Vulnerability In Road Networks

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1 Introduction

When considering a city's or town's infrastructure the primary point of concern would be the road network. A road network is critical for facilitating the movement of people, goods and services, which in turn sustain the area in question. In a technical context, the road network acts in a similar manner to any other network type, such as an electrical grid, blood vessel system, or tree roots. There is movement through the network in the form of traffic, which represents a state of flow. Flow here, is also governed by physical factors, such as the network's connectivity or blockages. Developing a city's road infrastructure to allow efficient flow is imperative to its function. A common concept of road network planning, especially in the case of established road infrastructures, is to identify the possible roads (or even junctions) that are prone failure so that the appropriate care towards these locations can be allocated.

Consider the impact of a blockage occurring on a local road allowing through traffic in a residential area. At a highly localized level, it is easy to predict the short-term outcome of this event: traffic will loop round through other connecting roads to make it to the other side. However, this quickly leads to follow up questions. What if a collision occurred on an arterial roadway? What if a certain number roads were blocked at the same time?

1.1 Problem Statement

With the above, we formalise the motivation of this study, which is to make use of a complex road network extracted from openstreetmaps and apply one of the many methodologies used in network science to highlight these locations prone to failure. In our case, with a limited amount of information available as open source and free, we have chosen to make use of the road network's inherent connectivity to test its resilience and assess the impact of disturbances made to these vulnerable points. Using free and open source data we also propose useful means and methodologies for local management authorities to cost effectively accomplish the same tasks that can be done with expensive software and proprietary data sources. We find that it takes very little to completely take apart a city's or town's ability to move around by way of vehicles. This is important to highlight since it makes any given road network highly vulnerable to problems which the authorities should be aware of and mitigate them by, for example, ensuring that specific blockages do not happen at the same time.

2 Related work

We aim to follow the main propositions made in Da Cunha et al. (2015). Whilst this research article aims to prove that the Module-Based Attack is the most efficient form of network attack we instead make use of it in the latter stages of this study. The research paper makes use of this methodology on several networks, none of which are road networks unfortunately. However, the US power grid network that is used in this research article can be considered to be planar and similar in nature to a road network and can provide a viable basis for comparison with the results in this study.

This study is unique in its approach to establish road network vulnerabilities and as such there is not much directly related work. We find that most vulnerability analysis uses methodology that requires edge utilization figures. Li et al. (2020) employs the idea of congestion propagation on Taipei road networks. The paper proposes an algorithm to help identify potential congestion bottleneck points using maximal spanning trees and Markov analysis together with helping understand how a congestion would spread across the road network with edge congestion correlation. It also makes use of network edges weighted with the congestion cost derived from average travel speed and road occupancy data and proposes a novel way to identify congested road segments whereby a fraction of the average travel speed is used as a threshold. This as opposed to a blanket threshold used by local management authorities. Any road segment with a travel speed less than this threshold is considered to be congested. In a similar respect, Thilakshan et al. (2020) makes use of the Google Maps API (Application Programming Interface) and a software called ArcGIS to obtain travel time data and use discrepancies in this data to find bottlenecks. Qu et al. (2019) also makes use of edge utilization data together with the Ford-Fulkerson algorithm to establish congestion points. These papers make use of proprietary data sources and suggest an important next step to this study, which is to utilize road traffic data.

3 Exploratory Data Analysis

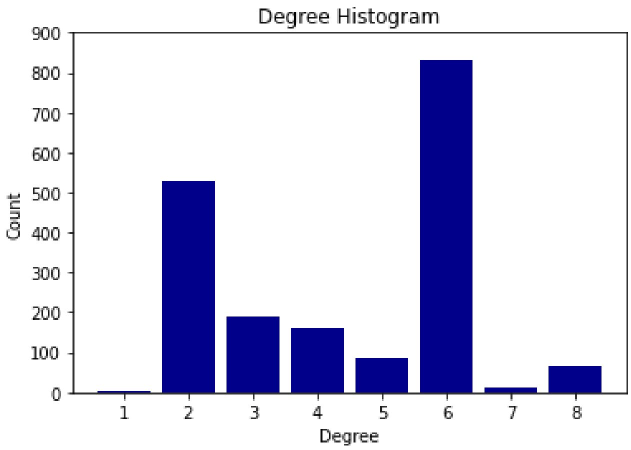
In our exploratory data analysis we look at my home town of Watford based on the north-west edge of greater London within the M25 orbital motorway. We compare it with a much more central part of a city such as Central London very much in the way the report Park & Yilmaz (2010) has approached its analysis. We compare briefly a few attributes of both road networks before working solely with Watford following on. Figure 1a shows a simplified extract of the vehicular road network of Watford extracted from openstreetmaps. Each node represents a junction between edges or roads.

