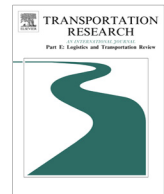




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# Increasing the resilience of air traffic networks using a network graph theory approach



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## ARTICLE INFO

*Article history:*

Received 30 April 2015

Received in revised form 22 September 2015

Accepted 26 September 2015

Available online 11 November 2015

*Keywords:*

Air traffic networks

Spatial hazards

Network theory

Resilience

Adaptation strategies

## ABSTRACT

Air traffic networks are essential to today's global society. They are the fastest means of transporting physical goods and people and are a major contributor to the globalisation of the world's economy. This increasing reliance requires these networks to have high resilience; however, previous events show that they can be susceptible to natural hazards. We assess two strategies to improve the resilience of air traffic networks and show an adaptive reconfiguration strategy is superior to a permanent re-routing solution. We find that, if traffic networks have fixed air routes, the geographical location of airports leaves them vulnerable to spatial hazard.

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## 1. Introduction

Air travel is critical to the functioning of countries and the world economy as a whole. In 2012 approximately 2.9 billion people used air transport to meet their business and tourism needs, with over 115 million passengers travelling using UK air carriers and over 736 million using US air carriers ([International Civil Aviation Organization, 2012](#); [The World Bank, 2013](#)). It has also been estimated that approximately 51 million tonnes of freight was carried by air transport in 2012 ([International Civil Aviation Organization, 2012](#)). These figures have been steadily increasing year-on-year, with a 5.5% increase in air passenger numbers from 2011 to 2012 ([International Civil Aviation Organization, 2012](#)), showing a growing demand and reliance on air transport, both for passengers (tourism and business) and freight.

The resilience of air traffic networks is therefore of great importance, and it is critical that the system is designed to minimise the impact to passengers and economic losses to businesses due to disruptive events, such as extreme weather events, strike action or terrorist threats, for example. However, many recent events have shown that air transport networks are particularly susceptible to disruption. To give an example, in February 2010 snowstorms along the Eastern coast of the US caused the cancellation of more than 20,000 flights (4.2% of all flights) scheduled during the month. On the peak day of disruption (10 February) 23% of scheduled flights were cancelled. This large number was mainly due to the near or complete closure of on a few Northeastern hub airports, including Washington Regan, John F. Kennedy, Baltimore Washington and Newark Liberty. The total cost of these cancellations is unknown due to the difficulties in quantifying the exact cost to each carrier (as this depends upon the carriers ability to rebook passengers); however, across all carriers it has been estimated that cancellations from snowstorms over the whole month cost between \$80–100 million ([Credeur and Schlangenstein, 2010](#)). Within the US the greatest proportion of weather-related events, on average, occurs during the winter months

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(December–February) when snowstorms can reduce the ability of an airport to function normally. In these months weather-related cancellations account for approximately half of all cancellations and the five worst months on record for weather-related cancellations have all occurred within the last 7 years (Bureau of Transportation Statistics, 2010). The US is not the only country to experience air traffic disruption due to snowstorms; in December 2010 Heathrow airport was closed for arrivals and departures on 18 December, with only a limited number of flights operating the next day, due to 70 mm of snow falling in one hour. This event caused the cancellation of over 4000 flights, disrupting the travel plans of many passengers during what was predicted to be Heathrow's busiest weekend of the year (Heathrow Winter Resilience Enquiry, 2011). One further notable example of air traffic disruption in recent years affected European airspace and was caused by the ash cloud from the erupting Eyjafjallajökull volcano (Iceland) in early 2010. This event caused parts of European airspace to become restricted and no fly zones to come into operation from the 14 April (Brooker, 2010). The resulting airport closures and flight cancellations caused more than 10 million passengers to be delayed and the event was estimated to have cost \$1.7 billion (in terms of revenue lost for air carriers between 15–21 April) (Mazzocchi et al., 2010). It is also worth noting that the majority of these disruptive events can be distributed over wide geographic areas and have the potential to affect multiple airports simultaneously.

In the UK, Heathrow airport has already taken steps to minimise disruption caused by extreme weather events, particularly snow/ice hazard, by reducing the capacity of scheduled flights per day in the winter season to 1279, in comparison to 1341 flights in the summer season (Transport Committee, 2013a). However, this is only a slight reduction and they 'do not believe that there is further scope to reduce the winter schedule without damaging the range of flights and destinations available to passengers' (Heathrow, 2013). Therefore additional strategies to increase the resilience of air traffic networks are needed.

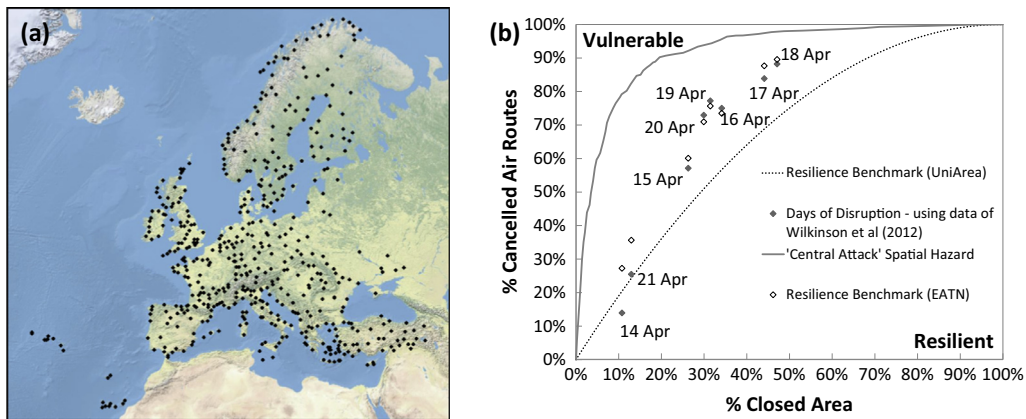
There are a number of academic studies that have assessed the impact of extreme weather events on transportation networks, including those by Koetse and Rietveld (2009), Suarez et al. (2005) and Chang et al. (2010). In one study Stamos et al. (2015) developed a framework that could be used by policy makers or planning authorities for assessing the resilience of passenger transportation networks (including air traffic networks). They expressed this impact in terms of passenger differentiated flows for several extreme weather events, including: wind gusts, snowfall, heavy precipitation and adverse temperatures to transportation infrastructure, and the impacts that this may have to consumers. However, there are far fewer studies which consider strategies aimed at adapting transportation infrastructure to cope with these extreme weather events. Those that do exist tend to focus on long-term strategies to overcome the potential impacts of climate change (Arnell and Darch, 2006; Schwartz, 2010; Rattanachot et al., 2015). There are a handful of previous studies that have considered increasing the resilience of air traffic networks to hazard, but these studies have tended to focus on the operations of individual air carriers, rather than the functioning of the air traffic network as a whole (Wuellner et al., 2010). The majority of studies regarding air traffic networks focus on using network graph theory to classify the topology of the network (Li et al., 2006; Bagler, 2008; Han et al., 2008) and have found that many air traffic networks including the European, US and China air traffic networks show the same topological characteristics (Dunn, 2014). Whilst, other network theory studies use measures to consider the importance of individual airports (Guimera et al., 2005) or focus on the optimisation and efficiency of the network (Li et al., 2010; Silva et al., 2014; Gillen et al., 2015).

