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Resilience of ground transportation networks: a case study on Melbourne

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Abstract

A city with a transportation system so well designed that failure of any arbitrary waypoint triggers no major event, is the major goal for every single urban planning and management board. However, city planning comes with inherent design constraints. Research is needed to understand the interaction between these constraints and city resilience. This understanding is useful for those planning for a new city and more importantly, when evaluating and designing cost-effective ways to improve the resilience of existing cities.

In this paper, we promote a proactive attitude for prevention. We use network analysis to estimate the resilience of ground transportation system in Melbourne. Real data extracted from GPS navigation maps of Melbourne is used and resilience is computed for train, tram and street networks. The interdependency and interaction of these networks is then used to risk assess Melbourne's transportation system. The system-level risk identification process paints a risk picture for Melbourne City ground transport system.

The approach can be generalised to any piece of ground covered by a GPS navigation map, being a promising cost-effective, systemic and structured approach to quantify and manage risk of virtually any city in the world.

1. Introduction

Over the last decades, our society tends, it seems, to become more and more dependent on complex, large scale transportation systems. As a critical infrastructure, transportation stands on its own in a unique category that differentiates it from other critical infrastructures such as electricity and water networks. Arguably, the physical domain – be it in the form of roads, tracks, cars, trains, trams, aircraft, etc – is melded with the cognitive domain with humans playing a central role in the overall operation of the system. While the human element is pertinent in every critical infrastructure, it clearly carries a higher weight in transportation that necessitates – we argue – a different treatment from other critical infrastructures. The human dimension in transportation systems controls the demand, the operators, and the perceptual stimulus that steers the system economically, politically and socially.

It is well known nowadays that the entire economy of cities, regions or even nations rely on how transportation networks are able to provide both efficient movement of commodities in normal conditions and efficient recovery in the event of any disturbance from normal operations. Beside this unprecedented dependence, the fast paced changes in cities' infrastructure which appears to be due to economic factors, population migration and natural or artificial shifts in the landscape increases the risk level even more. In such a society systems need to be designed for change. They must be able to embrace it, to cope with it, and to reshape it to their own advantages. In other words, they must be designed for resilience.

Resilience represents the system's ability to keep focusing on and meeting key objectives when faced with challenges in the surrounding operating environment. Hence – we argue – resilience should address the challenge of optimising the system as a whole to deal with change, shocks, and interruptions.

In this paper, we propose a systemic approach for estimating the resilience of ground transportation systems of regions which are covered by GPS navigation systems, considering as a case study the Melbourne metropolitan area. Real data extracted from GPS navigation maps of Melbourne are used for building the networks and resilience is computed for rail and street networks. The data extracted from GPS maps is converted into graph representations suitable for calculating network measures.

Resilience is then evaluated using some of the structural measures used in general graph theory, in order to validate their usage in transportation networks. These measures are calculated with regard to loss of network connectivity and cost of re-establishing the affected waypoints and paths in the event of one or more nodes' failing. The interdependency and interaction of these networks and the level of damage are then used to risk assess Melbourne's transportation system from a structural perspective.

2. Background Materials

Network resilience has been defined in many ways over the years, but none of the definitions was general enough to capture networks in the general case.

In general graph theory, researchers tried to analyse networks' resilience by performing statistical studies of different topological measures within the graphs' structure. Albert et al. (2000) showed that many of the large scale networked systems share a similar statistical characteristic, power law distribution of node degree, which provides them with high tolerance to random failures of nodes and very low tolerance to targeted attacks on highly connected nodes; they are so called scale-free networks. Callaway et al. (2000) used the same idea of node failure and introduced a generalised concept of percolation through which resilience is calculated for any type of graph based on the size of the giant component (largest connected cluster) after arbitrary failure of a node or set of nodes. Dall'Asta et al. (2006) performed an in-depth analysis of resilience of weighted networks, concluding that not only structural properties but also distances and traffic properties contribute significantly to network resilience, as well as costs of operation associated with them. They introduced new measures for resilience based on percolation theory, calculating network robustness through the amount of traffic left after failures of a set of nodes. Still, taking into account traffic and cost properties is not very suitable for a general approach, due to the differences between traffic models in different fields.

In the field of transportation networks, resilience is mainly thought in terms of reliability. Most of the literature in the field acknowledges the fact that resilience can be analysed using two main classes of methods, those related to connectivity reliability and those related to travel time reliability. Connectivity reliability (Bell and Iida, 1997) is calculated mainly using a binary model – functional and non-functional – for nodes or links as part of particular paths defined by pairs of source-destination (S-D) nodes. The probability that path S-D is functional, as a measure of reliability, is computed according to specific status of the established nodes or links. Time travel reliability (Clark and Wattling 2005) is also based on probabilistic study of the nodes and links, but more from the perspective of their usage and the effect on the travel time associated with the paths they belong to.

Other classes of methods have been introduced by different researchers. Chen et al. (2002) defined capacity reliability as "the probability that the network can accommodate a certain traffic demand at a required service level". According to this definition reliability can be seen as a complex interplay between the quantity of flow and the quality of services. Behavioural reliability (Yin and Ieda, 2001; Wattling, 2002) takes into account the effect of the drivers' behaviour on the general performance of the network, thus promoting the idea that reliability is the result of a game played by all the participants in the operation of a transportation system. Another class of methods attempts to analyse the potential reliability (Berdica, 2002; Jenelius et al., 2006). Here, the aim is to assess the risk implied by network operation through the identification of weak points, vulnerabilities, planning flaws and their effects at system level. These methods emphasize vulnerabilities as key issues in the analysis of resilience.