(a) Vehicular road network of Watford

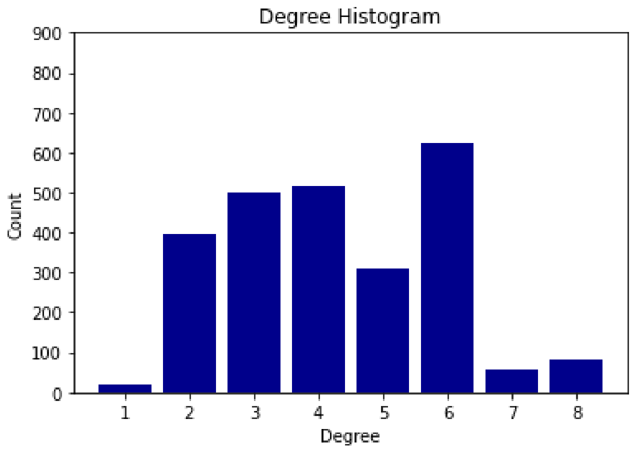
(b) Vehicular road network around Euston

Figure 1

From a cursory and visual inspection it can immediately be concluded that Euston has a much more denser road infrastructure. However, looking deeper at the degree centrality for both road networks as shown in Figure 2, we can see that a much more central area like Euston can have a very distinct degree distribution with nodes of degree 3,4 and 5 being more common compared to what is seen in Watford. Both road networks however have a high number of nodes with degree 6 as representative of a lot of 3 point junctions with edges entering and leaving the node. It is interesting that Watford would have marginally larger network density as seen in Table 1. This could be attributed to the fact that Euston would have more junctions meaning that Watford would be closer to a fully connected network pertaining to the definition of network density $\left(\frac{\text{Actual Connections}}{\text{Potential Connections}}\right)$. However, this difference is very small and can relate back to the fact that road networks are planar in nature (Park & Yilmaz 2010). Lastly, Figure 3 shows us the edge closeness centrality.



(a) Degree distribution for Watford

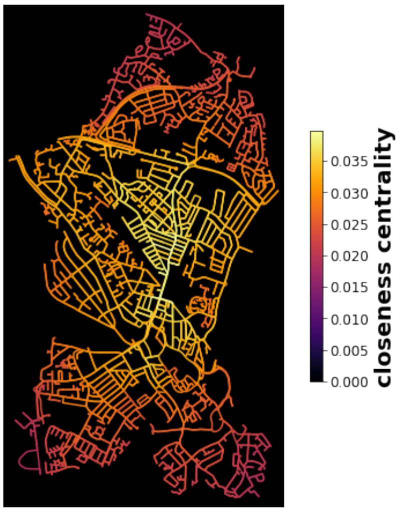


(b) Degree distribution for Euston

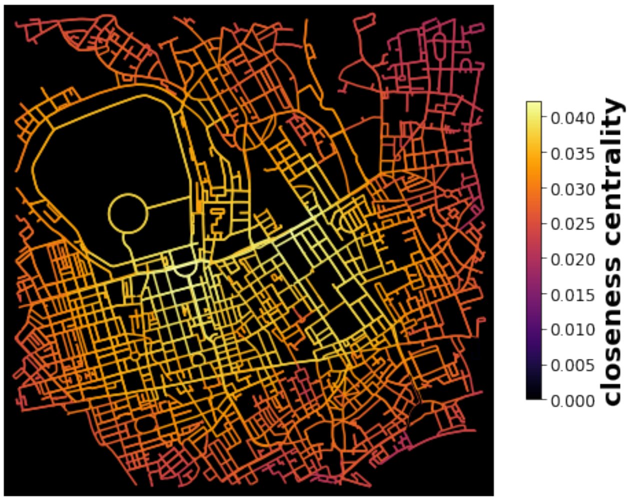
Figure 2

	Watford	**Euston**
Density	0.001179	0.000855
Nodes	1873	2506
Edges	4135	5366
Best Modularity	0.93	0.91
Number of communities	33	31
Number of inter-comm edges	162	356

Table 1: Network statistics



(a) Edge closeness centrality of Watford



(b) Edge closeness centrality of Euston

Figure 3

4 Module-Based Attack (MBA)

We now focus our attention solely on Watford's vehicular network. To assess network resilience and establish vulnerabilities we make use of a Module-Based Attack (MBA) as detailed in Da Cunha et al. (2015). We start by establishing the best community structure and this is done through the use of the Louvain Algorithm as a necessary part of the MBA procedure (Da Cunha et al. 2015). It is implemented with several runs and we pick out run that yielded the best modularity - a metric that calculates a ratio of edges between and within communities and gives an idea of community strength. Once we have the best modularity it is then required to establish the between-community edges and sort them from highest closeness centrality to lowest (Da Cunha et al. 2015). Next we remove edges in order of their closeness centrality and if they belong to the giant component of the network. This means that we can skip some between-community edges if they are not part of the giant component (Da Cunha et al. 2015).

