SUPPORTING THE DEVELOPMENT OF ACTIVE DEBRIS REMOVAL USING WEIGHTED NETWORKS

Rebecca J. Newland, Hugh G. Lewis, Graham G. Swinerd

University of Southampton, School of Engineering Sciences, Highfield, Southampton, SO17 1BJ, United Kingdom
r.j.newland | hglewis | ggs @soton.ac.uk

ABSTRACT

Active debris removal (ADR) procedures are necessary to reduce the risk posed by space debris. The choice of objects to be removed in an ADR campaign needs to be based on a robust selection process. Building on the techniques introduced in previous work, networks were constructed using data from a 'no new launches' simulation generated by the University of Southampton's DAMAGE model for a 21 year projection period between 2009 and 2030. The network *edges* were weighted according to the collision probability between objects. The *vertices* were weighted according to the 'vertex measures' which were the product of edge weight and the object mass. This paper quantifies how the removal of individual objects affects the topology of the network, using measures of *strength* and *affinity*. It is shown that by removing the objects represented by particular vertices, the connectivity of the network can be reduced, decreasing the potential for collisions.

1. INTRODUCTION

Recent work has shown that the space debris environment is unstable such that, even if there were no new launches, the number of debris in the environment will increase due to on-orbit collisions [1][2]. Reducing the risk posed by debris involves implementing mitigation practices, but also using active debris removal (ADR) strategies to deal with existing debris. ADR relies on the development of technology that can remove objects from the environment whilst minimising the creation of new debris. There are a number of proposals for ADR strategies, but the lack of technological maturity means that they are not currently in use [3]. Whilst the ideas for this technology are under development, identifying appropriate selection criteria for removals in any future campaign needs to be planned carefully. Robust selection criteria are essential to ensure that the objects that are removed have the greatest impact on reducing the number of future collisions and on stabilising the environment.

In a recent NASA study, the effectiveness of several ADR strategies was investigated [4]. In their approach, the objects were ranked according to the product of their collision probability and mass at the start of each projection year. Based on this ranking, 5, 10 or 20 objects from the top of the list were then immediately removed from the environment. Fig. 1 shows that increasing the removal rate reduces the effective number of debris leading to a linear growth and more stable future environment.

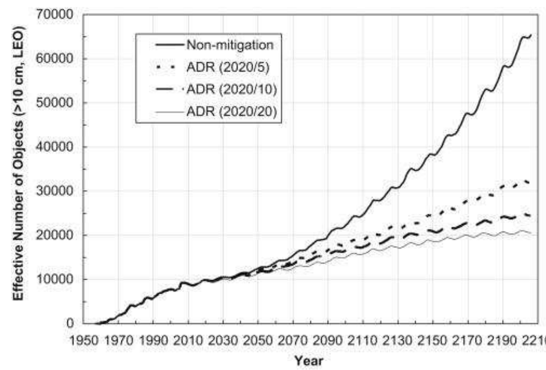

Figure 1. NASA case study results in which a non-mitigation scenario is compared to the removal of 5, 10 or 20 debris objects [4].

However, this ranking approach means that objects that have the potential for many collisions may remain in the simulation if they are not at the top of the ranking list. Consequently these objects may go on to cause a collision during the simulation. Therefore, a new method is needed to identify the objects that have a high overall probability of collision.

The need for a carefully targeted approach to removal based on a robust selection process is the motivation for using network theory. Network theory is used to investigate the environment both at system-level, as represented by the topology of the network and at the level of the individual *vertices* and *edges*, representing the debris objects and the potential connections between them.

In work by Lewis *et al*. (2008) the concept of using networks as a theoretical approach to analysing data from debris environment models was introduced [5]. In that work, network theory was used to quantify how specific debris objects affect the environment, as well

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as looking at how the environment is structured as a whole. This new study follows the initial work by analysing the structure of the networks and then identifying objects for removal based on the analysis of network measures. This allows for the development of strategies for targeting individual objects, taking into account the mass and collision probability by weighting the edges and vertices. Once objects have been identified using network measures, they can be removed in the modelling studies and the effectiveness of the network approach can be assessed by comparison to a non-mitigation scenario.