In this paper we develop two strategies to increase the resilience of air traffic networks when subjected to a 'growing' spatial hazard. One resilience strategy 'adaptively' modifies the topology of the network as airports become closed by the hazard (crisis management) and the other 'permanently' modifies the topology (hazard mitigation). We apply these resilience strategies to the European air traffic network (EATN) as a case study example, as its hazard tolerance and evolution has previously been studied in detail by Wilkinson et al. (2012). We initially quantify the ability of these two strategies to increase the resilience of the EATN by plotting the proportion of cancelled air routes against the proportion of closed airports and closed area (defined as the area covered by the spatial hazard). We then assess the change in connectivity and performance of the network by applying two network graph theory metrics, maximum cluster size (MCS) and shortest average path length (APL).

## 2. Network model and identification of network resilience

We have chosen to use a network graph analysis of the air traffic networks in this paper, for several reasons. Firstly, air traffic networks are dynamic, with new routes continually opening and old routes expiring. Therefore, using modelling techniques that are applicable to specific networks are only valid at one point in time, whereas this approach is capable of capturing the generic properties of many real world networks. This has previously been shown by Albert et al. (1999), who argue that many real world systems actually share very similar patterns of connectivity and that generic networks with similar properties can be generated using simple rules (i.e. network generation algorithms). Secondly, network graph theory is most applicable for modelling the topological characteristics and connectivity of generic networks and also the impact that the resilience strategies has to this. And finally, network theory includes several measures that can be applied to assess the ease of navigation, or movement, around a network that can be used to compare networks of different types.

To develop a network model of the EATN we use the data of Openflights (2010), which contains 525 airports and 3886 air routes (Fig. 1(a)). Following network graph theory we use nodes to represent the individual airports and links to represent the air route connections between them (for a detailed discussion of using network theory to represent real world infrastructure networks the reader is directed to Dunn et al. (2013)). It is worth noting that in a similar manner to Wilkinson et al.

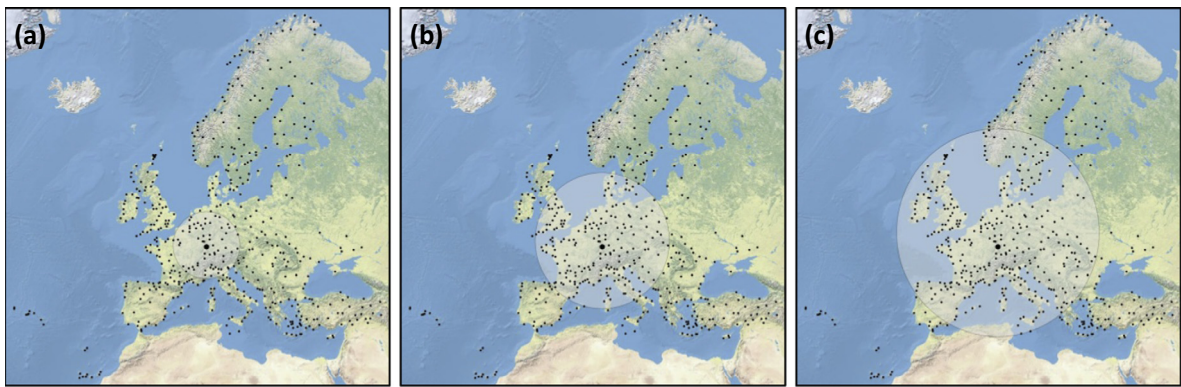


**Fig. 1.** (a) Showing the geographic locations of the 525 airports in the European air traffic network (black dots); (b) showing the proportion of travel disruption (cancelled air routes), relative to the proportion of closed air space, during the Eyjafjallajökull eruption of 14th–21st April 2010 (labelled dots), plotted using data from Wilkinson et al. (2012). Also shown in (b) are two resilience benchmarks, one with the same nodal locations as the European air traffic networks (hollow dots) and the other a uniform with area nodal configuration (black dotted line). The vulnerability of the European air traffic network when subjected to the ‘central attack’ spatial hazard is also shown (grey line) (Fig. 2). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(2012) as we are only interested in whether transfer between airports is possible, we only consider the presence of an air route and not the number of individual flights or the number of passengers travelling along each air route.

The resilience of this network, to spatial hazard, has previously been considered in a study by Wilkinson et al. (2012). In their study, they quantified the impact of the Eyjafjallajökull eruption to the EATN for each particular day of disruption, shown in Fig. 1(b). We compare the results of their analysis to two random networks (termed ‘resilience benchmarks’ in this paper) to determine the resilience of the EATN to that event. These resilience benchmarks have the same number of nodes and links as the EATN and are subjected to the same hazard, but have a different spatial configuration of nodes. In traditional network theory studies where only topology is considered (i.e. spatial distribution is ignored) topological random networks are normally used as a benchmark of network resilience. The reason for this is that they have homogenous topology (i.e. each node has approximately the same number of connections) and therefore the removal of any node will have the same impact on the network. In this paper, we are assessing the resilience of spatial networks and therefore we need to extend this purely topological approach to include spatial dependence. We do this in two different ways by assigning each node a geographical location. In the first instance we assign nodal location by using the same nodal locations as the EATN, while in the second instance we locate nodes uniformly in space (uniform with area). Our reason for adopting a uniform with area nodal configuration is that a hazard over any part of the network will remove approximately the same proportion of nodes. Including a spatial distribution of nodes allows us to form an assessment of how both topology (i.e. connectivity of links) and spatial configuration (i.e. spatial arrangement of nodes) affects the hazard tolerance of the EATN. Comparing the results of the Eyjafjallajökull volcano, shown in Fig. 1(b) to those of the resilience benchmark with the uniform with area nodal configuration, shows that the EATN was vulnerable to all locations and sizes of the ash cloud, with the exception of the 14 April 2010. However, comparing the results to the resilience benchmark with the same nodal locations as the EATN shows that the network was either resilient, or had the same resilience, to all locations of spatial hazard. The reason for this is because the ash cloud from the Eyjafjallajökull volcano (on the 14 April 2010) mainly affected the perimeter of the network and did not affect the area where there is a high density of highly connected airports located around the geographic centre.