Another approach for analysing resilience in the field of transportation networks arises from the type of the event that generates the need of analysis. All methods discussed above take into account events which are small scale and likely to happen in the day-to-day system operation (e.g. minor accidents, road maintenance, failures in traffic signalling); some other methods tend to take into account large scale disasters (e.g. major earthquakes, floods, landslides, volcanic activity) that trigger major damage at system level. Sakakibara et al. (2004) examined the resilience of transportation networks in terms of "robustness" against catastrophic disasters, taking as a case study a region in Japan, which was subject to major damage produced by earthquakes. They introduced the "topological index", a special system-level measure for topological reliability which is appropriate for large scale damage characterisation.

Evans et al. (2007) acknowledge the fact that most of the planning and reliability assessment of Australian transportation systems was based on the classical station-based approach, like those explained above. They highlight the idea that the Melbourne Integrated Transport Model (MITM), Brisbane Strategic Transport Model (BSTM) and the Strategic Transport Model of Sydney (STM) are all mainly based on the Four Stage Travel Demand Model (FSM) (McNally, 2000; Mathew and Rao, 2007) or variations of it. They agree that using such models was and still is inevitable, but they also argue that the increased complexity involved by the resultant management systems makes them expensive. They also criticise the extremely high specialisation needed for their operation, which makes them accessible to a reduced set of highly trained staff/boards/companies. Their doubts about the future of these models are somehow confirmed by the authorities and the organisations involved in transportation systems' planning. Victorian authorities (VPPIA, 2008) and other organisations (CMTT, 2007) based in Melbourne signal that new challenges regarding fast population growth, carbon emissions and increasing people's demands request more efficient and cost effective thinking, that can provide simple and more elastic evaluation models for the future.

In all studies so far, the definition of a network in a transportation network has not been challenged. In the traditional view nodes in the network are viewed as stations or crossroads, while links are the rails or streets which connect them. Analysing networks modelled in this manner can be suitable for some applications, but is certainly questionable in terms of resilience. That is due to the fact that most of the incidents tend to take place on the way, between stations or crossroads. As such, the tendency to represent stations as nodes and lines between stations as links, we argue, can make it difficult for analysing the true resilience of a network.

3. Methodology

3.1 Network definition and data sets

As discussed above the traditional station-based representation of transportation networks may not be sufficient for studying resilience and sometimes may lead to misperception in where the vulnerability really exists. For example, in the case of the train network, the majority of the network is tracks exposed outside the stations. From one perspective, a failure on a track does not depend on where this failure occurs. From another perspective, it does since this track may cross different areas with different population sizes, and a failure that occurs in a point that is close to a tram track – for example – would carry different impact from one that occurs in a point that is isolated from any other transportation link.

Therefore, the GPS data come with an extra feature, that a node in a transportation network is defined by a change in the network rather than the traditional definition of being a station, or an intersection of several links (e.g. a crossroad). Hence, the graphs that we use for analysis are built as follows: any node in the network is a waypoint defined by waypoint ID and position (latitude and longitude), while links are undirected pairs of waypoints. Thus, a waypoint is not necessarily a station in the case of rail network and not necessarily a crossroad in the case of road network, so that the resultant graphs for rail and road networks do not follow the layout of the station-based models which are currently used for planning and operation (e.g. those posted on the Melbourne's website of public transportation – http://www.metlinkmelbourne.com.au/). We claim that a network defined as in the GPS-based approach can represent the system in a more comprehensive manner, allowing the tools from graph theory to be applied more effectively in the investigation of resilience of transportation networks.

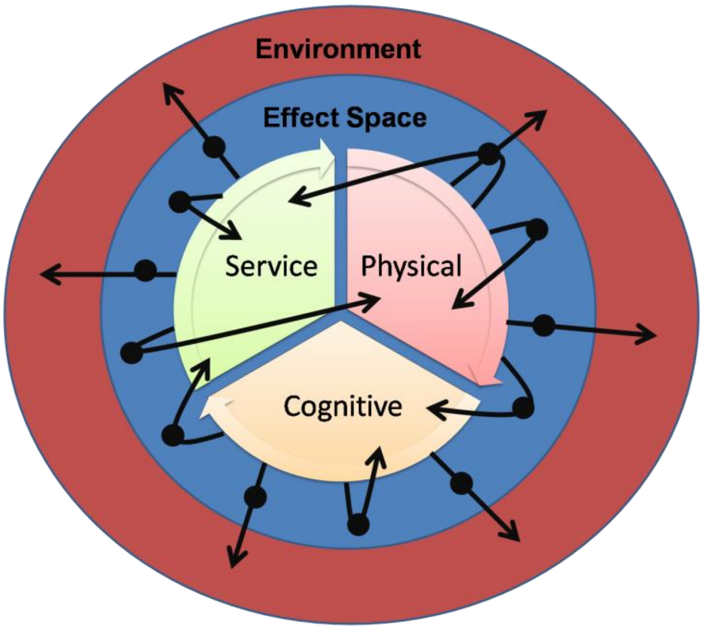
The real data necessary for network analysis is obtained from O*pen Street Map* navigation system, by accessing Open Street Map website (http://www.openstreetmap.org/ and http://www.osmaustralia.org/) and exporting the area of interest, Melbourne Metropolitan in our case, in XML format. We extract from the XML database the rail network divided in train and tram networks, and the road network divided in four networks according to the existing speed-limits: 60, 70, 80 and 100 km/h. The train network consists of 4675 nodes, the tram network has 3632, while the street networks consist of 2448, 1525, 2083, and 4212 for streets with speed limit of 60, 70, 80 and 100 km/h respectively.

