

ENHANCING THE RESILIENCE OF LIFELINE SYSTEMS USING NETWORK GRAPH THEORY

S. Dunn¹ and S. M. Wilkinson¹

¹ School of Civil Engineering and Geosciences, Newcastle University, Newcastle upon Tyne, UK (corresponding author e-mail: sarah.dunn@ncl.ac.uk)

ABSTRACT

Our modern communities are becoming increasingly reliant of the services that are provided by our infrastructure systems. The functioning of these systems is particularly important after a major disaster and can either aid, or hinder, rescue efforts and longer term recovery plans. These systems consist of many components and each is designed to have a particular probability of failure. Whilst this design approach is satisfactory under normal operating conditions, when these systems become damaged (in an earthquake for example) it is likely that some components will have failed, but it is the ability of the system to continue to provide some level of service that is considered important. In this paper, we introduce a new approach, using network graph theory, which has previously been used to model the complex interactions between components in social and biological networks. The paper shows how traditional network graph theory can be modified to model infrastructure systems with greater accuracy; including the development of spatial models and the inclusion of a flow element within the analysis.

1. INTRODUCTION

Earthquakes can have potentially devastating effects to our communities, both in terms of initial primary effects (e.g. damage to buildings, roads and loss of communication) and longer term secondary effects (e.g. spread of disease due to lack of a clean water supply). The severity and lasting impact of these effects are often linked to the resilience of the critical infrastructure systems, or lifelines, which underpin our communities and support the people within them. They do this by delivering a flow of services from areas of where they are stored or generated (e.g. power stations) to areas of demand (e.g. communities). The importance of these systems to communities, particularly after a major natural disaster, cannot be overstated. To give an example, Haitian infrastructure could be classes as amongst the world's worst even prior to the 2010 earthquake. The resulting damage from the earthquake to the communication, transportation and electrical systems, hampered rescue and aid efforts and lead too many long term problems, including lack of sanitisation and spread of disease.

The design approach for these critical infrastructure, or lifeline, systems is to design the individual components to have a particular probability of failure. Whilst this is sufficient under normal operating conditions, it can be found lacking when these systems are damaged. After a major earthquake it is likely that some system components will have failed, however, what is important is that the system can still operate, at least in a reduced capacity. To achieve this, methods to assess the performance of the system are needed. These systems are normally modelled using traditional physically based models (e.g. a hydraulic model for a water distribution system). Although, these models are useful at providing scenario based information, they can be found lacking when used to inform us of the resilience of the system and highlight structural inadequacies, due to their complexity.

To find a solution to this problem, recent studies have turned to network graph theory. This approach has previously been applied to social and biological networks to model the complex interactions in these systems. In this approach, only the topology of the system is considered and is modelled as a series of nodes and connecting links. Recent studies have used this approach to model infrastructure systems and have discovered

that many systems show an underlying pattern of nodal connectivity. These patterns can be used to ‘classify’ the system and allow us to gain an insight into the inherent resilience of the system.

This paper demonstrates how network graph theory can be used to analyse and assess the resilience of infrastructure systems. The paper shows how traditional network graph theory can be modified to model infrastructure systems with greater accuracy; including the development of spatial models and the combination of network theory measures and physically based measures to improve the predictive skill of identifying weak/vulnerable areas in these systems.

2. DEFINITION OF RESILIENCE

To ensure that our infrastructure systems are resilient and can continue to support our communities after a major disaster, we must first define what we mean by resilience. The meaning of this term should be relatively simple to define; however, its meaning can change depending on the research area and the context in which it is used. For example, ecology, systems and information engineering and risk management all have a different definition of the term. With regards to infrastructure, the UK Government has recently formed its own definition of resilience based on that of the Pitt Review (2008) in which resilience was defined as: ‘*the ability of a system or organisation to withstand and recover from adversity*’ (Cabinet Office 2008). In this expanded definition, the UK Government defines resilience as ‘*ability of assets, networks and systems to anticipate, absorb, adapt and / or recover from a disruptive event*’ (Cabinet Office 2011) and states that resilience is formed of four principal components (Figure 1).



Figure 1: The four components of infrastructure resilience, according to Cabinet Office (2011).