In this paper, we assess the ability of two resilience strategies to increase the resilience of the EATN when subjected to a spatial hazard; however, we do not consider the actual Eyjafjallajökull event, but instead use a spatial hazard located at the geographic centre of the network (over the area where there is a high density of airports), as we want to consider the worst possible case of disruption. This area around the geographic centre of the network, encompasses all of the London airports (UK), Charles de Gaulle (France) and Schipol Airport (Netherlands), among others, and is considered to be the ‘weak spot’ of the EATN (Scaini et al., 2014). This spatial hazard ‘grows’ outwards from the geographic centre of the network and airports are closed, and their connecting air routes cancelled, as they become enveloped by the hazard (Fig. 2). Whilst the location of this spatial hazard results in the ‘worst case’ impact, the circular shape of the hazard is somewhat arbitrary and while not necessarily consistent with real spatial hazard (e.g. areas susceptible to heavy snowfall or ash cloud formation) it is the most generic for considering spatial hazard. We initially subject the EATN, without applying either of the resilience strategies and a benchmark random network, to this location of spatial hazard to form our resilience benchmarks for comparison. The results for the unmodified EATN are shown in Fig. 1(b), where it can be seen that the disruption caused to the EATN from this location of spatial hazard is greater than that observed in the Eyjafjallajökull event, for example closing only 5% of airports results in the cancellation of approximately 60% of air routes and is also more vulnerability than both random networks.



**Fig. 2.** Showing three sizes of the simulated 'central attack' spatial hazard, in which the hazard starts on the geographic centre of the network (large black dot) and grows outwards until all airports have been removed (i.e. from (a) to (b) to (c)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 3. Resilience strategies

In both of these resilience strategies, several assumptions have been made to ensure that they are realistic and could be used as a basis for informing more sophisticated methods (accounting for social and economic elements, as well as the movement of individual aircraft). It is assumed that the location of airports cannot be altered and that existing airports cannot be removed, nor additional airports introduced. Similarly, it is assumed that air routes cannot be added to the network. In the most extreme case adding additional air routes to create a homogenous network, where every airport is connected to every other airport, would no doubt create the most resilient network, but conversely would also be the least economically viable. We also assume that in the 'adaptive' strategy under normal operational conditions the EATN is optimally configured to maximise social and economic benefits; therefore, introducing new air routes to link previously unconnected airports (that have yet to be impacted by the hazard), would serve little benefit. It is also assumed that airports have a certain amount of surplus capacity that can be utilised, particularly at short notice in the event of a hazard scenario (e.g. as air routes become diverted, potentially whilst the aircraft is in flight).

The first resilience strategy considered proposes to 'permanently' alter the topology of the network and in doing so considers a trade-off between the optimised social and economic factors of the actual EATN and the resilience of the network. In this strategy, we use the network generation algorithm developed by Wilkinson et al. (2012) to generate synthetic proxies for the EATN, but limit the maximum number of air routes that can be connected to any one airport. Reducing the number of air routes connected to a hub airport, should decrease the impact that the closure of this airport has to the remaining network (as fewer air routes will be affected). In their algorithm, Wilkinson et al. (2012) begin with a series of starting nodes,  $m_0$ , which are all connected, via air routes (or links), and assigned a spatial location. In this paper, we assign these nodes a location that corresponds to one of the actual airports in the EATN. At each step, a new node is added to the network and we again assign a spatial location corresponding to one of the actual airport locations. We then generate, between 1 and  $m_0$ , links and calculate the probability of attachment of this node to nodes in the existing network based upon the degree of all nodes within a neighbourhood radius,  $r$ , around the node we are attempting to attach to. Where the size of the radius,  $r$ , represents the distance people are prepared to travel overland to reach an airport. Following Wilkinson et al. (2012) we also allow a proportion of links to form between pairs of pre-existing nodes (simulating the establishment of new air routes between existing airports). This process is illustrated using a flow diagram, Fig. 3. We generate the networks in this paper, by using the same input values for  $m_0$  and  $r$  as Wilkinson et al. (2012) (0.15 and 0.8 respectively), but equate the probability of attachment that a link (air route) will connect to an existing airport to zero for airports that have reached their maximum permitted capacity.

We generate a range of networks, with different maximum values of air routes per airport (20, 50 and 100), to gauge the impact on resilience (for comparison the most connected airport in the network model, London Stansted, has 133 connected air routes). The degree distribution, defined as the cumulative probability distribution of the number of connections that each node has to other nodes, for these generated networks (and the EATN) is shown in Fig. 4, along with the spatial degree distributions for these networks. By limiting the number of air routes that an airport has the disruption caused when that airport is closed by hazard should be reduced compared to the unmodified EATN, thereby increasing the resilience of the network. It is acknowledged that many airports, including Heathrow, are reluctant to decrease the number of air routes they operate (for financial reasons) and that this could significantly reduce the viability of implementing this strategy; however, we develop and assess this 'permanent' strategy to quantify its potential for increasing the resilience of the EATN compared to implementing an 'adaptive' strategy.

In the second resilience strategy air routes are 'adaptively' redirected from airports that have become enveloped by the growing spatial hazard to their closest operational airport (i.e. the closest airport outside the hazard) provided that there is