3.2 Resilience assessment framework

Apart from defining the networks in the GPS based approach, as we discussed above, we are interested in actually using this approach in a framework for resilience assessment. We start building the framework from the idea that a transportation system can be laid out in three distinct interweaving layers: physical, service and cognitive. The physical layer represents those components that are situated in the physical domain such as road infrastructure, equipment, machines, associated communication networks, and also conceptual representations of the airways and air routes. The service layer includes information flows in the network (e.g. commodities transported to meet a company's demand), the network acting as a mean for people to get to their jobs, schools and homes, or as an infrastructure that supports industries such as the mining supply chains. The cognitive layer captures the human dimension including people, their perception of the system, their information processing, decision making, and problem solving capabilities, their actions, reactions, mistakes and objectives, and their cognitive and ergonomic factors that affect and are affected by the system.

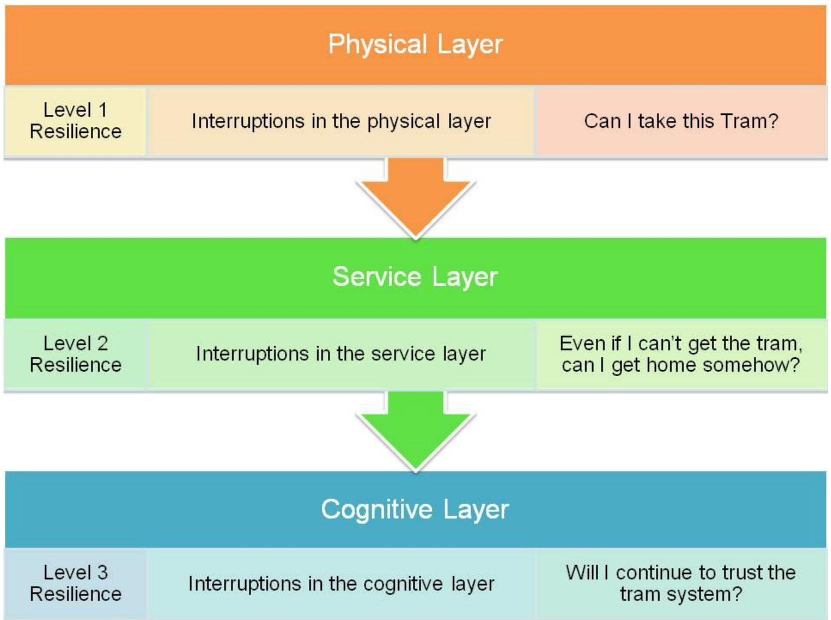
The three interwoven layers interact and achieve what we call effects. Each action – be it in the physical, cognitive or service domain – generates an effect in the environment. Some of these effects affect the environment; some affect one of the three layers; thus affecting the transportation system itself; while others affect both – the internal system and external environment. A pictorial representation of this description is presented in Figure 1. The image constitutes the foundation for investigating the resilience of the Melbourne's transportation system. The guiding principle of the analysis is that the starting point for building resilience in a system is to identify the critical points and vulnerabilities of the system. The vulnerability analysis magnify the problems that need attention, while remedies for these problems then become the strategies that the system needs to adopt to increase its level of resilience.

Figure 1: The Layers of Transportation systems



Thus, the resilience of a transportation system is seen in our approach in terms of the three layers discussed above. The following figure depicts the three levels of resilience:

Figure 2: Resilience – three layer assessment framework



The above diagram represents the generic framework that we use to study resilience in a transportation network. It emphasizes the cognitive layer and the role of people in this critical infrastructure. It also emphasizes – through the service layer – that the network is part of many different supply chains and services; and therefore, for a transportation network to be resilient, change and impact need to be measured in all three layers.

We emphasise though that this study is neither comprehensive nor complete, but it lays out the logic of the methodology and supports this logic with a preliminary analysis so that some meaningful conclusions can be drawn. Hence, we focus at this stage on the physical layer of the framework with the intention to validate the usage of the GPS based network approach. Therefore, we wish to demonstrate that the GPS based network approach provides support for a systemic assessment of resilience, by allowing the abstract tools used in general graph theory to be easily applied in real transportation tasks. We claim that the power of the GPS based network approach is that it can provide meaningful assessment for a Melbourne-scale system with extremely low level of processing power and resources.

3.3 Measures for physical resilience

The first set of measures captures the network structure itself. We calculate the most significant structural measures: degree, betweenness and clustering coefficient (Newman, 2008). These measures can highlight possible reliability flaws induced by the structural properties of a network, without considering operational/flow issues such as traffic and failures.