The *resistance* element is focused on providing the strength, or protection, to resist the hazard or its primary impact. The *reliability* element is concerned with ensuring that the components are designed to operate under a range of conditions and can therefore mitigate damage from the hazard. The *redundancy* element concerns the capacity of the system and the availability of backup facilities, or spare capacity, to enable operations to be switched or diverted. The final element *response and recovery* aims to enable a fast and effective response to and recovery from hazards.

Therefore, for a system to be classed as resilient it should incorporate all of these four elements; the lack of one of these elements could result in the decrease of the system as a whole. For example, if the components of a system lacked the strength to resist the primary impact of the hazard (*resistance*), then even though there was an effective management plan in place (*response and recovery*) there would still be an increased recovery time, due to the increased initial damage to the system components.

To ensure that infrastructure systems are resilient not only should the resilience of each individual component be considered, but also the interactions between these components. For instance, it is not possible to ensure that the system incorporates the element of *redundancy*, without considering how this extra capacity is distributed around the system, ensuring that in the event of a hazard any damaged components can be bypassed as the service is transferred from the areas of supply to those of demand.

3. ANALYSIS OF INFRASTRUCTURE SYSTEMS AS NETWORK MODELS

Infrastructure systems have traditionally been analysed using physically based models and, depending of the sophistication of the model, they can be useful at providing scenario based information. However, as the understanding of the system comes from interpreting the results of the model, rather than form the model itself, it does not easily lend itself to optimisation and does not therefore provide information on how to increase the resilience of the system. To solve this problem recent studies have employed network graph theory to try and understand the behaviour of these complex interacting systems. In this approach, only the topology of the system is considered and is represented as a series of nodes and connecting links. For example, in an electrical distribution system the nodes could be used to represent power stations, substations and communities, with the links representing the physical connection between these components (e.g. the transmission lines). Not only does this approach reduce the computational effort of the analysis, but it enables the fundamental properties of the system to be described. Previous studies have shown that many real world systems (including infrastructure systems) naturally configures to specific network architectures (classes).

These network classes describe different patterns of nodal connectivity (i.e. different arrangements of the nodes and links) and are each characterised by a ‘degree distribution’. It is this distribution that allows for the distinction between different classes of network and also gives an insight into the inherent resilience of the network. The degree distribution of a network is first made by obtaining the degree of each node, which is equal to the number of links attached to it (for example, if a node has 3 links attached to it, then it has a degree of 3). The degree distribution of the network, $P(k)$, gives the cumulative probability that a selected node has k or greater links. $P(k)$ is calculated by summing the number of nodes with $k = 1, 2, \dots$ links divided by the total number of nodes. There are three main classes of network model that are used in the analysis of infrastructure systems and the degree distributions for these are shown in Figure 2.

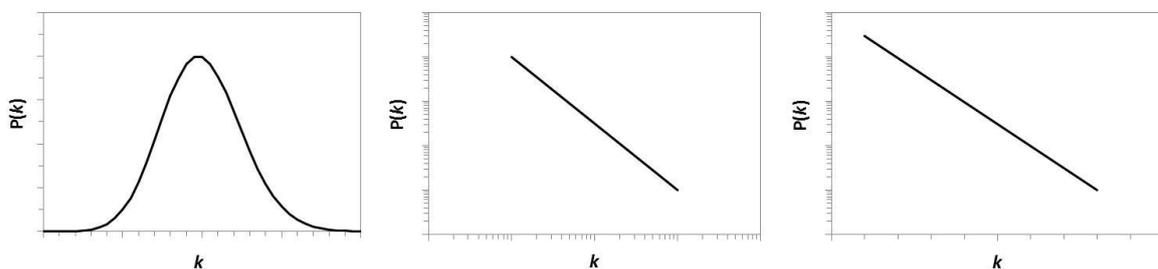


Figure 2: The shape of the degree distribution for (a) the random network, (b) the scale-free network and (c) the exponential network.