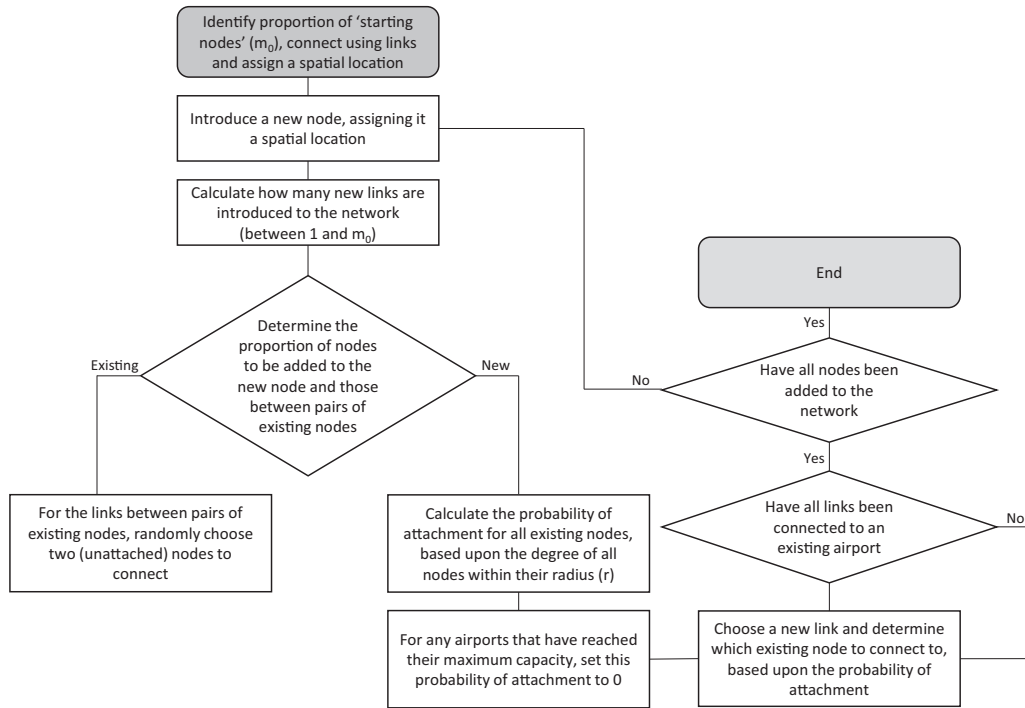


Fig. 3. Flow chart illustrating the methodology used in the 'permanent' resilience strategy.

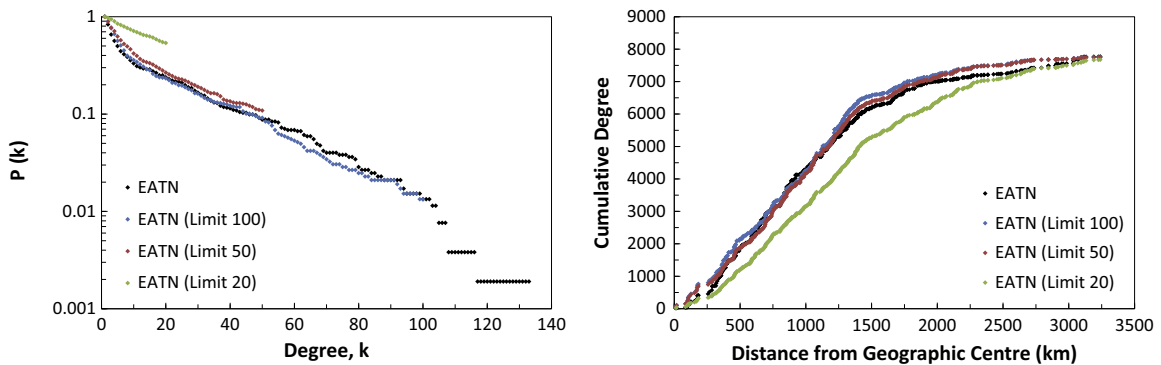
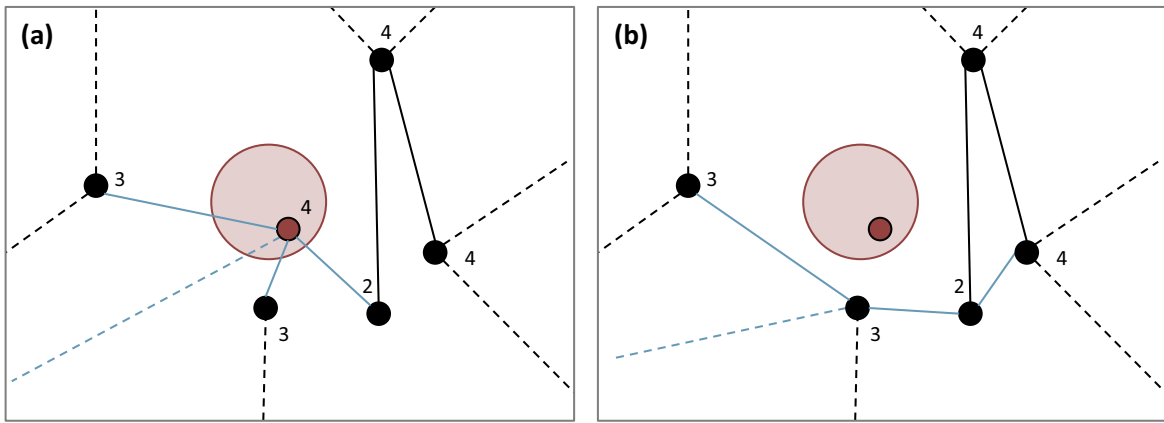


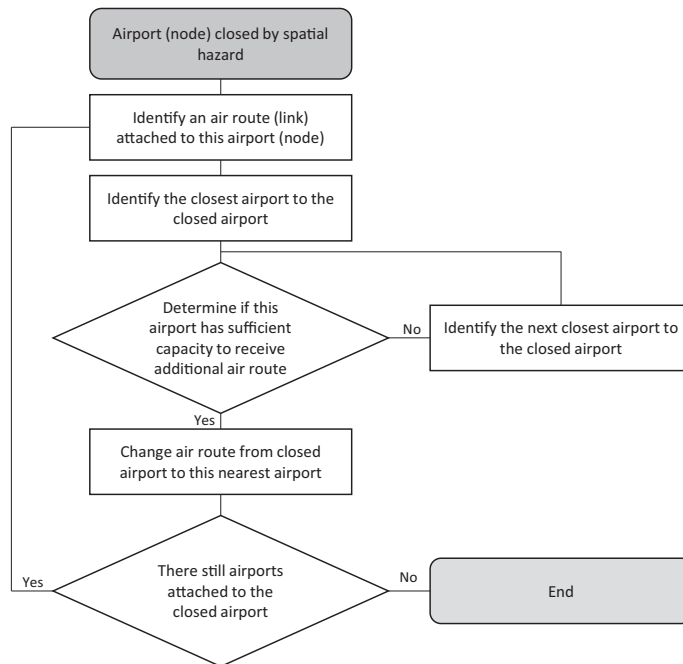
Fig. 4. Showing (a) the degree distribution and (b) the spatial degree distribution for the European air traffic network and the three 'permanently' modified networks. The degree distribution of a network,  $P(k)$ , gives the cumulative probability that a selected nodes has  $k$  or greater links.  $P(k)$  is calculated by summing the number of nodes with  $k = 1, 2, \dots$  links divided by the total number of links in the network. The spatial degree distribution is obtained by first calculating the weighted geographic centre of the network and then summing the degree of each node (i.e. the number of connections a node has) within a given radius.

sufficient surplus capacity to do so (illustrated in Fig. 5 and also shown as a flow chart in Fig. 6). The amount of air traffic arriving and departing from airports can vary depending on the time of day, day of the week or season. As such, the vast majority of airports do not continuously operate at maximum capacity; for example, in the summer of 2012 it has been reported that London Gatwick airport had 12% of unused runway slots, whilst London Stansted and Luton had 47% and 51% unused slots respectively (Transport Committee, 2013b). We assume that each airport has a certain proportion of surplus capacity, with which it can receive redirected air routes, based upon the proportion of air routes that it has under normal operational conditions; for example if we assumed that all airports had a surplus capacity of 10%, an airport with 20 air routes (under normal operational conditions) would be able to accept two air routes from a closed airport (e.g. 22 air routes in total).