The average degree in a network is a simple and intuitive local measure that gives an idea about the local connectivity of nodes. It is calculated by adding the number of nodes each node is connected to and dividing this sum by the total number of nodes. In essence, it represents the average number of connections a node has.

Betweenness also shows the importance of a specific node but takes into account the global influence of other nodes. Betweenness of a node *i* is defined as the fraction of shortest paths between other nodes that pass through node *i*. It emphasises that a node may be involved in greater or fewer of the paths between randomly selected nodes in the network. A node with betweenness much higher than the average (if exists) could act like a bottleneck, and it is likely to be a structural flaw especially if alternative routes are not provided.

The measure which intrinsically contains the amount of alternative routes available over the network is the clustering coefficient, which we also calculate to complete our view on structural performance. The clustering coefficient simply indicates how much the transitivity relationship holds in a network (i.e. if x is connected to y and y is connected to z, how often we find that x is also connected to z).

The second set of measures is based on the concept of node removal. We primarily used two measures here: Topological Integrity and Distance Gap.

In topological integrity, we count the number of non-overlapping sub-graphs in a network. We would normally start with a fully connected graph (one can get from any node to any node on the network). After a node is removed, this graph may become disconnected and the removal of that node splits the network into two components. In topological integrity, we simulate failures for each node of the analysed network and observe the effect of node removal on network fragmentation by counting the number of components or sub-graphs (Barabasi et al., 1999; Albert et al., 2000). It is likely that some of the nodes fail and leave the network unaffected, while others cause the network to break in several stand-alone disconnected pieces. We then calculate the probability that removal of a node *k* breaks the network in *n* pieces and transform the results into a probability density function (PDF) representing the topological integrity measure. The cumulative probability distributions of these PDFs are used to compare different networks.

The case in which failure of a node disconnects the network by breaking it into pieces raises the question of damage cost associated with the failure. In this case, we calculate the distance gap created by the removal of a node. Assume that we have three nodes x, y, and z. Assume that y is connected to both x and z. When y is removed, we measure the distance between x and z (remember, each of these nodes has a longitude and latitude associated with it). This distance is used as a possible proxy to estimate the cost of re-establishing network. In order to do that assessment, we consider the distance gap produced by the removal of each node and then calculate the probability that a removal of a node *k* generates a distance gap *d* and visualize the corresponding estimated probability density function of the generated distribution.

We should note again that both the structural measures and the failure related ones are usual tools for network analysis. We use them here to demonstrate that they are effective tools when used together with the GPS based networks as part of the three layer assessment framework. Of course, they account only for the physical layer, providing information about potential structural or operational flaws.

The third class of measures focuses on the spatial distribution of risk, in an attempt to advance from purely structural issues towards the superior levels of our framework. Both topological integrity and distance gaps are mapped spatially to their original location in the longitude and latitude coordinate. Contours of length 5km are drawn around the city centre to represent what we call zones. Topological integrity and distance gaps are visualised and calculated on the level of a zone to assess the spatial distribution of potential damage. We then group nodes with similar topological integrity and distance gaps in each suburb and the population size of that suburb is used as a proxy for the possible impact of an event on local population.

We are aware that despite the measures in the third class provide some amount of information about the effect of failures on the population they cannot be seen as tools for assessment at the service or cognitive layers. They have been introduced as a novelty element that enlarges and completes the structural assessment, offering the starting point for further tools that must be found for service and cognitive layers.

4. Results

Data displayed in Table 1 show that for all the analysed networks, the structural performance is relatively low. The average degree shows that all networks are relatively weakly connected and additionally, they contain nodes with betweenness roughly ten times higher than the average. This suggests the existence of bottlenecks within their structures, which is confirmed by the extremely low values of the clustering coefficient. This places the analysed networks in the category of tree-like or even pure tree structures. Taken together, these aspects highlight one possible (and very important) structural flaw: lack of alternative routes.

Yet, we should not neglect to say that the tram network seems to have the highest structural performance from the whole set of analysed networks. It can be seen that it has the highest average degree and also the highest clustering coefficient. At the same time, though, the tram network also exhibits the highest average betweenness among the analysed networks. It can be argued that a high average betweenness signals a high probability for the existence of bottlenecks, and hence this fact should raise some questions about the structural performance of the tram network.

Still, we argue that the betweenness centrality is based on the shortest paths, so that a high betweenness indicates the concentration of a high amount of “shortest” paths through the nodes of interest, without excluding the existence of alternate longer paths. That is why we used the clustering coefficient as a complementary tool for assessing the existence of alternate paths. As shown in Table 1, the clustering coefficient for the tram network is significantly higher when compared to the rest of the networks, and hence we could assume that more alternate paths for the potential bottlenecks are indeed provided.

In conclusion, we state that the tram network can be considered as having the highest structural performance, but we acknowledge that we only used a set of basic tools which provided a preliminary assessment. Still, the proposed tools support our main goal of demonstrating the applicability of those measures in our network model and framework.