2. NETWORKS

Networks are composed of *vertices* representing debris objects and *edges* representing the encounters between the objects. A network is described mathematically using an adjacency matrix,

$$\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

An unweighted network has a binary adjacency matrix where $a_{ij}=1$ represents an edge between vertices i and j and $a_{ij}=0$ represents the lack of a connection. The values in an adjacency matrix of a weighted network are not binary as the values describe the probability of a conjunction occurring.

The topological features of a network have a strong impact on its physical properties such as robustness to targeted attack [6]. Whilst unweighted networks can be used to represent simple aspects of complex systems, many real-world systems have additional interesting features that can be highlighted in weighted networks. A study by Barthélemy *et al*. (2004) showed that the modelling of complex networks must go beyond topology and incorporate interaction strength to characterise real-world networks [7][8].

An unstable space debris environment translates into a highly-connected network. As such, the aim of the work by Lewis *et al*. (2008) was to disrupt the connectivity of a space debris environment network in order to stabilise the environment [5]. In this new paper we extend the work and show that analysis of weighted networks allows the risk posed by objects to be quantified more robustly. For this paper, we use the ranking methods in the Liou and Johnson (2009) study as a starting point [4]. The edges are weighted according to the collision probability between objects. These edge weights are then used to calculate vertex measures of *strength* and *affinity* to quantify the importance of vertices for the connectivity of the network.

2.1. Targets

Objects can be targeted by quantifying their risk to future collision activities. It is possible that this risk is not only due to their mass and collision probability, but also other factors that may affect ADR effectiveness, such as altitude. Typically, most objects only have the potential to interact with one or two other objects. However, there are a small number of objects that have the potential to interact with many others. If these objects could be removed, the likelihood of the generation of new on-orbit debris would be reduced.

Removing objects in the space debris environment translates into removing vertices with the aim of reducing the connectivity of the network. The part of a network containing the majority of connected vertices is called the *giant component*. Attacking a network by removing vertices reduces the giant component into smaller clusters that can no longer interact with other parts of the network, thus reducing its connectivity. If the giant component is broken down beyond a critical threshold, then the network is described as having failed. Removing vertices at random from some networks will lead to a failure, whereas vertices in certain types of networks, called scale-free networks, need to be targeted specifically before the network will fail [9]. For random attacks, no threshold for fragmentation of the giant component is observed; instead, the size of the giant component slowly decreases [10]. However, the random attack tolerance of scale-free networks comes at a high price as these networks are extremely vulnerable to targeted attacks [10]. Consequently, network theory can provide an indication of actions that can be performed in order to optimise the effectiveness of ADR [11]. For the space debris environment, the goals are to induce a network failure, to reduce the network connectivity and to increase the stability of the environment by limiting the future generation of on-orbit debris.

2.2. Quantifying the Risk

The network analysis measures used here are weighted variations of those used by Lewis *et al*. (2008) [5]. The risk posed by individual objects is quantified here using measures of *strength* and *affinity*. These measures quantify the importance of individual vertices to the connectivity of the network as a whole. Strength and affinity are both related to the degree of a vertex.

The connectivity of an individual vertex is given by its *degree*, k_i which is calculated from the adjacency matrix, a_{ij},

$$k_i = \sum_{j}^{n} a_{ij} \qquad (2)$$

For a weighted network, the equivalent measure is strength, s_i,

$$s_i = \sum_{j=1}^{n} a_{ij} w_{ij} \qquad (3)$$

where w_{ij} is the weight on the edge between vertices i and j.

