model will be more adequate for this purpose. Such a model can represent imperfect travel information, en-route decisions and the knock-down effects generated by an unplanned disruption (Cats and Jenelius 2014). However, the stochasticity and computational complexity of such a model might prohibit the full scan approach undertaken in this study. Note that the simplifications made in this study are likely to result with an underestimation of travel delay as travellers are assumed to have perfect information and no spill-over effects to neighbouring links are considered. Future studies may also analyse the impact of multiply link failures as well as node closures.

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REFERENCES

Angeloudis, P. and Fisk, D. (2006) Large subway systems as complex networks. *Physica A* 3, pp. 553-558.

Ash, J. and Newth, D. (2007) Optimizing complex networks for resilience against cascading failure. *Physica A* 380, pp. 673-683.

Barthelemy, M. (2010) *Spatial networks*. Available at : http://arxiv.org/abs/1010.0302

Börjesson, M., Jonsson, D. and Lundberg, M. (2013) An ex-post CBA for the Stockholm metro. CTS working paper 34.

Cats, O. and Jenelius, E. (2014) Dynamic vulnerability analysis of public transport networks: mitigation effects of real-time information. *Networks and Spatial Economics* 14, pp. 435-463.

Cox, A., Prager, F. and Rose, A. (2011) Transportation security and the role of resilience: A foundation for operational metrics. *Transport Policy* 18, pp. 307-317.

De-Los-Santos, A., Laporte, G., Mesa, J.A. and Perea, F. (2012) Evaluating passenger robustness in a rail transit network. *Transportation Research Part C* 20, pp. 34-46.

Deng, Y., Li, Q., Lu, Y. and Yuan, J. (2013) Topology vulnerability analysis and measure of urban metro network: The case of Nanjing. *Journal of Networks* 8 (6), pp. 1350-1356.

Derrible, S. and Kennedy, C. (2010) Characterizing metro networks: state, form and structure. *Transportation* 37, pp. 275-297.

Freeman, L.C., Borgatti, S.P., White, D.R. (1991) Centrality in valued graphs: A measure of betweenness based on network flow. *Social Networks* 13, pp. 141–154.

Jenelius, E. (2009) Network structure and travel patterns: explaining the geographical disparities of road network vulnerability. *Journal of Transport Geography* 17 (3), pp. 234-244.

Jenelius, E. and Cats, O. (2014) The value of new cross-radial link for public transport network resilience. *Second International Conference on Vulnerability and Risk Analysis and Management (ICVRAM).*

Mackie, P., Worsley, T. and Eliasson, J. (2014) Transport appraisal revisited. *Research in Transportation Economics* 47, pp. 3-18.

Ramli, M.A., Monterola, C.P., Khoon, G.L.K. and Guang, T.H.G. (2014) A method to ascertain rapid transit systems' throughput distribution using network analysis. *Procedia Computer Science* 29, pp. 1621-1630.

Reggiani, A. (2013) Network resilience for transport security: some methodological considerations. *Transport Policy* 28, 63-68.

Rodriguez-Nunez, E. and Garcia-Palomares, J.C. (2014) Measuring the vulnerability of public transport networks. *Journal of Transport Geography* 35, pp. 50-63.

Schmitt, P., Harbo, L.G., Dis, A.T. and Henriksson, A. (2013) Urban Resilience and Polycenricity: The case of Stockholm Urban Agglomeration. *Resilience Thinking in Urban Planning*, eds A. Eraydin and T. Tasan-Kok, 106, pp. 197-209, Springer, Netherlands.

Scott, D.M., Novak, D.C., Aultman-Hall, L. and Guo, F. (2006) Network robustness index: A new method for identifying critical links and evaluating the performance of transportation networks. *Journal of Transport Geography* 14 (3), pp. 215-227.

Stockholm City, the City Planning Administration (2011) *The walkable city*, Stockholm city plan.

von Ferber, C., Berche, B., Holovatch, T., and Holovatch, Y. (2012) A tale of two cities: Vulnerabilities of the London and Paris transit networks. *Journal of Transportation Security* 5 (3), pp. 199-216.

Zhang, J., Xu, X., Hong, L., Wang, S. and Fei, Q. (2011) Networked analysis of the Shanghai subway network, in China. *Physica A* 390, pp. 4562-4570.