Table 1: Structural measures – degree, betweenness and clustering coefficient

network	degree		betweenness		clustering coefficient
	max	average	max	average	
Train	5	2.0273	0.3873	0.0308	0.0007
Tram	4	2.0297	0.3043	0.0389	0.0027
Street 60	5	1.991	0.0579	0.005	0
Street 70	4	1.9685	0.0206	0.0016	0
Street 80	4	1.9759	0.1449	0.0121	0.0008
Street 100	4	1.9829	0.0353	0.0046	0.0011

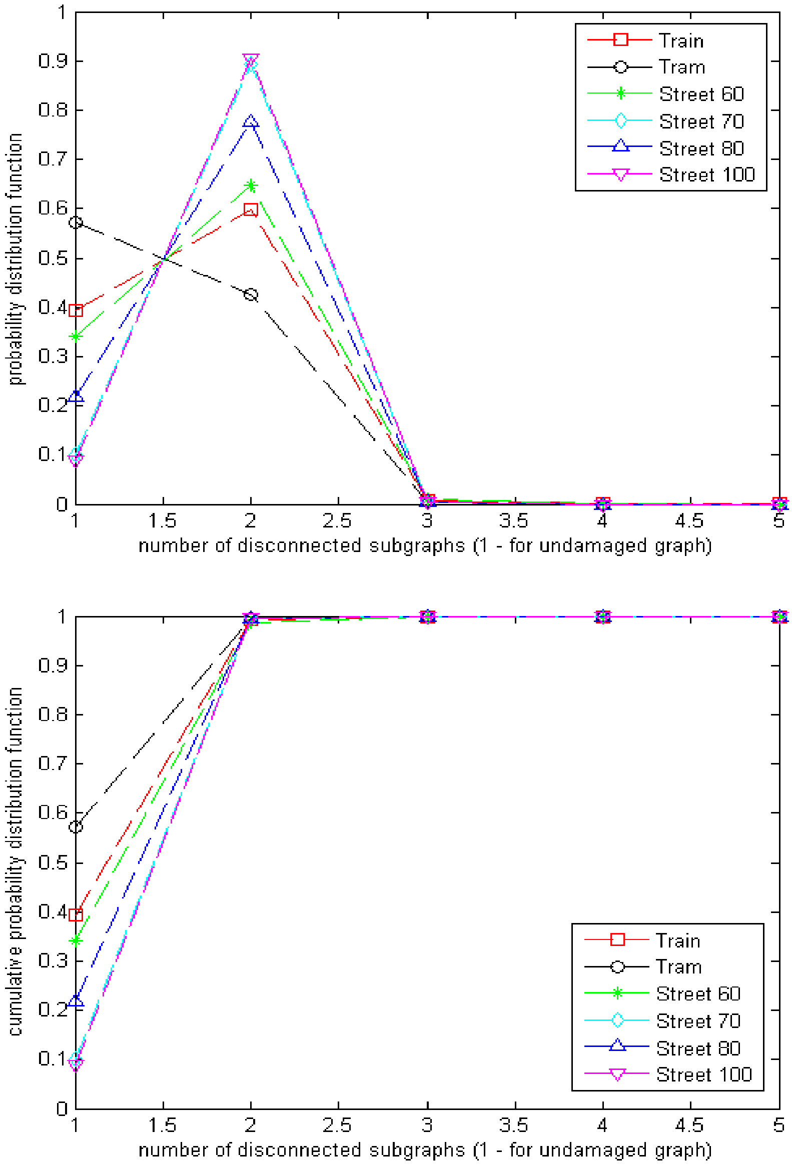
Figure 3 depicts the probability density function drawn from estimating the topological integrity measure. All of the analysed graphs, except the tram network, show fairly similar behaviour, with slight differences among them. The probability density function shows a low probability that failure of an arbitrary node leaves the network undamaged and high probability that failure of an arbitrary node breaks the network in two disconnected sub-graphs. The probability that removal of a node disconnects the graph in more than two separate fragments is very low. In the case of the tram network, the plot shows a much higher resilience compared to the rest of the networks. The probability that the graph remains undamaged is much higher than the rest of the networks, while in the case of some damage being produced, the probability is significantly lower. It can be also seen that the maximum damage that can be provoked in the tram network is 2 sub-graphs while for all other graphs the maximum damage reached 5.

The concept of first degree stochastic dominance (Goodwin and Wright, 2009) is pertinent in this graph, whereby a cumulative distribution such as the Tram network fully dominates (better in all points) another distribution (Street 100). Based on stochastic dominance, the Tram network is the strongest.

Topological integrity is a good enough albeit intrinsic measure of resilience. As it is, the structure of the graph offers information about possible vulnerabilities of the network related to lack of redundancy, or presence of highly connected nodes that bond different pieces of the network and act like bottlenecks, reducing thus the overall resilience of the whole structure.

