SECOND EUROPEAN CONFERENCE ON EARTHQUAKE ENGINEERING
AND SEISMOLOGY, ISTANBUL AUG. 25-29, 2014

Understanding the Fundamental Resilience of Lifelines

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ABSTRACT

Failures of Lifelines during earthquakes and other natural hazards can have a disproportionate effect on communities both in the immediate aftermath of the event and in the subsequent recovery process. How resilient these systems are and how best to improve this resilience is an ongoing area of investigation. Recent work has shown that these systems tend to form specific architectures and that they may have generic properties including how tolerant they are to hazards. In this paper we assess the fundamental resilience of lifelines by subjecting a number of synthetic networks to different spatial hazards. The geographically distributed synthetic networks are generated using the exponential model of Wilkinson et al. (2012) that has been shown to replicate air traffic networks. The algorithm starts with randomly distributed seeds confined within a predefined spatial boundary. The network is then grown using a modified version of the preferential attachment algorithm of Barabasi and Albert (1999). The modification allows low degree nodes to capitalise on their close spatial proximity to a high degree node, thereby increasing the probability of attachment, resulting in the exponential networks observed in lifeline systems (Crucitti et al. 2004; Rosas-Casals et al. 2006). To test generic resilience to hazard, we use three different methods of introducing nodes namely: 1) in order of distance from the geographic centre, 2) proportional with distance from the geographic centre and 3) randomly; and then subjected them to two spatial hazards. We generate ten geographically distributed exponential networks and scale-free networks, for each of the three node introduction orders (60 networks in total) and show that all of these networks have the same degree distribution, but that the spatial degree distribution changes depending on the order in which the nodes are introduced.

As each class of network has the same degree distribution irrespective of node introduction order, based on the work of Albert et al.(2000), it can be said that they will have the same topological hazard tolerance (i.e. they are resilient to random attack but vulnerable to targeted attack). To understand the hazard tolerance of these networks to spatial hazards the synthetic networks are subjected to two spatial hazards, namely; a ‘growing’ spatial hazard located over the centre of the spatial domain ‘central attack’ and a perimeter based hazard “perimeter attack’. As these hazards grow nodes are removed as they become enveloped. We demonstrate that the order in which the nodes are introduced is the governing factor in determining the location of the high degree nodes and subsequently the hazard tolerance of the network to spatial hazard.

We show networks where the nodes are introduced in order of distance from the geographic centre show and increased vulnerability to a central attack due to the high concentration of high degree nodes in the centre of the network. In contrast, networks where the nodes were introduced randomly show a

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surprising level of resilience to this spatial hazard, having the same hazard tolerance as a random (benchmark) network. This can be attributed to the dispersion of the high degree nodes throughout the spatial layout of the network. Therefore, as the hazard 'grows' outwards from the centre, high degree nodes are removed but a large number of small degree nodes are also removed. These results are important because as populations grow they often do so from a central location outwards, as the lifelines that enable them to do this mimic this growth they can be left vulnerable to centrally located hazards.

INTRODUCTION

The aim of any disaster risk reduction strategy is to minimise the disruption and suffering that a community experiences as a result of a hazardous event (Devi 2012). There are a number of ways to achieve this; however the most effective is to mitigate against the event by adequately preparing for it (Devi 2012). Since the San Fernando earthquake (and arguably before that) it has been recognized that lifelines play a key role in supporting both the relief effort and the continued existence of the remaining members of the community (O'Rourke 1996; Katayama 2006). The reason for this is that, as the name implies, lifelines are essential infrastructure that provide the necessary services that enable people to exist in the crowded urban situations that over half of the world's population now live in (O'Rourke 2007). And yet time and again significant failures of lifelines have been shown to have disproportionate consequences to the communities that rely on them (Wilkinson, Grant et al. 2013) (Wilkinson, Alarcon et al. 2012). We currently do not know what are the key features of resilient networks (O'Rourke 1996) - for example, resilience requires some form of redundancy – but how much and at what geographic separation should it be provided to ensure that the redundancy is not lost in a widespread disaster. At present these questions are answered by analysing each system and assessing the performance to different scenarios, for example we may ensure adequate performance in the immediate aftermath of a natural disaster by ensuring lifelines have both a high level of resistance (so that these services have low probabilities of failure) and can be quickly reinstated if any failure does occur, but without an understanding of the generic properties of lifelines, specific rules for ensuring best performance remain elusive and optimal design of lifelines cumbersome.