4.1 Results and Discussion

To understand the response the removal of edges gives in the network a graph of the probability of a node being in the giant component as a function of percentage of edges removed is seen in Figure 4.

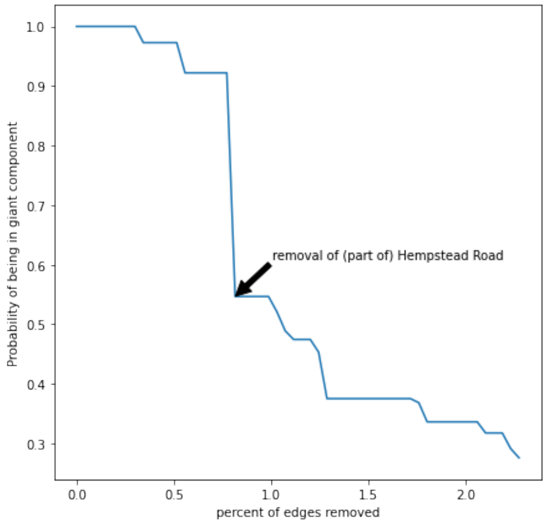
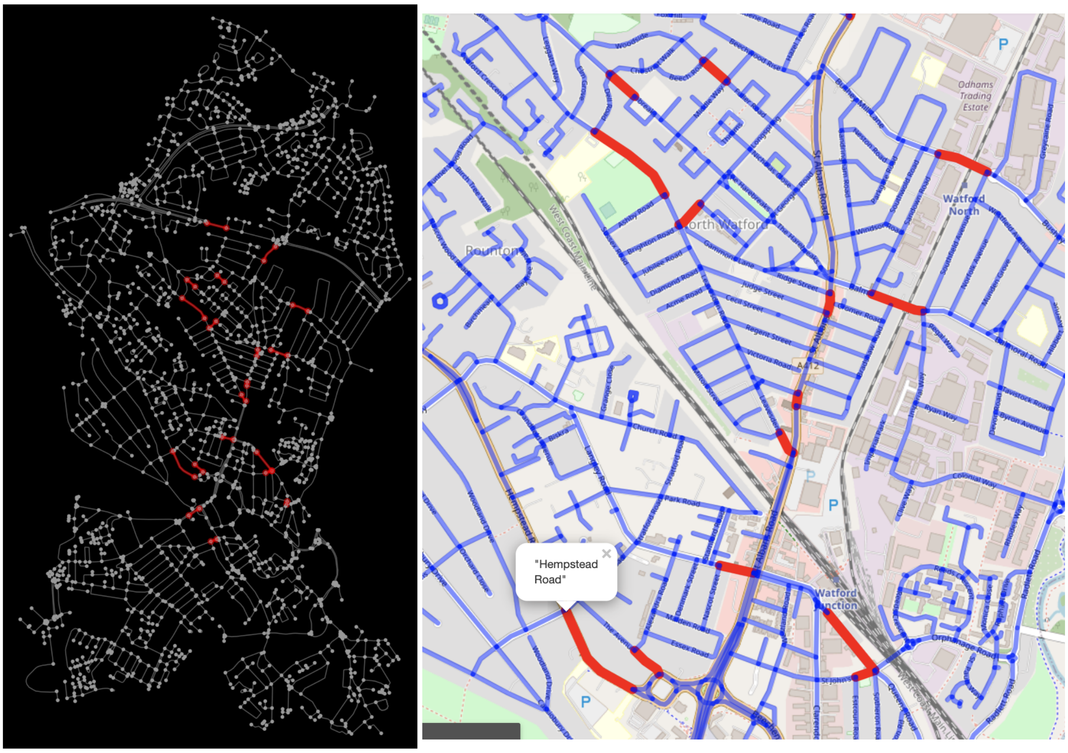