Lewis *et al* (2008) concluded that vertices with a high degree (objects having a probability of interacting with many other objects) acted as hubs [5]. Hubs have a higher degree compared to other vertices in the network. The *assortativity, r,* identifies hubs in a network by calculating the correlation between the degree of vertex i and the degree of its neighbour, vertex j. Assortativity values can be positive or negative, corresponding to assortative or disassortative networks respectively. Lewis *et al*. (2008) found that space debris environment networks are likely to be disassortative and, therefore, have a few hubs that may be targeted for removal. For a weighted network, the *affinity* provides a measure corresponding to assortativity,

$$a_i = \frac{1}{s_i} \sum_{j=1}^{n} w_{ij} k_j \qquad (4)$$

The values for individual vertices are called vertex measures and it is important to note, these are calculated using edge weights. The vertex measures can be averaged over the whole network to give network measures which describe the topology. In network theory characteristics of an object, such as mass, are labelled as vertex attributes, but no method yet exists to analyse networks that are initially weighted according to their vertices [12]. It is important to do so however, as the mass of an object in the space debris environment affects the outcome of a potential collision. To address this problem, the vertex measures were calculated using edge weights, following the current literature, and then multiplied by the mass of the object to provide weights for the vertices which measure the 'importance' of an object.

The efficiency of the network method used to select objects for removal was measured by an efficiency factor, η. This efficiency factor measures the ratio of the number of objects removed to the difference between the number of vertices in an ADR scenario and a non-mitigation scenario. A successful method will have a high efficiency factor.

3. METHOD

The data used to build the networks were generated using the University of Southampton's debris model, Debris Analysis and Monitoring Architecture for the Geosynchronous Environment (DAMAGE). DAMAGE is a three-dimensional model that was initially aimed at simulating debris within the geosynchronous orbital regime but has since been upgraded to allow investigations of the low Earth orbit (LEO) to geosynchronous Earth orbit (GEO) debris environment. As with other evolutionary models, DAMAGE is able to simulate the historical and future debris populations ≥ 10 cm using a Monte Carlo (MC) approach, whereby multiple projection runs are performed to establish reliable statistics on the outcome. Projections covering the historical period from 1957 to 2009 employ launch and fragmentation information from ESA's Database and Information System Characterising Objects in Space (DISCOS) and historical monthly averaged solar flux F10.7 values combined with the CIRA-72 atmospheric model for atmospheric drag calculation. Future projections use long-term F10.7 projection based on a repeating sine function and fragmentation events are simulated using the NASA Standard Breakup Model [13]. Non-fragmentation sources of debris, except mission-related objects included in DISCOS, are not considered. All objects are propagated forwards using a semi-analytical orbital propagator that includes Earth's J_2, J_3, $J_{2,2}$, luni-solar gravitational perturbations, solar radiation pressure (with cylindrical Earth shadow) and atmospheric drag. Collision probabilities are estimated using a fast, pair-wise algorithm based on the 'Cube' approach adopted in NASA's LEO-to-GEO Environment Debris model (LEGEND) [14]. A 'no future launches (NFL)' (2009 – 2030) scenario without further mitigation was used for 10 MC runs by DAMAGE to provide data for this investigation.

For each of the 10 MC runs, DAMAGE recorded information about all the collision events occurring in the projection period, between intact vs intact or intact vs fragment objects ≥ 10 cm. This information included the identification, mass, size and orbit of each object, as well as the collision probability and energy. The same information was recorded for encounters between objects occurring during snapshots taken at the start of each year between 2020 and 2030. It is important to note that the objects that have encounters in the snapshots do not form part of the normal projection [15]. The snapshot information can be used to determine a mass × collision probability criterion for ranking objects that contribute to the future hazard, following Liou and Johnson (2009) [4]. In this work, this information is used to construct networks. A freely available software tool, entitled 'Cytoscape', was used to display the resulting networks [16]. The networks were then analysed according to the vertex and network measures described above. Twenty objects identified by the network analysis as those having the highest strength and affinity were then removed and the simulation was re-run using DAMAGE.

4. RESULTS AND DISCUSSION

DAMAGE uses a Monte Carlo simulation approach to build a picture of the collision 'potential' of each object in the environment. The networks describing the encounters between objects were constructed by combining the data generated in each MC run. For each of the MC runs, 200 snapshots were taken of the network at the start of each simulation year between 2020 and 2030. These snapshots used the collision algorithm to estimate the collision probability of every object in the simulated environment. The combined snapshot data from each MC run could then be split according to the year that the snapshots represent. One small network can be produced for each of the ten years, typically having a few short chains or pairs of objects. This enables a collision or explosion, which 'seeded' the environment during the simulation, to be identified. Fig. 2 shows the data from 2020. As the conjunctions from each year are added, the network becomes more connected and complex. Fig. 3 shows the next step in the process and after every year is added together, the result is the network shown in Fig. 4.