This difficult in optimising lifelines results from the fundamental differences they have to other forms of infrastructure (such as buildings). These differences can be summarised as 1) they are geographically distributed networks 2) are more concerned with the service that they provide rather than the physical infrastructure that provides that service 3) are systems where the functioning of the system is important rather than the state of individual elements and 4) are complex systems that evolve over time.

This last point is a feature of the evolving populations that lifelines serve and the demographics shifts that they must accommodate and thus they too evolve and/or reconfigure themselves. This evolution has been shown to result in lifelines possessing particular architectures (Crucitti, Latora et al. 2004) (Carvalho, Buzna et al. 2009) and their evolution is believed to be governed by a few simple rules, that optimize their ability to provide services to the populations that rely on them (Gastner and Newman 2006) (Bettencourt, Lobo et al. 2007).

These observations raise the question, "if lifelines evolve to from particular architectures to optimize service provision, are these architectures also inherently robust or are they inherently vulnerable and if so, can we use this knowledge to better design our lifelines?"

To test this, we use the exponential model of Wilkinson et al. (2012) to generate a series of geographically distributed networks and subject them to two different hazards. We assess their hazard tolerance by comparing the disruption that these networks may experience due to these hazards to the disruption caused to a benchmark network and conclude by summarising the implications for real-world networks.

NETWORK GENERATION

We use the exponential model of Wilkinson et al. (2012) to generate a series of synthetic geographically distributed networks as reported in Dunn (2013). The algorithm employed starts with randomly distributed seeds confined within a predefined spatial boundary. The network is then grown using a modified version of the preferential attachment algorithm of Barabasi and Albert (1999). The modification allows low degree nodes to capitalise on their close spatial proximity to a high degree node, thereby increasing the probability of attachment, resulting in the exponential networks observed in lifeline systems (Crucitti et al. 2004; Rosas-Casals et al. 2006). In this paper, we distribute the nodes so that they are located uniformly in space and use three different methods of introducing nodes namely: 1) in order of distance from the geographic centre, 2) proportional with distance from the geographic centre and 3) randomly. An example of each of the networks is shown in Figure 1 and demonstrates that if the network grows out from the centre of the spatial boundary, then the high degree nodes will be located close to the centre of the network, whereas random growth results in a uniform distribution of high degree nodes. This is intuitive as the nodes that are introduced first have more time to attract links than the nodes that are introduced towards the end of the evolution of the network.