Figure 4: Network response through the removal of edges

Figure 4 shows us that the network can be perceived to cease to function with approximately 2% of its edges removed. This falls in a similar range to the comparable planar network of the US power grid used in Da Cunha et al. (2015) whereby it took approximately 3% of edges to cause "maximum damage". A large response is also seen if just short of 1% of edges are removed - a mere 22 edges (This is subject to best community detection run and can vary up until 1.5%. This experiment however caused a large response in the smallest number of edges - i.e the most efficient attack). This can possibly also cause serious disturbance in the vehicular road network and can be more likely to happen instead of a full network breakdown in a fully coordinated network attack (removal of 54 edges). The edge or road deletion causing the massive response was named "Hempstead Road". However, digressing slightly from the research article Da Cunha et al. (2015), it can be assumed that if the edges leading up to this response could also be of significant relevance as these edges, if deleted in a different order, may have the same impact with the last edge deletion causing a similar large response seen in Figure 4. Following in line with this argument, Figure 5a shows the network with the edges deleted that led to the large response and "Hempstead Road" highlighted in the map in Figure 5b as the left-most edge towards the bottom causing the large response.



(a) Edges leading to large response

(b) Zoomed map (bottom left of red edges)

Figure 5

In an attempt to quantify the impact a disturbance to these edges would have on the road network without the use of an abstract probability measure we assess the diameter of an ego network where the interaction distance has been set to be the time it takes to travel out of a specific location. In doing so we primarily have to obtain the traversable time for each edge (i.e. the minimum time it takes to drive through the road at the speed limit assuming no braking and slowing down). The graph extracted from openstreetmaps fortunately had edge lengths in meters and some edges had been given their appropriate speed in miles per hour. For the edges without a speed feature an assumption was made for "residential", "unclassified" and "tertiary" roads to have a speed of 30 miles per hour and "secondary","primary" and "trunk" roads to have a speed of 50 miles per hour with the rest taking a speed of 70 miles per hour. These assumptions have been derived by looking at OSM (2021) and a basic understanding of driving laws in the United Kingdom. A simple conversion of miles per hour into meters per minute together with the length of edges allowed for a calculation of the *traversable time (mins)* feature for each edge or road. Using my home road of "Stratford Road" and its appropriate closest node, Figure 6 was obtained once the *traversable time (mins)* feature was calculated.

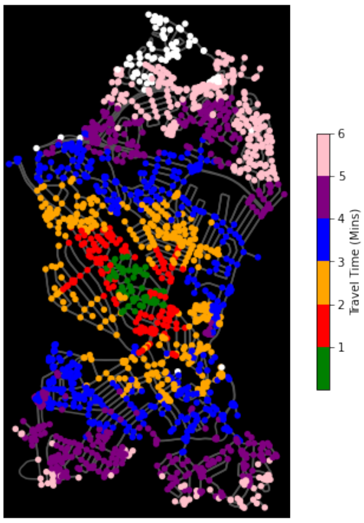
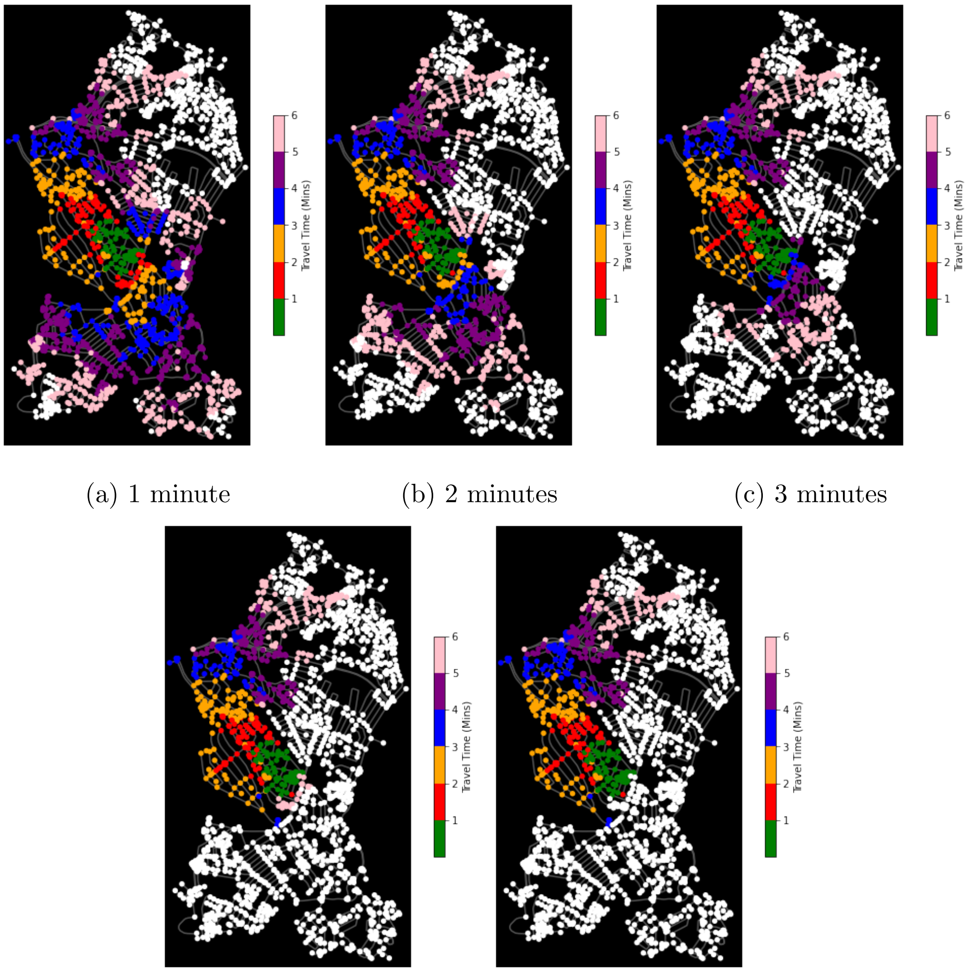


