# Core and critical cities of global region airport networks

**Abstract**

Air transport is one of the key infrastructures of today's global economy. Connections between airports define airport networks, where nodes are cities served by airports, connected by edges if there is at least one direct flight connecting them. The aims of this research are to relate structural properties of airport networks which explain how these networks respond to isolation of critical nodes, and to gain insight into relevant socio-economic factors that influence the development of airport networks. We split the world airport network (WAN) into seven global region airport networks (GRANs), using the divisions established by OAG database. We gather information about structural properties of each GRAN determining *core cities* through $k$-core decomposition, and *critical cities* through robustness analysis. We find that differences of robustness across GRANs can be explained by the fraction of core cities relative to total cities. Furthermore, analysis of multilevel structure reveal relevant differences between GRANs, rooted on geographical and socio-economic factors, and give insight about how network robustness in airport networks can be enhanced.

*Keywords:* Air transport networks, Complex networks, Core cities, Critical cities

## 1. Introduction

Many of today's key infrastructures that facilitate the exchange of goods, people and information across the world are networked systems. The study of these systems is the aim of complex networks theory. This theory has been extensively applied to transportation systems, such as urban traffic (Porta et al., 2006; Crucitti et al., 2006), railway (Seaton and Hackett, 2004) or subway (Latora and Marchiori, 2002) networks. An important networked transportation infrastructure is air transport, which can be modelled as an airport network, where airports or cities are represented by nodes connected by an edge if there is at least a direct flight between them (Zanin and Lillo, 2013; Lordan et al., 2014a).

The structural properties of airport networks have been extensively analysed, at the local or regional level (Li-Ping et al., 2003; Li and Cai, 2004; Guida and Maria, 2007; Bagler, 2008; Zhang et al., 2010; Wang et al., 2011; Kai-Quan et al., 2012), and also globally (Guimerà and Amaral, 2004; Guimerà et al., 2005). In particular, Guimerà et al. (2005) found that the world airport (WAN) network has a degree distribution with a truncated power-law decaying tail, and a multi-community structure. The later property refers to the presence of central nodes with a low number of connections. These nodes are a consequence of WAN regions with a high density of routes, connected with other regions through a few central gateway airports. This structure is the result of legal, commercial and technical considerations, as airport networks are shaped by the aggregation of airlines (Lordan et al., 2016) and airline alliances (Lordan et al., 2015) decisions, building their route networks trying to maximize their profit keeping with existing regulations (Lordan et al.,

2014a). Recent research has presented techniques of detections of structural properties of complex networks, using $k$-core decomposition to define the multilevel structure, which classifies nodes into core, bridge and periphery levels (Verma et al., 2014). This multilevel analysis allows the definition of a highly connected sub-network of *core* nodes. Core nodes are an alternative to high degree nodes to identify well-connected nodes, as multilevel analysis takes into account the whole network structure. WAN regions can presente differences of multilayer structure, which can determine their properties.

An important property of complex networks is *robustness*, defined as resilience facing node isolation. This property is specially important in transportation networks, as airport closure can have large impact in terms of delays and economic looses (Voltes-Dorta et al., 2017). Contrarily to random networks, scale-free networks are resilient to isolation of random nodes (errors), but not to isolation of specific nodes (attacks), selected with a criterion of centrality or importance (Albert et al., 2000). This has been empirically confirmed in the case of air transport networks, where attacks are simulated isolating nodes sequentially using a node selection criterion, and examining the evolution of the size of the largest connected component as a function of the fraction of disconnected nodes. An effective node selection criterion detects the *critical* nodes of the network, as the ones whose isolation leads of a fastest disconnection. These stream of research (Chi and Cai, 2004; Lordan et al., 2014b) has confirmed that airport networks are resilient to errors, but not to attacks. This can be explained by their truncated power-law distribution (Albert et al., 2000), but extant research suggest that networks having similar degree distributions can behave differently when exposed to attacks.

For instance, while a node selection criterion based on modal analysis is effective to break the power grid (Petreska et al., 2010), the same criterion is not as effective when applied to the WAN (Lordan et al., 2014b). These results suggest that the behaviour of networks exposed to attacks can depend on other structural properties, in addition to degree distribution. The comparison of robustness to attacks of different regional networks can help to gain insight into structural properties that can influence robustness.