In this paper, we use five different values of surplus capacity (5%, 10%, 20%, 50% and 100%), to gauge the impact that this has to the resilience of the EATN. We acknowledge that in real world air traffic networks there will be very few, if any,



**Fig. 5.** Illustrating the strategy used to ‘adaptively’ rewire air routes (links) in the event of a spatial hazard. In both parts of the figure only a section of the EATN is shown for clarity and the airports (nodes) are indicated by dots and the air routes (links) by connecting lines (solid lines indicate a link between two shown nodes and a dotted line between two nodes where one has been omitted for clarity). The numbers beside each node indicate the degree of the node (equal to the number of air routes attached to it). In (a) it can be seen that one airport (red dot) has been enveloped by a spatial hazard (shaded red circle). The blue air routes are ‘rewired’ to the closest airport, the result of this can be seen in (b). It is worth noting that in this example, it is assumed that each airport has sufficient capacity to accept the new air routes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

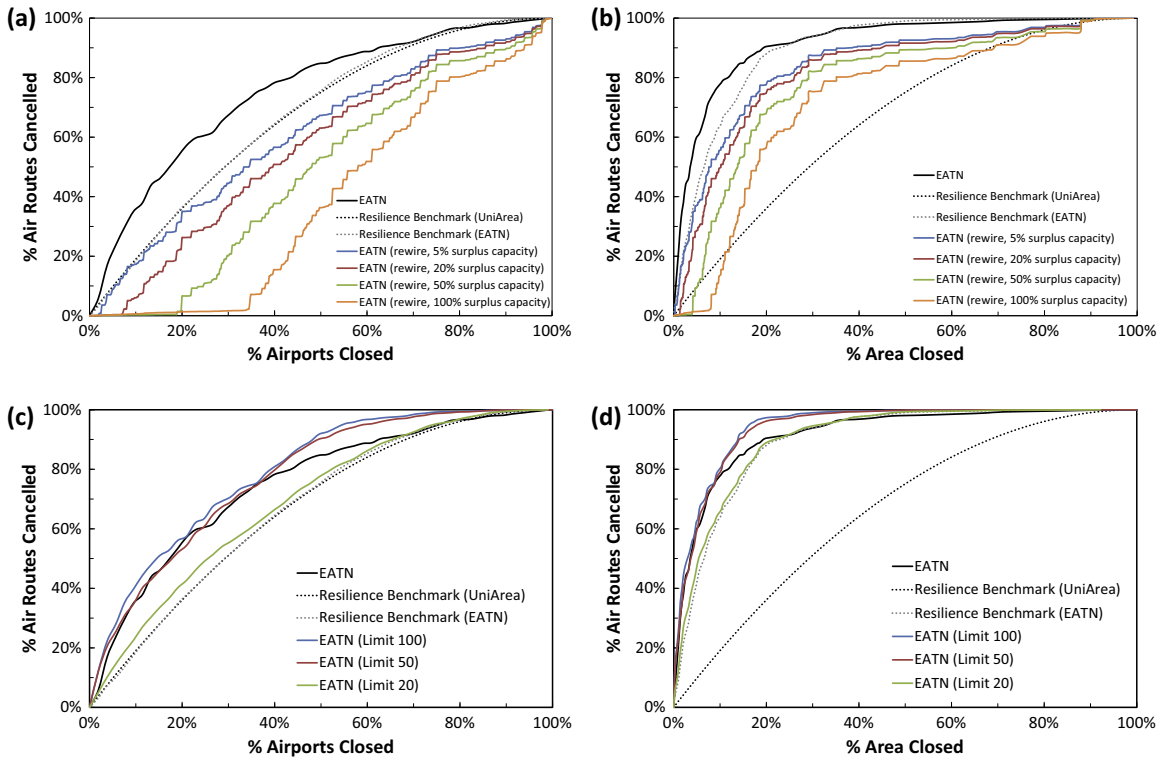


**Fig. 6.** Flow chart illustrating the methodology used in the ‘adaptive’ resilience strategy.

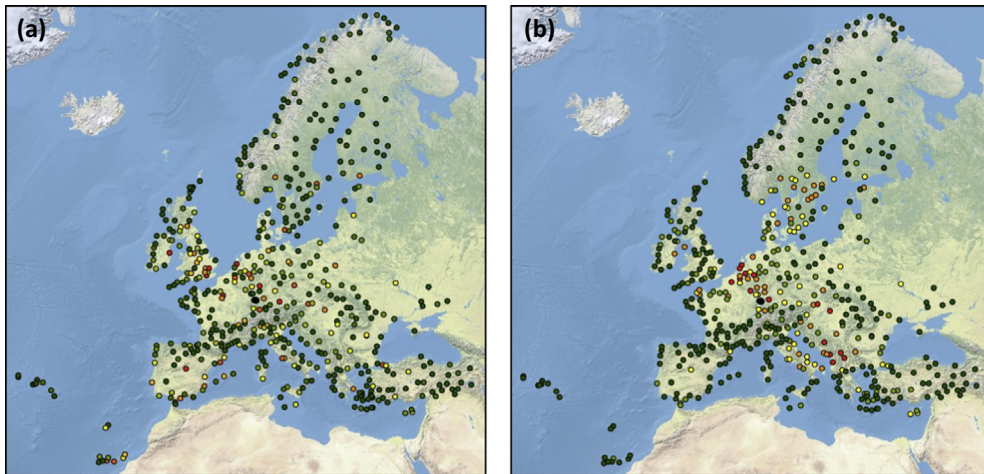
airports that have a surplus capacity of 50% or 100%, however we use these values to assess the limits to extra capacity for improving the resilience of a network.