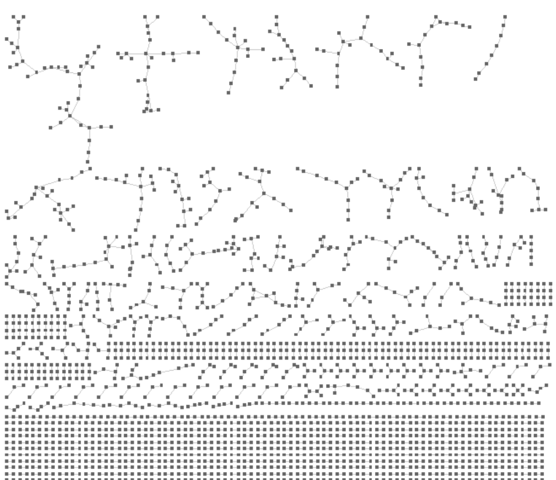

Figure 2. Simulation data from 2020 showing 2,198 vertices and 1,609 edges.

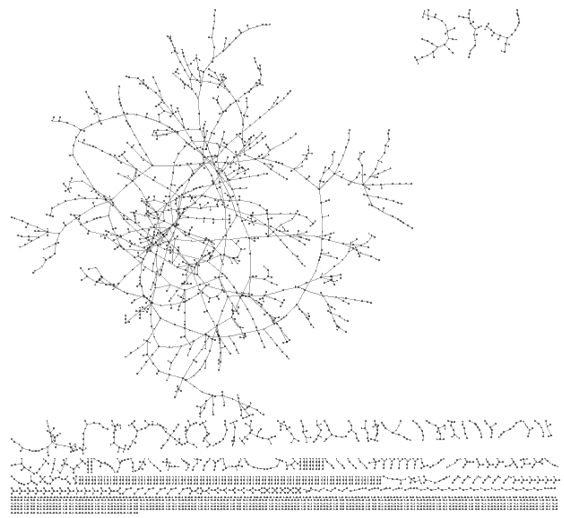

Figure 3. Simulation data from 2020 and 2021 which shows 3,429 vertices and 3,098 edges.

4.1 Unweighted Network

The output from the DAMAGE simulation produced a set of 14,405 encounters involving 7,368 objects which were displayed in the Cytoscape network software (Fig. 4). Most objects (95%) were found in the giant component and the remainder were found in pairs or short chains of three to seven vertices. The network had a complex, well-connected topology which made it difficult to distinguish any features by visual inspection.

4.2. Weighted Network

The network in Fig. 2 was weighted according to the vertex measures. Fig. 5 shows part of the giant component. Each vertex has a size based on the value of the object mass and the vertex measure of strength.

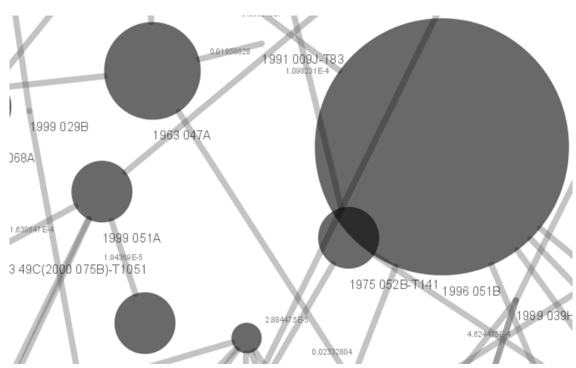

Figure 5. A portion of the giant component weighted according to mass $\times$ strength.