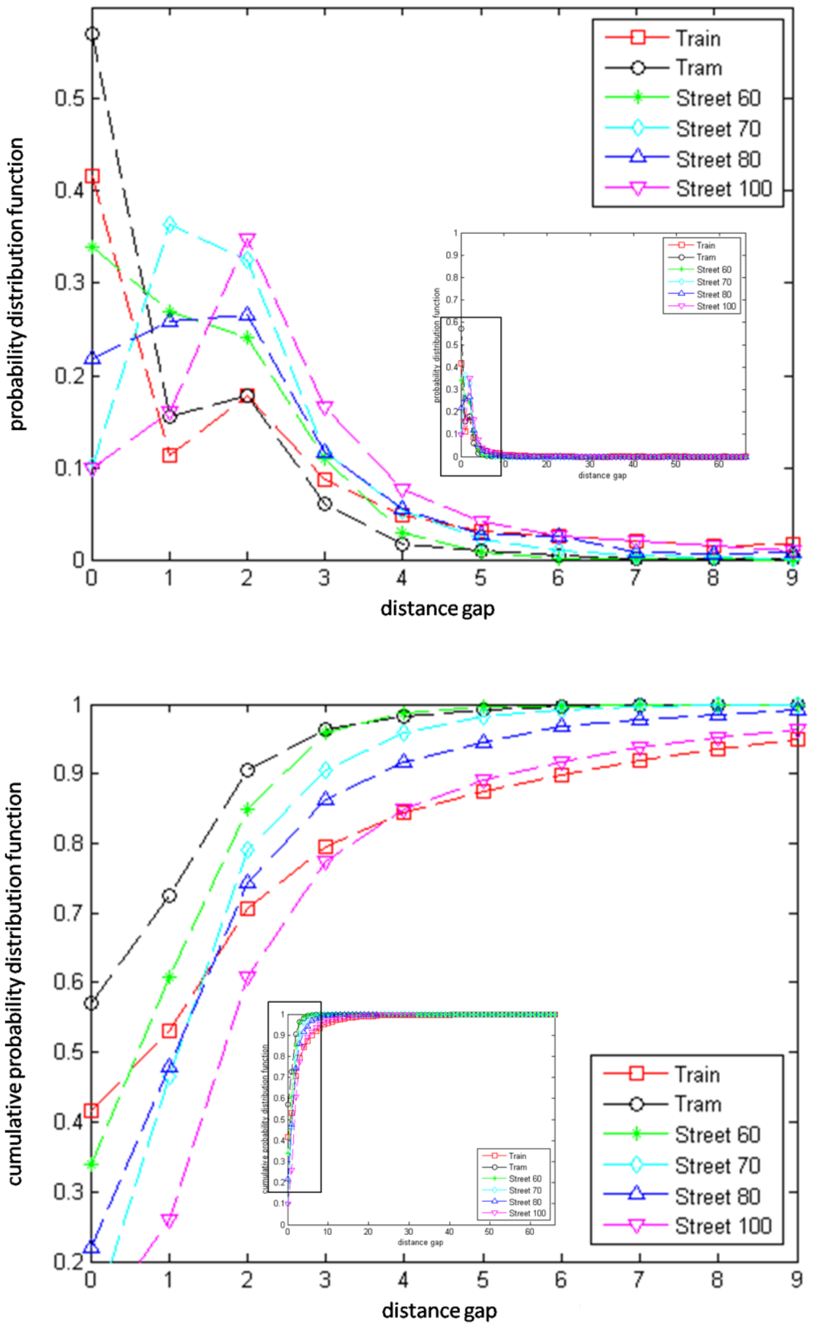
Real networks, though, are located in space and their resilience implicitly depends on the distances among different waypoints. In the case of disintegration of the network as a result of arbitrary failures of nodes, distance gaps between disconnected pieces (if exist) can be calculated, in order to estimate the amount of damage. Calculating the distance gap would give a good idea about the cost implied by the recovery of a gap, if we consider the cost as a function of the length of the damaged path (e.g. rail to be maintained or replaced, road to be consolidated or rebuilt).

Figure 3: Topological integrity – probability density function (top) and cumulative distribution (bottom)



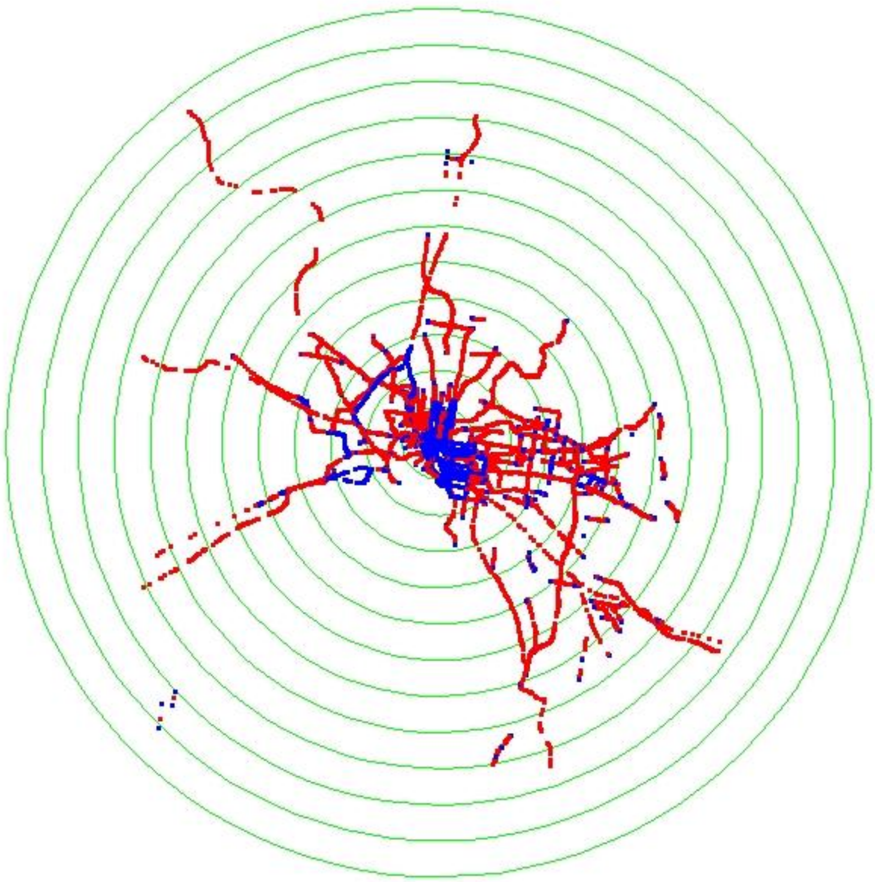
In the case of calculating the resilience from distance gap point of view, results can be seen in Figure 4. Distances are rounded to 100m. The insights of the plots show that the maximum distance gap produced by network disintegration is around 7000 meters. The main plots only depict the meaningful data which is in the limit of a distance gap of 1000 meters. All of the analysed graphs show fairly a similar behaviour, with slight differences among them. As the probability density function doesn't give us a clear understanding about which network is more resilient, we use again the cumulative probability distribution function. However, because the cumulative curves intersected with each other, we have to use second order stochastic dominance to establish an order on the networks in terms of their resilience. Second order stochastic dominance requires the calculation of the areas in each intersection between two curves to calculate dominance. The resultant order of resilience based on the distance gap measurement shows that the most resilient network is again the tram network followed by the train and streets networks.