**4. Initial quantification of resilience**

To initially assess and quantify the impact that the ‘adaptive’ and ‘permanent’ strategies has to the resilience of the EATN, we plot the proportion of cancelled air routes and the proportion of closed airports and closed (or affected) area, shown in Fig. 7. From this figure, it can be seen that the ‘adaptive’ resilience strategy enhances the resilience of the EATN, making the network resilient to all sizes of spatial hazard when compared to both of the benchmark networks (dashed lines), when plotting the results in terms of the proportion of cancelled air routes and closed airports (Fig. 7(a)). To quantify this change in



**Fig. 7.** The results of the (a, b) adaptive and (c, d) permanent resilience strategies, applied to the EATN, when subjected to the 'central attack' spatial hazard (Fig. 2). Showing the results plotted in terms of the proportion of links (air routes) removed and the proportion of (a, c) nodes (airports) and (b, d) area (airspace) removed. Also showing the EATN (blue line) without any applied resilience strategy and two random benchmark networks, one with the same nodal configuration as the EATN (grey dotted line) and the other a uniform with area configuration (black dotted line).



**Fig. 8.** Generated GIS images showing the degree of all nodes in (a) the EATN and (b) a synthetic network, generated using the 'permanent' resilience strategy with the maximum number of air routes connected to any airport limited to 100, on a red (highly connected) to green (weakly connected) scale. The geographic centre of the EATN is also shown (black dot). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

resilience compared to the EATN, rewiring air routes for a surplus capacity of 5% results in 18% points fewer cancelled air routes when 10% of airports are closed by the hazard, and a surplus capacity of 20% results in the cancellation of 29% points fewer air routes for the same size hazard. Comparing these results to those for the 'permanent' resilience strategy shows that the 'adaptive' strategy is superior for this case. The 'permanent' strategy does not noticeably increase the resilience of the

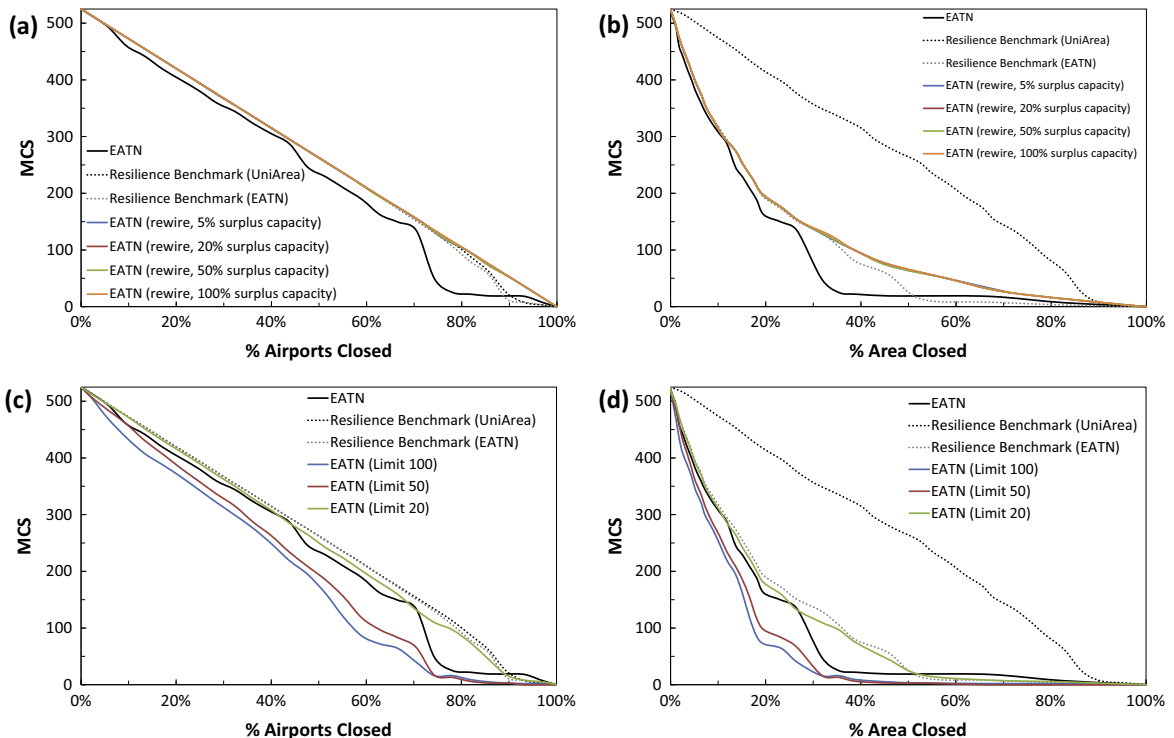
EATN (by reducing the proportion of cancelled air routes) until the size of the largest airport is limited to 20 connected air routes (Fig. 7(c)). This is due to the location of the majority of highly connected ‘hub’ airports around the geographic centre of the network (shown in Fig. 8). The removal of these ‘hub airports’ has a disproportionate impact to the remaining network, causing the network to be vulnerable to all sizes of this location of spatial hazard.

This resilience is also shown by the ‘adaptive’ resilience strategy when the results are plotted in terms of the proportion of cancelled air routes and closed area and compared with the resilience benchmark with the same nodal configuration (Fig. 7(b)). However, when compared with the resilience benchmark that has a uniform with area nodal configuration this resilience is not replicated. This is due to the differences in the nodal configurations of the EATN, which has a high density of airports around the geographic centre of the network (Fig. 2), and the benchmark network, which has an even spread of nodes over its network area. As such, the benchmark network shows the same resilience to all locations of spatial hazard, but the EATN shows vulnerability to hazards located over the geographic centre, as a small increase in hazard size closes a disproportionately large number of airports and consequently a disproportionately large number of air routes.

## 5. Investigating the change in connectivity

To investigate the impact that the two resilience strategies have to the connectivity of the network, we apply the MCS graph theory measure. The MCS of a network is defined as the total number of nodes in the largest cluster of the network and for a network that is not fragmented (i.e. where all nodes are connected via links) this value is equal to the total number of nodes in the network (Nojima, 2006). For a fragmented system, this measure gives an indication of how many nodes can still be reached via links within the largest remaining component. Applying this measure to the EATN will reveal the proportion of the network that can be travelled via air routes and if the network is resilient then it will have the same value as the benchmark random network (where the removal of one node, causes the MCS to drop by one).

The results of this analysis have been plotted in Fig. 9, where it can be seen that the unmodified EATN shows a reasonably high level of resilience to the spatial hazard, when the results are plotted in terms of the proportion of airports closed (Fig. 9 (a) and (c)), and only shows a significant decrease in connectivity when 70% of the airports have been closed by the hazard. However, this resilience, to both benchmark networks, is not replicated when the results are plotted in terms of the



**Fig. 9.** Showing the change in connectivity (assessed using MCS) for the (a, b) adaptive and (c, d) permanent resilience strategies, applied to the EATN, when subjected to the ‘central attack’ spatial hazard (Fig. 2). The results are plotted in terms of MCS and the proportion of (a, c) nodes (airports) and (b, d) area (airspace) removed. Also showing the EATN (blue line) without an applied resilience strategy and two random benchmark networks, one with the same nodal configuration as the EATN (grey dotted line) and the other a uniform with area configuration (black dotted line).



proportion of area removed (Fig. 9(b) and (d)). The network remains resilient when compared to the benchmark network with the same nodal configurations, but not to a uniform with area configuration, indicating that this vulnerability is again due to the high density of airports around the geographic centre of the network.