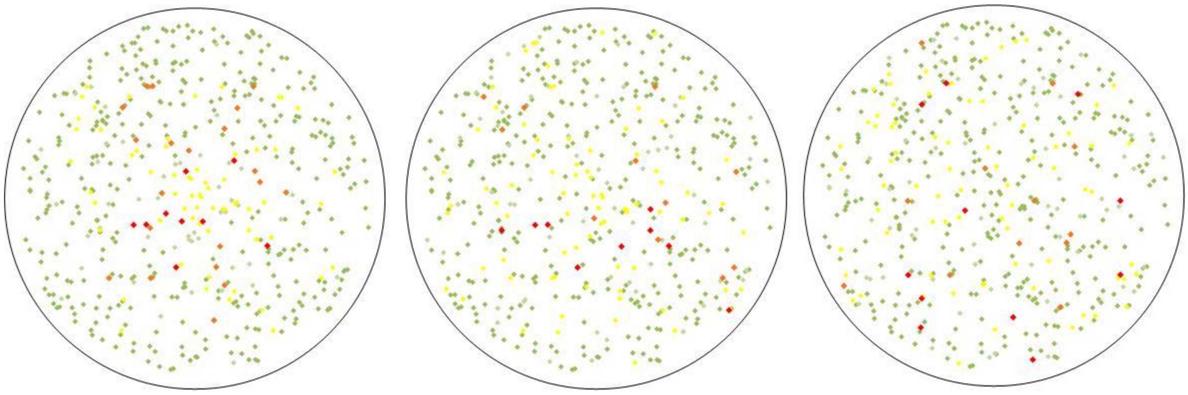

Figure 1: Three exponential networks with a random nodal layout, where the order the nodes are introduced are (a) with distance, (b) proportional to distance and (c) randomly. The colour of the node indicates its degree, with red nodes having a high degree and green nodes a low degree. It can be seen that the most ordered network (a) distributes the high degree nodes centrally resulting in vulnerability to a centrally located spatial hazard, while the random introduction (c) distributes them uniformly and removes this vulnerability (the distribution of (b) is somewhere in between).

To compare the fundamental properties of these networks the average degree distribution and the spatial degree distribution are plotted Figure 2. In this figure, it can be seen that the order in which nodes are introduced has no effect on the degree distribution of the network, but does affect the spatial degree distribution. This can be attributed to the length of 'time' that nodes have been present in the network, the nodes that were introduced first have a higher chance of 'attracting' links from new nodes. As the degree distribution is similar for all node introduction orders. The networks should have the same topological hazard tolerance (i.e. they will be equally robust to a hazard that affects nodes relative to their degree) but will have different hazard tolerances for spatial hazards