Figure 4: Distance gap – probability distribution function (top) and cumulative distribution (bottom)



We now turn attention to the third group of measures. Figure 5 visualises, in latitude-longitude coordinates, all nodes from all networks colour-mapped based on topological integrity. A spatial representation of the vulnerabilities in all networks is presented. The first inner circle is centred on a point in Melbourne city and has a radius of 5km. Each subsequent circle represents a radius of 5km away from the previous circle. The red colour represents nodes with topological integrity of 2, the blue colours correspond to 1, and the black colours represent those with a value greater than 2. The figure demonstrates that vulnerabilities decline as we move further away from the city. Despite that the result seems logical since most transportation activities occur closer to the city centre, it raises some issues about the resilience of the different networks.

Figure 5: The spatial distribution of topological integrity of nodes divided into circular zones.



The previous figure demonstrates the information visually. We needed to transform this information into measurable quantities that we can use to objectively estimate resilience. We count the number of nodes with topological integrity of 2 in each zone. Zones are drawn circularly using a radius of 5km from the centre of the city. Figure 6 demonstrates the cumulative distribution of the vulnerable nodes in each network over the zones.

Once more, it is clear that the vulnerability of these networks is concentrated in or closer to the city centre. A 15km radius around the city contains almost 100% of the tram vulnerable nodes, while a radius of 30km contains close to 90% of all vulnerable nodes including – surprisingly – streets with 100 km/h speed limits.

The last measure is the impact of a vulnerable node with topological integrity of 2 as measured by the size of local population (Figure 7). For each network, we identify the suburbs within which each node with topological integrity of 2 is located. We then identify all suburbs for all of these nodes in one network and calculate the average population size. This measure is a proxy for the impact of vulnerable nodes on local populations. Figure 7 shows a high impact of the road networks with speed limit of 60 and 100 km/h on the population, from the population size point of view. We found (figure not showed in the paper) that the roads with the speed limit of 100 km/h are the main radial roads that connect the inner to outer parts of the city and relate the high populated peripheral residential areas to the metropolitan area. Hence, the highest impact on the population. In a similar manner, the roads with speed limit of 60 appear to be a mesh of main roads mapped over the metropolitan area, which connects the metropolitan residential areas with high impact on the served population.

Figure 6: The Cumulative Distribution of Vulnerable Nodes with topological integrity of 2