The main aim of this research is to relate structural properties of airport networks other than degree distribution that explain how these networks respond to isolation of critical nodes. To achieve this, we take advantage of the multi-community structure of the air transport network to define global region airport networks (GRANs). This research design allows us to explain differences of behaviour facing node isolation through differences in structural properties. In particular, instead of relying on node degree to detect well-connected nodes, we use $k$-core decomposition to detect the core nodes of the network, and instead of relying in betweenness to detect central nodes, we use robustness analysis to detect critical nodes. The second aim is to use core and critical nodes analysis to gain insight into relevant socio-economic factors that influence the development of a regional airport network.

The paper is structured as follows. In the two following sections, GRAN's core nodes are detected through multilevel structure analysis, and critical nodes trough robustness analysis. Then, we report that the fraction of total nodes included in the main core influences network robustness. In the closing section, we summarize the insights obtained comparing GRANs.

## 2. Global regional airport networks

To perform our analysis, we retrieved data about air traffic of August 2015 from the OAG (`https://www.oag.com/`) database. OAG's database contains data about scheduled flights from most of world's commercial airlines, providing an exhaustive sampling of existing airports, needed to get a precise perception of airport networks (Belkoura et al., 2016). OAG also provides information of the main city served by each airport, then we have chosen to define network nodes as cities, similarly to previous research (e.g, Guimerà et al. (2005), Du et al. (2016)). As for connections, data include flights offered by full-service carriers and low-cost carriers. While the former program their flights on a hub-and-spoke basis, offering to customers tickets with connecting flights, customers can enhance self-connectivity (Voltes-Dorta et al., 2017) programming their own multi-scale route buying flights of low-cost carriers. Based on OAG subdivisions, we have defined seven global regions for the WAN: Africa (AF), Asia (AS), Europe (EU), Latin America (LA), Middle East (ME), North America (NA) and Southwest Pacific (SW). Given the particular conditions of the Alaskan region (Guimerà et al., 2005; Lordan et al., 2014b), which may distort the results obtained for North America, we have also considered a global region consisting of North America excluding Alaskan airports (NA-AK).

For each of the global regions an global region airport network (GRAN) is defined, each with a set $\|\mathcal{N}\|$ of $N$ nodes representing cities included in each region. As the vast majority of connections are reciprocal, each airport network can be treated as an undirected network (Lordan et al., 2014b). So, each GRAN is an unweighted, undirected network defined by its adjacency

matrix $\mathcal{A}$, whose components $a_{ij}$ equal one if cities $(i, j)$ have a direct flight between them, and zero otherwise.