Comparing the results for the two resilience strategies again shows that the ‘adaptive’ strategy is superior at increasing the resilience of the EATN, because it ensures that connectivity is maintained as the hazard size increases. This adaption strategy has the same resilience as both benchmark networks when the results are plotted in terms of the proportion of airports closed, indicating that it is still possible to travel to all open airports in the network via air routes (Fig. 9(a)). However, in a similar manner to the actual EATN this connectivity is not maintained when the results are plotted in terms of the proportion of area closed, due to the high concentration of airports around the geographic centre of the network (Fig. 9(b)). It is also interesting to note that the same result is calculated when airports have a surplus capacity of 5% and 100%, indicating that only a small surplus capacity is needed to produce a more resilient network using this network measure. The ‘permanent’ resilience strategy actually decreases the resilience of the EATN when the maximum number of connected air routes is limited to either 50 or 100, and only shows a slight increase when this is limited to 20 air routes (Fig. 9(c) and (d)). This is again due to the concentration of high degree airports around the geographic centre of the network, meaning that for only a small size spatial hazard (in this location) the majority of the ‘hub’ airports are removed and therefore not only does the proportion of air routes removed decrease disproportionately (Fig. 7(c) and (d)), but so does the connectivity of the network.

## 6. Investigating the change in efficiency

To investigate the change in efficiency of the network (i.e. the ease of travel around the network), we use the shortest APL, which is determined using Eq. (1) (Boccaletti et al., 2006). This measure is defined as the average number of steps along the shortest path between all pairs of nodes (or airports) in a network (Barthelemy, 2011). The higher the value of APL the more inefficient the network (as on average there are more air routes between each pair of airports). If the network is fragmented then this value is calculated using the largest connected component (i.e. the largest cluster).

$$L = \frac{1}{N(N-1)} \sum_{ij \in \mathcal{N}, i \neq j} d_{ij} \quad (1)$$

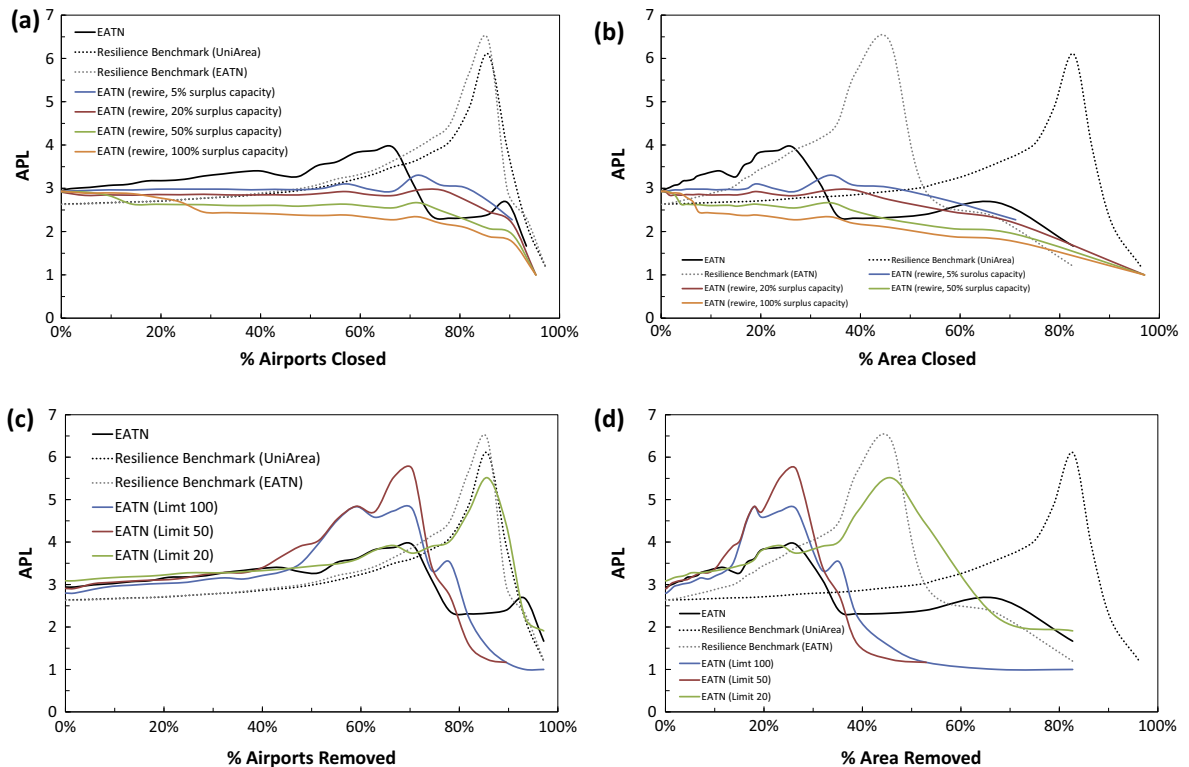
where  $L$  is the shortest average path length of the network,  $N$  is the total number of nodes and  $d_{ij}$  is the shortest path length between node  $i$  and node  $j$ .

However, when using APL it is important to recognise that this measure can give misleading results when the network becomes degraded by hazard and breaks into clusters. In this case, the measure can show an apparent increase in efficiency, which is only a result of the reduced MCS, at this point APL can no longer be considered a valid measure of efficiency (Nojima, 2006). For example, this measure can be used to indicate the efficiency of the resilience benchmark network until 83% of airports are closed where the APL peaks at 6.10 (Fig. 10(a)), after which the APL of the network decreases dramatically.

Applying this measure to the unmodified EATN shows that this network maintains a reasonable level of efficiency compared to the resilience benchmark, until around 50% of the airports in the network have been closed by the spatial hazard, when the efficiency reduces (i.e. the APL increases) with the APL peaking at 3.94 when 70% of the airports are closed. However, this resilience is not replicated when the results are plotted in terms of the proportion of closed area, with the peak APL value occurring when only 27% of the area is closed; this can again be attributed to the high density of airports around the geographic centre of the network. Whilst, the two benchmark random networks maintain efficiency until around 50% of airports are removed when they rapidly decrease in efficiency. The benchmark network with the same nodal locations as the EATN becomes more inefficient quicker than the uniform with area benchmark network when the results are plotted in terms of the area closed; which is again due to the high density of nodes around the geographic centre of the EATN nodal configuration.