Figure 6: Distances that can be traversed in minutes with no delay

We now reconsider the edges in Figure 5a. Rather than their deletion we can alter the *traversable time (mins)* parameter to range from 1,2,3,5 and 10 minute traversable times to simulate a delay and visually see the impact to the ego networks. In successive iterations it can be seen that the ego networks recede and become smaller in size with a traveller being constrained to the top left of Watford for a 6 minute journey as shown in Figure 7e.



(a) 1 minute (b) 2 minutes (c) 3 minutes

(d) 5 minutes (e) 10 minutes

Figure 7: Edges involved in large response with increased traversable time

Looking at the largest ego network for the distance that can be travelled for each of the delay experiments we can plot the following graph shown in Figure 8. A comparison with a randomized selection of the same number of edges with the same delays shows that the averaged diameter (across 50 experiments for each time delay) of the largest ego network remains fairly unchanged. What this essentially proves is that vehicles are able to easily circumnavigate a blockage on a non-vulnerable road. In the case of vulnerable roads seen in Figure 5a, increasing delays contribute significantly to a decline in diameter and paralyse movement.

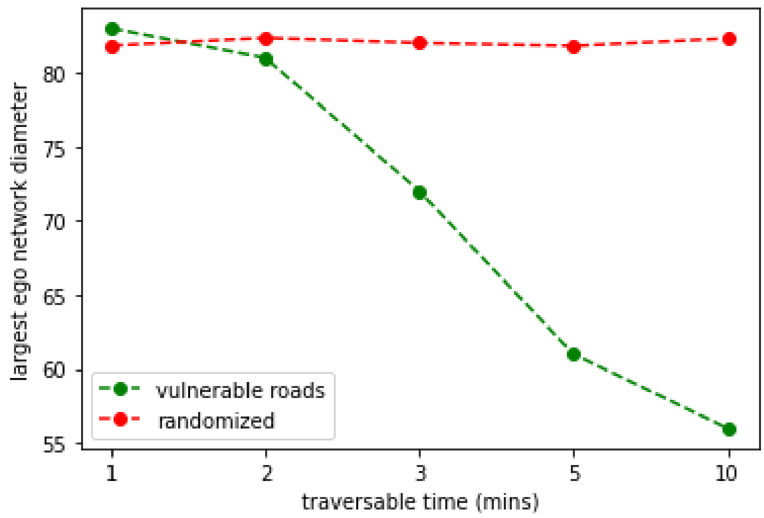


Figure 8: Diameter of largest ego network with increasing traversable times

5 Next Steps

As such, we cannot conclude that a road networks inherent connectivity is related to the way travellers in vehicles behave. For instance, it might be the case that a certain section of road could belong to an industrial complex and only facilitate only a certain type of vehicle or perhaps people would not even have the need to go there. Therefore it is convenient to also, in conjunction with the methodologies used in this study, make use of road traffic or capacity data which can be obtained from services such as google maps or ArcGIS whereby ideas used in Qu et al. (2019) can be implemented. The Ford-Fulkerson algorithm or a Max-flow Min-cut algorithm can be used to find the edges that are most prone to congestion and compare with the results obtained from the Module-Based Attack. It is essential to note however that with Ford-Fulkerson and Max-flow Min-Cut we have to specify origin and destination points within the network. Unless known explicitly, to generalise this would require a permutation of these origin and destination nodes and acquire an aggregated result of experiments. It can also be possible to follow what Qu et al. (2019) refers to as the "super-OD method" and create an additional origin and destination node in the general area and direction of travel (i.e north-south, west-east, or vice-versa).

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