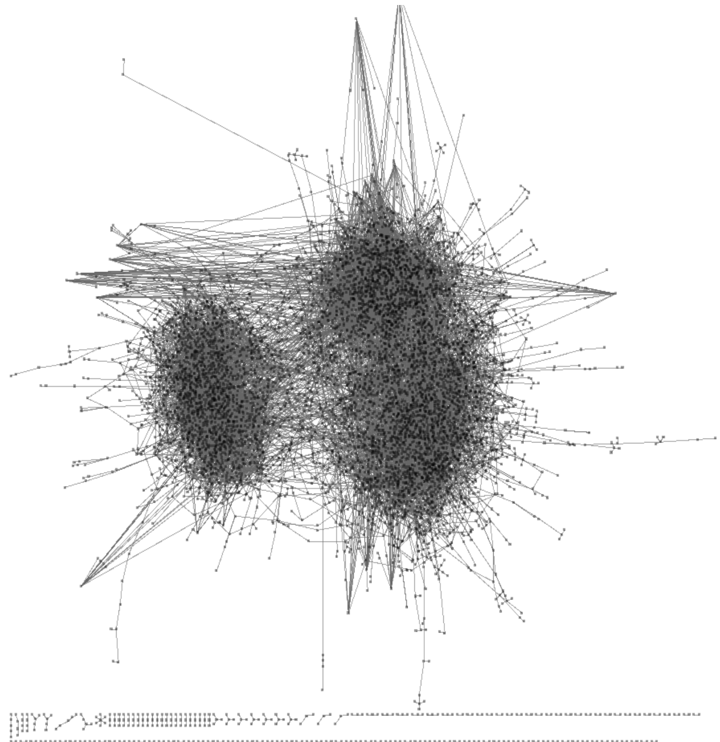

Figure 4. The network with 7,014 vertices and 14,187 edges in the giant component, displayed using the 'organic' layout in Cytoscape.

It is important to note that the objects chosen for removal using the network approach are based on the analysis of simulations and are not meant to identify the real objects that should be removed from the environment. Rather, this approach highlights the objects that should be removed to reduce the connectivity of the networks built in this study.

4.3. Removing Vertices

Using the vertex measures of strength, s_i and affinity, a_i, and the mass, m_i of each object, the vertices can be given a risk value, R_i,

$$R_i^{(1)} = m_i \times s_i \qquad (5)$$

$$R_i^{(2)} = m_i \times a_i \qquad (6)$$

The objects were ranked separately to find the twenty highest $R_i^{(1)}$ and $R_i^{(2)}$ values. The twenty objects with the highest values of $R_i^{(1)}$ were found within the first 34 lines of the ranked list of $R_i^{(2)}$ values. As there was a strong correspondence between the two criteria rankings, the twenty objects with the highest values of $R_i^{(1)}$ were chosen for removal. These twenty objects were removed from the population files before the simulations were repeated. The objects had $R_i^{(1)}$ values that ranged from 1138.735 to 2496.723 and the objects had degree, k_i ranging from 6 to 13. Each object had a degree and mass × strength value that was higher than that of the average for the network as shown in Tab. 1.

Table 1. A comparison of network measures.

Measure	Original network	Object removal
Number of vertices	7368	7240
Strength × Mass	16.455	16.208
Affinity × Mass	1463.741	1460.520
Degree	3.519	3.595

The simulations were repeated and the new average network statistics were compared to the original network (Tab. 1). Removing twenty objects before the start of the simulation had an efficiency, η of 16% as, there were 108 fewer objects without the potential for collisions in the second simulation. However, removing twenty objects was not enough to break down the giant component.

Repeating the simulation using random removal confirms that a targeted approach is more efficient.

When twenty randomly chosen objects were removed before the simulation, the efficiency, η was only 13%.

5. CONCLUSION

A weighted network more accurately represented the risk from the objects than an unweighted network for quantifying removal criteria. The addition of vertex weights takes into account the characteristics of an object and its relationship to other objects in the environment. Objects were ranked according to the vertex measures of strength × mass and affinity × mass. By removing the twenty objects that had the highest vertex values, the potential for collisions decreased and the connectivity of the network was reduced.

Future work will include investigating other object characteristics, such as altitude, that will be important when considering the cost and feasibility of an ADR scenario. Furthermore, the temporal aspect of the networks will be explored as the topology of the network changes as the space debris environment evolves.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

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