Comparing the results for the two resilience strategies, again shows the ‘adaptive’ strategy to be superior, as these networks maintain efficiency as the hazard size increased, with the network that has a surplus airport capacity of 5% having a maximum APL value of 3.30 (16% lower than the unmodified EATN) (Fig. 10(a)). This maintenance of efficiency is also replicated when the results are plotted in terms of the proportion of area closed (Fig. 10(b)). The results for the MCS showed that modifying the EATN using this ‘adaptive’ strategy caused the network to maintain connectivity, where it is possible to travel to all open networks, and from the APL results it can be concluded that it is still relatively easy to travel to any of these open airports.

The networks generated using the ‘permanent’ resilience strategy maintain approximately the same efficiency as the unmodified EATN until 40% of the airports have been closed, after which the efficiency of the networks where the maximum number of connected air routes is limited to 50 or 100 decreases when compared to the EATN (Fig. 10(c) and (d)), peaking at 5.71 and 4.83 respectively. Therefore, the ‘permanent’ resilience strategy not only causes the connectivity of the networks to decrease, compared to the EATN (Fig. 9(c) and (d)), but also causes them to become more inefficient when subjected to hazard. However, it is interesting to note that the network where the maximum number of connected air routes was limited to 20 shows a similar level of efficiency as the benchmark network (with the same nodal configuration as the EATN) and is due to the homogeneous nature of the network (i.e. each airport has approximately the same number of connections) (Fig. 10(c)).



**Fig. 10.** Showing the change in performance (assessed using APL) for the (a, b) adaptive and (c, d) permanent resilience strategies, applied to the EATN, when subjected to the ‘central attack’ spatial hazard (Fig. 2). The results are plotted in terms of MCS and the proportion of (a, c) nodes (airports) and (b, d) area (airspace) removed. Also showing the EATN (blue line) without any applied resilience strategy and two random benchmark networks, one with the same nodal configuration as the EATN (grey dotted line) and the other a uniform with area configuration (black dotted line).

## 7. Conclusions

In this paper we have considered two methods of increasing the resilience of air traffic networks to spatial hazard (caused by weather-related events, for example). One strategy ‘adaptively’ modified the topology of the network, moving air routes as one of their connected airports was enveloped by the spatial hazard, whilst the other ‘permanently’ modified the topology of the network. We applied both of these resilience strategies to the EATN and subjected the networks to a growing spatial hazard located over the geographic centre of the network, choosing this hazard location to cause the most disruption to the network. We quantified the resilience of the networks by initially plotting the proportion of cancelled air routes and the proportion of closed airports and area, and then by applying a network graph theory measure of connectivity (MCS) and performance (APL).

From this analysis we have gained several managerial insights into the function and operation of air traffic networks. We have shown that the ‘permanent’ strategy has little benefit to the resilience of the EATN. This strategy is largely ineffective until the maximum number of air routes per airport is severely reduced (to 20 compared to 133 observed in the actual EATN) and this only results in a maximum 15% point reduction in cancelled air routes. This is a result of the geographic layout of the airports dominating the resilience, rather than the air route connections (i.e. there is no generic solution to improving resilience based on optimising linkages and therefore dynamic contingency plans are essential). The US and China air traffic networks have been observed to have similar topological characteristics as the EATN and as such, it is likely that the same conclusions apply to these networks. We also considered an ‘adaptive’ strategy, showing that it is superior for increasing the resilience of the EATN, as this strategy not only increased the connectivity of the EATN (allowing all open airports to be reached via air routes), but also maintained the efficiency of the EATN (meaning that it is still relatively easy to navigate to all open airports). This is because for a specific hazard, there are possible solutions to disruption; however they need to take the location of the hazard into account. The ‘permanent’ strategy is unable to do this. We also gained an insight into the surplus capacity required to have a positive impact to the resilience of the EATN in the ‘adaptive’ strategy’. If all airports had a small surplus capacity of 5% which could be utilised in a hazard scenario, then 18% fewer air routes are cancelled for a relatively small spatial hazard (covering 10% of the network area) compared to the unmodified EATN. This also enables the network to maintain connectivity, with an MCS value equal to that of the resilience benchmark networks, and performance,

with an APL value 16% lower than the unmodified EATN. Therefore, even a relatively small increase in capacity, of 5%, can dramatically increase the resilience of the EATN. It has previously been discussed that airports do not continually operate at maximum capacity, therefore rerouting air routes in hazard scenarios is a feasible option. This strategy should also be possible to implement, but would depend upon dialogue between airports (particularly the major hub airports) to develop procedures for redirecting air routes in the event that an airport(s) is affected by hazard. This should include provision, and priority, for air routes that are essential to the connectivity of the EATN (or another continent) to the rest of the world and also those with a high number of passengers. Transport options between airports should also be considered, in order to minimise the impact to passengers and also freight.

At this stage, it is not possible to quantify the economic benefits of the 'adaptive' resilience strategy, as this depends upon a number of factors. Firstly, the ability of air carriers to reroute air routes, as carriers would ideally need to reroute to an airport that they currently serve (i.e. with their ground staff and change of air crew if needed). Secondly, this benefit depends upon passengers' willingness to travel to a nearby airport and seek another form of transportation for the end of their journey (it is anticipated that those with longer journey distances would be more willing to travel than those flying within the same country). The work of [Wilkinson et al. \(2012\)](#) shows that people are likely to travel 250 km (approximately 2–3 h driving) under normal operational conditions. Finally, this depends upon the distance between the airport impacted by the hazard and that which the air route is now connected to (and the transportation options available between the two airports). In this effort, the interdependency of air traffic networks with other forms of transport should be considered, ensuring that passengers who have been diverted to a nearby airport can still reach their original destination; in some cases it may be desirable to redirect the air route to a more distant airport, but one that has better transport connections to the original destination airport. It is suggested that air traffic networks form dynamic contingency plans that can be quickly initiated to instigate temporary new routes that utilise spare capacity at neighbouring airports to minimise disruptions. These plans should include ring fencing spare capacity at airports for this essential re-routing. Strategies that do not consider re-routing options, fail to appreciate the inherent vulnerability produced by the current location of airports and are likely to be ineffective. This methodology also has the potential to be applied to other networks, where resources are not transmitted through rigid physical connections, but further work is needed to determine if an 'adaptive' solution is best at increase the resilience of other (more physical) infrastructure systems.

## Acknowledgement

This research was partly funded by an Engineering and Physical Sciences Research Council (UK) Doctoral Prize Fellowship (Grant Number: EP/K502893/1 (DTG 2012)) and their support is gratefully acknowledged.

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