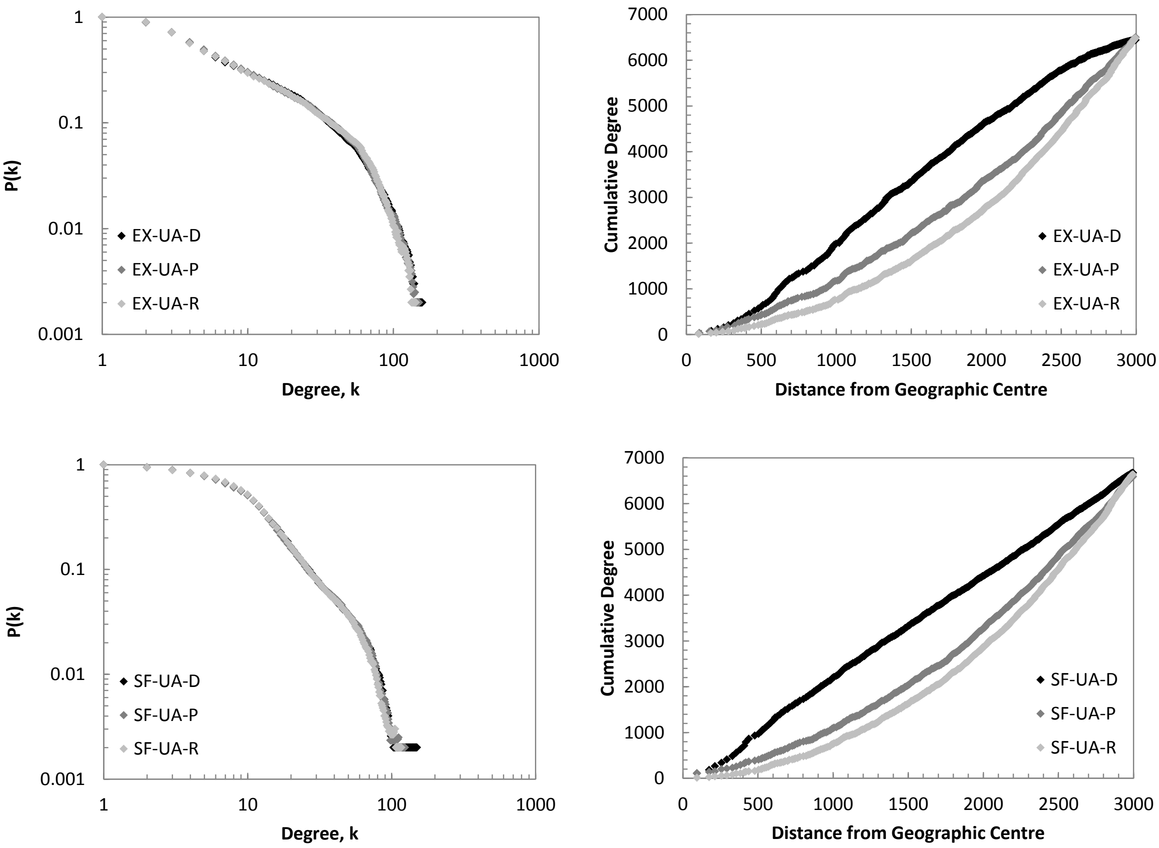

Figure 2 Showing (a) the degree distribution for exponential networks, with a uniform with area nodal layout, and three different node introduction orders; (b) the spatial degree distribution for the same exponential networks; (c) the degree distribution for scale-free networks, with a uniform with area nodal layout and three different node introduction orders; (d) the spatial degree distribution for the same scale-free networks. (The notation in the legend is as follows, EX – exponential degree distribution; SF –scale free degree distribution; UA – nodes are uniform with area, D – nodes introduced in order of distance from centre of network; P – nodes introduced in proportion with distance from centre of networks, R – nodes introduced randomly)

To confirm the networks tolerance to spatial hazard, we have generated ten geographically distributed exponential networks, for each of the three node introduction orders (30 networks in total) and ten geographically distributed scale-free networks and subject them to two different spatial hazards, which both have a fixed centre from which the hazard ‘grows’ outwards. The centre of the first hazard is located on the geographic centre of the network (‘central attack’) and the second is located on the spatial boundary of the network (‘perimeter attack’). Nodes are considered to have ‘failed’ if they are located within the spatial hazard and the links attached to these nodes are removed from the network. Only nodes that are located within the hazard are considered to have failed and not nodes that have become isolated (due to the removal of links).

The results for the ‘central attack’ spatial hazard have been plotted in Figure 3 for both the percentages of nodes and links removed and the percentages of area and links removed. In this figure we have also plotted a benchmark network with which to compare our results. This benchmarkd network has nodes randomly located in space and a random degree distribution and therefore can be considered to be the most basic network. From Figure 3 it can be seen that node introduction order has a significant effect on the hazard tolerance of a network. For both the exponential and scale-free networks, introducing the nodes randomly show a surprising level of resilience to this spatial hazard, having the same hazard tolerance as the random network. This can be attributed to the dispersion of the high degree nodes throughout the spatial layout of the network (see Figure 1). Therefore, as the hazard ‘grows’ outwards from the centre, high degree nodes are removed but a large number of small degree nodes are also removed. In contrast, networks where the nodes were introduced with distance from the geographic centre show an increased vulnerability to this hazard (as they have a higher percentage of removed links for a given percentage of removed nodes or area than the other two node introduction orders; Figure 3). This increased vulnerability is due to the high concentration of high degree nodes in the centre of the network, which is also the area of the network which is first removed by the 'central attack' spatial hazard. To quantify this difference, for the exponential networks removing 20% of nodes results in the removal of 60% of links when introducing nodes with distance and 30% of links when removing nodes introduced randomly (30% points difference). Networks where the nodes were introduced proportional with distance, have a hazard tolerance level between the other two introduction orders unlike the randomly introduced nodes.