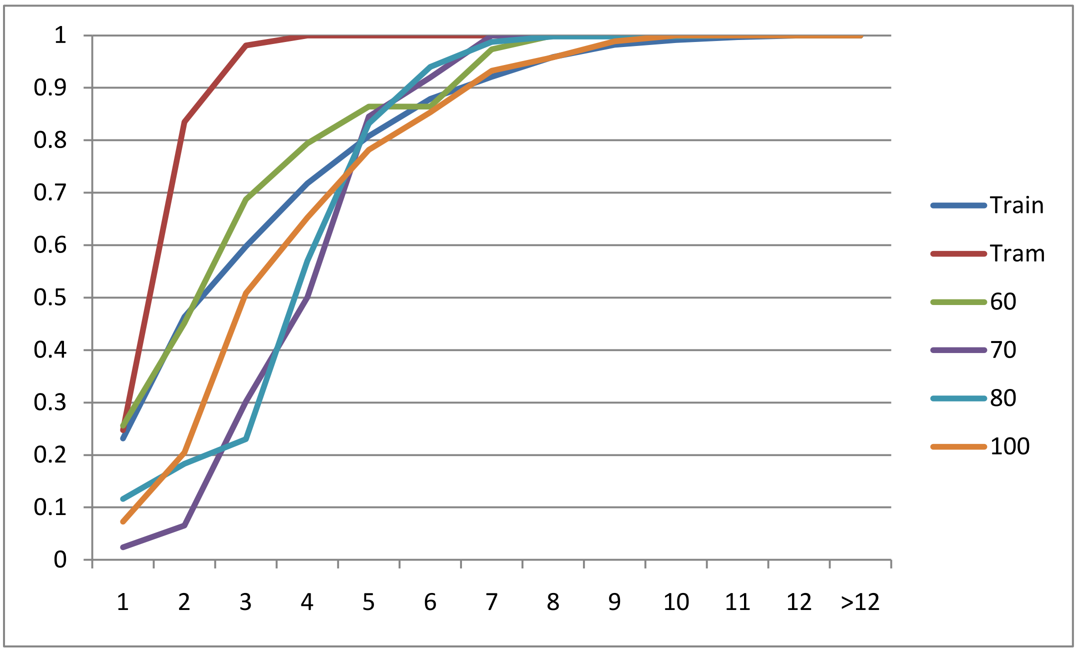
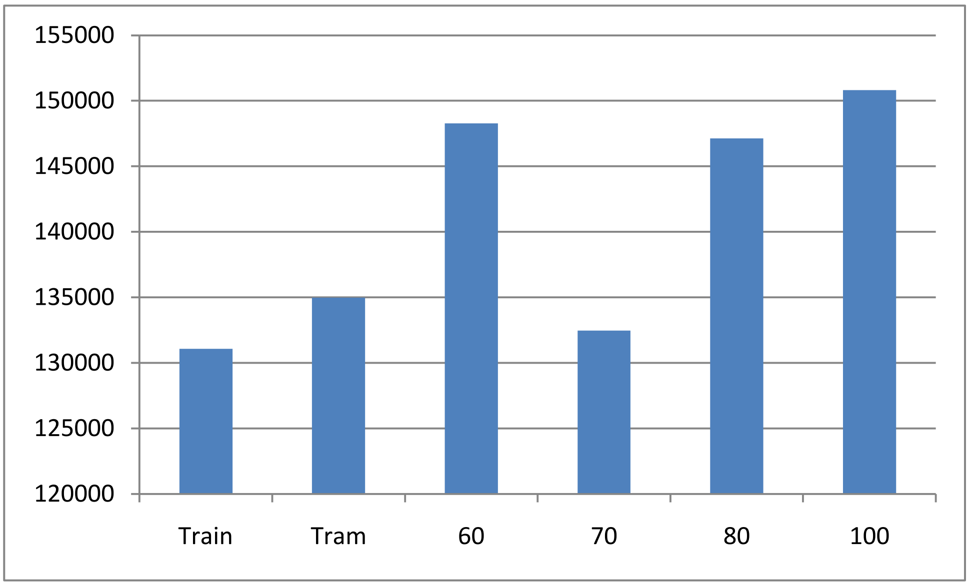


Figure 7: The average population size in areas with nodes having a topological integrity value of 2.



5. Conclusions

This study can be seen as an attempt to offer an alternative to the complex and expensive existing evaluation frameworks, which are based on Four Stage Travel Demand Models. As the largest cities in Australia use such systems for evaluation and planning, the proposed framework intends to be a low-cost, effective and versatile solution which could offer elasticity and improved manoeuvrability in relation with fast paced landscape changes.

The three layer assessment model that we introduced is based on changes in the landscape, rather than routes and stops as in the classical representation of transportation networks. It provides, in connection with GPS systems, simplicity and effectiveness for preevent analysis, which can be successfully used by planning boards in the future. We should highlight that our main purpose was to validate the GPS based definition of the transportation networks and demonstrate its practical usability in conjunction with different measures which are usually used as abstract tools in the graph theory research.

Therefore, the paper presented in a systemic way different measures that can be used to assess the physical resilience of Melbourne city. We should add that the chosen measures are simple, intuitive and can create a fair picture of the overall system resilience, but we acknowledge the existence of many other tools that could be successfully applied with our model (e.g. investigation of networks' modularity, assortative mixing, diameter etc.) and generate a more comprehensive and valuable assessment.

We presented a multi-layer approach – physical, service and cognitive – for analysing the resilience of a transportation network and focused on the physical layer. The methodology is general and can be easily applied for other cities or areas which are covered by a GPS map. At this stage, we concentrated on the Melbourne area.

The analysis of Melbourne's transportation system provided valuable information about the size of the investigated networks and also about the level of the vulnerability that can be produced by arbitrary failures of nodes. We found that the tram network had the highest level of resilience when compared to other networks analysed in the study. We should add though that we did not intend to promote in this paper a hierarchy among the different transportation networks within the system. The classification of their performance has been made only in order to demonstrate the fact that the GPS based definition of the framework is practically applicable. Furthermore, we considered the Melbourne area as being a single large transportation system, and we referred to it as to the "Melbourne transportation *system*", while when referring to its components (tram, train, streets) we used the term "*networks*".

However, the analysis presented in the paper indicates the potential existence of some structural and operational weaknesses, such as: lack of redundancy in the system, low alternative routes, and existence of bottlenecks.

For future work, we will characterise situations and networks where the Four Stage Travel Demand Model would generate different conclusions from the measures used in this paper. We will also design a database of measures for transportation resilience, which in general, is a hard task. More visualisation of spatial vulnerabilities can be used to communicate the results. Finally, we need to further investigate the resilience at the service and cognitive layers for which we need to find the proper measures and the appropriate validation methods.

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