From these degree distributions (Figure 2) it can be deduced that the nodes in random networks tend to have the same value of degree. A sample random network has been shown in Figure 3(a), where this can be confirmed visually. This type of network class has been shown to be a poor representation of infrastructure systems (Newman 2003), but are often used as a benchmark in tests of network resilience (Batagelj and Brandes 2005; Lewis 2009). The more structured scale-free and exponential networks both comprise a small number of high degree nodes and a large number of smaller degree nodes (which can be seen in their degree distributions,

Figure 2(b) and (c)). Unlike the random network, both of these network classes have been shown to be a good representation of infrastructure systems; which may appear surprising as an air traffic network is seemingly very different from an electrical power grid, however they share very similar characteristics. The Internet (Albert et al. 2000) and the World-Wide Web (Albert et al. 1999; Barabasi et al. 2000) have been shown to belong to the scale-free network class of network. Whilst, power grids (Crucitti et al. 2004; Holmgren 2006) and air traffic networks (da Rocha 2009; Wilkinson et al. 2012) have been shown to belong to the exponential network class.

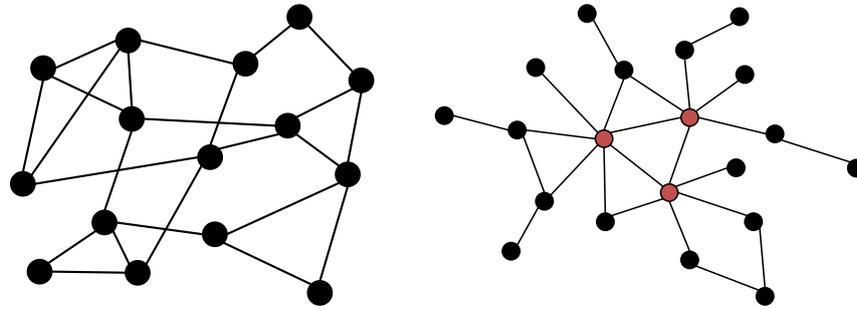


Figure 3: Showing (a) a random network and (b) a scale-free network; where the dots indicate the nodes and the black lines are the connecting links. The high degree nodes in the scale-free network have been shown in red.

One of the main advantages of classifying these systems (using their degree distributions) is that we can use this information to gain an insight into the inherent hazard tolerance of each system. For example, scale-free and exponential networks have been shown to be resilient to a random hazard (e.g. failure due to random events, such as lack of maintenance), but vulnerable to targeted attack (e.g. a targeted terrorist attack). This is because a random hazard has a small chance of removing the important nodes (i.e. those with a high degree) whereas a targeted attack will often remove these important nodes seeking to cause the maximum disruption to the network (Albert et al. 2000). It can be seen from Figure 3(b) that the removal of one of the three high degree nodes (red) will cause a larger impact to the network than the removal of one of the seventeen smaller degree nodes (black).

4. CURRENT RESEARCH USING A NETWORK THEORY ANALYSIS APPROACH

Network graph theory was developed for social networks where only the interaction between pairs of nodes is considered to be important. However, in an infrastructure system the spatial location of the nodes and the flow of service around the system both need to be considered in order to ensure that the system is modelled accurately.

In terms of the spatial component, it is the impact of spatial distance on the connectivity of nodal pairs that receives the most attention. This has previously been considered by Gastner and Newman (2006) and Qian and Han (2009), who both propose a model for connecting links between pairs of nodes based upon their separation distance. However, less considered is the resilience of these spatial networks. One study, by Wilkinson et al. (2012), analysed the resilience of the European air traffic network and found that this network belongs to a class that should be resilient to random hazards and vulnerable to targeted attack. However, they showed that the European air traffic network was in fact vulnerable to the Eyjafjallajökull volcanic event, thus contradicting previous theory. Through further analysis, they showed that this contradiction was due to the lack of a spatial component in the analysis of both the hazard and the network. They expanded their topological model to include these spatial components and used this model to show that the European air traffic network is vulnerable to not only the Eyjafjallajökull volcano event, but also other spatially coherent hazards. Therefore, many real

world networks that have previously been shown to belong to a class of network that is resilient to random hazards may in fact be vulnerable to spatial hazards.