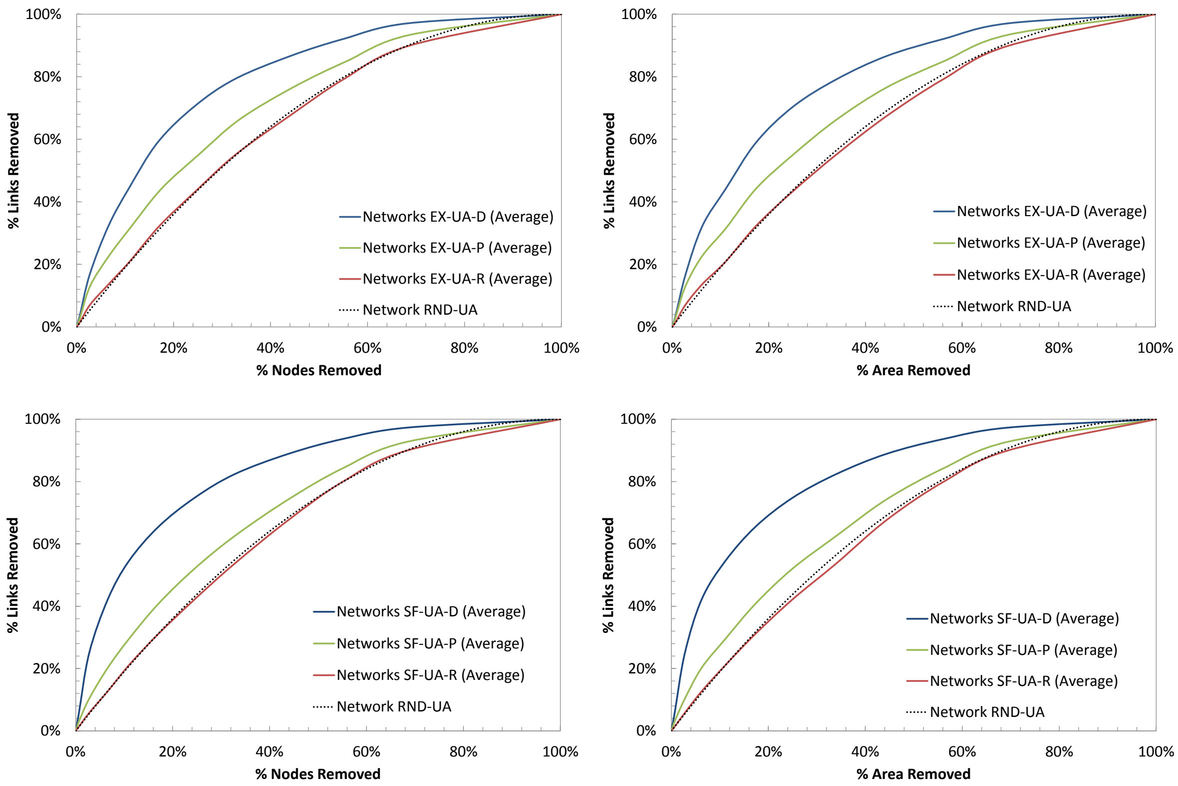

Figure 3: Showing the results of subjecting (a, b) the exponential networks and (c, d) the scale-free networks to the 'central attack' spatial hazard. (a, c) plot the percentage of nodes and links removed, and (b, d) plot the percentage of area and links removed. Each line of results represents an average of 10 networks. It is worth noting that there is only a small scatter in the results for each of the 10 networks

Figure 4 shows the results of the same networks subjected to the 'perimeter attack'. From these results it can be seen that networks where the nodes were introduced proportional to distance and randomly show approximately the same resilience as the benchmark random network.

Whereas, the networks where the nodes were introduced with distance are resilient until around 35% of the network area has been removed and then become vulnerable with further expansion of the spatial hazard. This can be attributed to the location of the high degree nodes in the centre of the network. The hazard starts on the perimeter of the network, where the low degree nodes are located and therefore removes a small percentage of links compared to the percentage of nodes removed. The network becomes vulnerable after 35% of the area has been removed, as this is when the spatial centre of the network is reached, causing a dramatic increase in the percentage of removed links for only a small increase in the percentage of nodes removed. Quantifying this difference, for the scale-free networks when 20% of the nodes have been removed, results in the removal of 28% of links when introducing node with distance and 36% of links when removing nodes introduced randomly (8% points difference). However, the hazard tolerance of these two node introduction orders reverses when over 35% of the network area is removed. When 50% of the nodes have been removed, 85% of links have been removed for the nodes introduced with distance and 73% of links have been removed for nodes introduced randomly (12% points difference).