The impact that the flow of service has to the resilience of an infrastructure system receives even less attention. In network theory there are many measures that exist which can highlight 'important' nodes in a network (i.e. those nodes that are critical to the functioning of a network) (Borgatti and Everett 2006). Many studies have used these measures to identify and rank the importance of nodes in a network (Cadini et al. 2009; Derrible 2012). However, the vast majority of these studies do not incorporate an element of flow and do not remove the node to measure its impact to the network when removed to validate the network measure (Cadini et al. 2009). One study to consider this problem, by Dunn and Wilkinson (2012), showed that the inclusion of a flow element to the analysis of the network changes the ranking of important nodes. In their study, they developed a reduced complexity flow model and used it to calculate the flows around a sample network. In this sample network the importance of nodes were ranked using two network theory measures, a physically based measure (flow) and one combination of these measures. They then removed nodes from the sample network to assess the resulting change in flow around the system and correlated this change with the four importance ranking methods. They found that the combination of network theory and physically based measures showed a better predictive skill at identifying the nodes that produced a larger change to the flow in the network when removed (i.e. the important nodes), rather than considering these measures in isolation. Therefore, in order to accurately rank the importance of nodes in an infrastructure network the flow around the system should be considered and incorporated into importance measures.

5. CONCLUSIONS

The importance of our infrastructure systems in underpinning our communities, promoting social well-being and supporting economic growth and productivity, cannot be understated. The functioning of these systems is particularly important after a disaster and can either aid, or hinder, rescue efforts and longer term recovery plans. Currently the individual components within these systems are designed to have a particular probability of failure. However, we have shown that for a complex interacting system that this approach can be deficient when used to ensure the resilience of the system. In this paper, we have presented a new approach which has previously been used to model the complex interactions between components in social and biological networks. We have also shown how many recent studies are adopting, and adapting, this approach to provide greater accuracy when modelling an infrastructure system, by considering the spatial layout and the flow of service in these systems.

6. ACKNOWLEDGEMENTS

This research was partly funded by the Engineering and Physical Sciences Research Council, UK, and their support is gratefully acknowledged.

7. REFERENCES

- Albert, R., Jeong, H. and Barabasi, A. L. (1999). "Internet - Diameter of the World-Wide Web." *Nature* **401**(6749): 130-131.
- Albert, R., Jeong, H. and Barabasi, A. L. (2000). "Error and Attack Tolerance of Complex Networks." *Nature* **406**(6794): 378-382.

- Barabasi, A. L., Albert, R. and Jeong, H. (2000). "Scale-free characteristics of random networks: the topology of the World-Wide Web." Physica A **281**(1-4): 69-77.
- Batagelj, V. and Brandes, U. (2005). "Efficient generation of large random networks." Physical Review E **71**(3).
- Borgatti, S. P. and Everett, M. G. (2006). "A graph-theoretic perspective on centrality." Social Networks **28**(4): 466-484.
- Cabinet Office (2008). The Pitt Review: Learning Lessons from the 2007 Floods.
- Cabinet Office (2011). Keeping the Country Running: Natural Hazards and Infrastructure.
- Cadini, F., Zio, E. and Petrescu, C.-A. (2009). Using Centrality Measures to Rank the Importance of the Components of a Complex Network Infrastructure. Critical Information Infrastructure Security. R. Setola and S. Geretshuber, Springer Berlin / Heidelberg. **5508**: 155-167.
- Crucitti, P., Latora, V. and Marchiori, M. (2004). "A topological analysis of the Italian electric power grid." Physica a-Statistical Mechanics and Its Applications **338**(1-2): 92-97.
- da Rocha, L. E. C. (2009). "Structural evolution of the Brazilian airport network." Journal of Statistical Mechanics-Theory and Experiment.
- Derrible, S. (2012). "Network Centrality of Metro Systems." Plos One **7**(7).
- Dunn, S. and Wilkinson, S. (2012). "Identifying Critical Components in Infrastructure Networks Using Network Topology." Journal of Infrastructure Systems.
- Gastner, M. T. and Newman, M. E. J. (2006). "The spatial structure of networks." European Physical Journal B **49**(2): 247-252.
- Holmgren, A. J. (2006). "Using Graph Models to Analyze the Vulnerability of Electric Power Networks." Risk Analysis **26**(4): 955-969.
- Lewis, T. G. (2009). Network science: theory and practice, John Wiley & Sons.
- Newman, M. E. J. (2003). "The structure and function of complex networks." Siam Review **45**: 167-256.
- Qian, J. H. and Han, D. D. (2009). "A spatial weighted network model based on optimal expected traffic." Physica a-Statistical Mechanics and Its Applications **388**(19): 4248-4258.
- Wilkinson, S., Dunn, S. and Ma, S. (2012). "The vulnerability of the European air traffic network to spatial hazards." Natural Hazards **60**(3): 1027-1036.