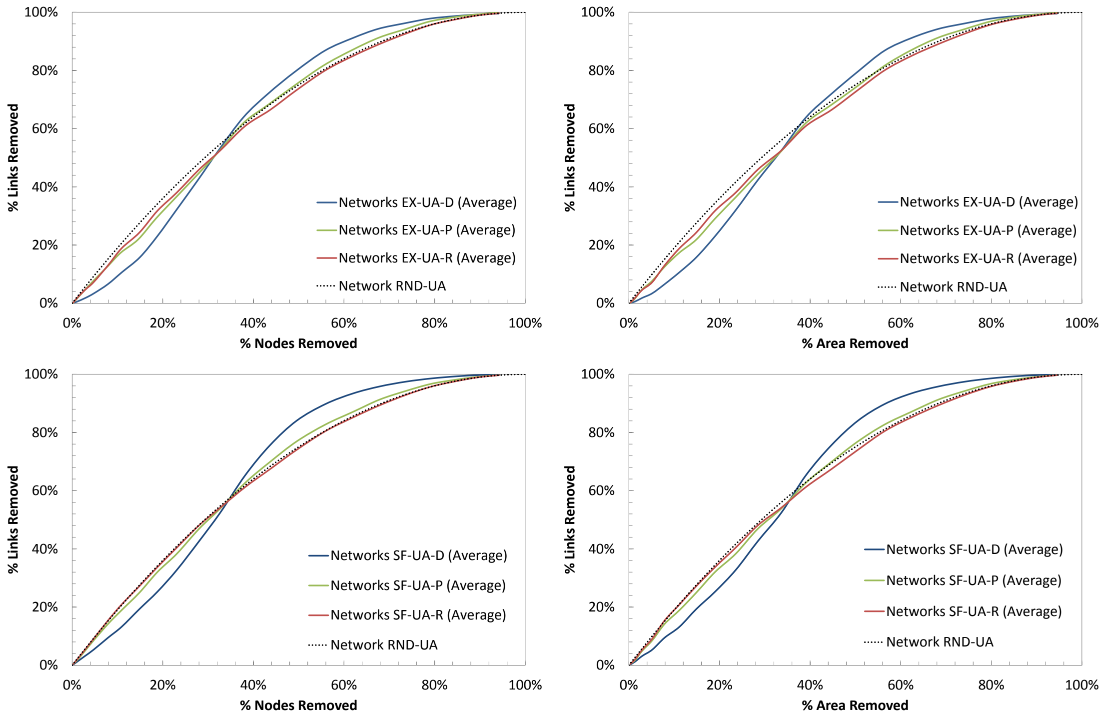

Figure 4 Showing the results of subjecting (a, b) the exponential networks and (c, d) the scale-free networks to the ‘perimeter attack’ spatial hazard. (a, c) plot the percentage of nodes and links removed, and (b, d) plot the percentage of area and links removed. Each line of results represents an average of 10 networks. It is worth noting that there is a small scatter in the results for each of the 10 networks.

CONCLUSIONS

We have tested the resilience of a number of scale-free and exponential networks. In our experiments we have varied how the nodes are introduced into the network and compared the hazard tolerance of these networks to a benchmark random network. As the degree distribution of our scale-free networks is independent of node introduction order, they are all resilient to random attacks but vulnerable to targeted attack. The same is true for our exponential networks although the relationship is not as strong. On the other hand, the spatial hazard tolerance of our networks is crucially dependent on the node introduction order. Networks where nodes are introduced in order of their distance from the centre of the network show a 60% reduction in the number of links in the network for only 20% of the space covered by the hazard as opposed to 30% in the random network. For the perimeter attack the results are reversed. For small hazards (less than approximately 30%) networks where the nodes are introduced in order of their distance from the centre of the network are more tolerant to spatial hazard than random networks (for example 20% area covered results in 20% reduction in the number of links as compared to 30% in the random network).

These results are important because as populations grow they often do so from a central location outwards, as the lifelines that enable them to do this mimic this growth they can be left vulnerable to centrally located hazards.

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