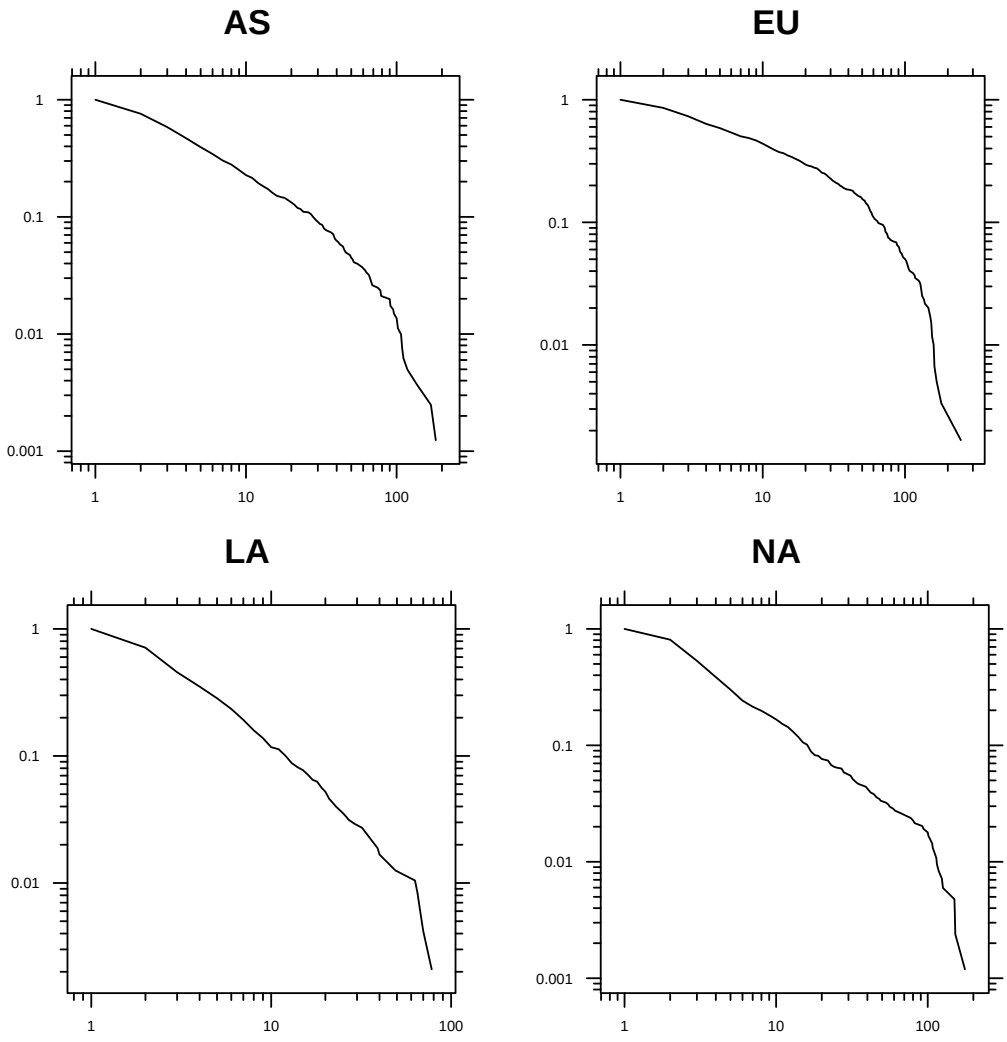
In Table 1 are listed descriptive measures of GRANs. These measures are number of nodes $|\mathcal{N}|$ and edges $|\mathcal{E}|$, average node degree (number of connections of each node) $\langle k \rangle$, network density $d$, defined as the quotient between existing and maximum possible edges, diameter $D$, defined as the shortest path of maximum length, the average value of shortest paths or average path length $L$, efficiency $E$ defined as the harmonic mean of shortest path lengths and average clustering coefficient $C$ or average value across nodes of the probability that two nodes connected to a given node have a direct connection. Values $L_{rel}$ and $C_{rel}$ are the values of $L$ and $C$ normalized with a random network of the same nodes and edges than the incumbent network. The largest GRANs are North America with 838 cities (638 if we exclude Alaska), followed by Asia, Europe and Latin America with 805, 598 and 478 cities, respectively. Europe has a much larger number of connections (6,637) than Asia and North America (4,100 and 3,443, respectively), and far more than Latin America (1,268). The average path length of all networks is similar to a random network, and clustering coefficients much larger to a random network, therefore all these networks have the small world property (Watts and Strogatz, 1998).

Some structural properties of a complex network depend of its degree distribution, which gives the probability $P(k)$ that a node has degree $k$. Figure 1 depicts the cumulative degree distribution for the GRANs of Asia, Europe, Latin and North America. GRANs of all four global regions have a two regime power law distribution. Degree distributions are similar, although

| | $\lvert\mathcal{N}\rvert$ | $\lvert\mathcal{E}\rvert$ | $\langle k \rangle$ | $d$ | $D$ | $L$ | $L_{rel}$ | $C$ | $C_{rel}$ | $E$ |
|---|---|---|---|---|---|---|---|---|---|---|
| AF | 338 | 871 | 5.148 | 0.015 | 8 | 3.405 | 0.915 | 0.699 | 42.718 | 0.324 |
| AS | 769 | 3,852 | 10.010 | 0.013 | 8 | 3.271 | 1.044 | 0.709 | 54.437 | 0.333 |
| EU | 602 | 6,397 | 21.246 | 0.035 | 6 | 2.682 | 1.108 | 0.622 | 17.561 | 0.410 |
| LA | 483 | 1,252 | 5.176 | 0.011 | 8 | 3.324 | 0.847 | 0.718 | 67.021 | 0.325 |
| ME | 105 | 421 | 8 | 0.077 | 5 | 2.533 | 1.035 | 0.776 | 10.103 | 0.450 |
| NA | 899 | 3,540 | 7.860 | 0.009 | 13 | 4.088 | 1.159 | 0.677 | 78.004 | 0.286 |
| SW | 323 | 684 | 4.235 | 0.013 | 8 | 3.598 | 1.130 | 0.692 | 51.307 | 0.308 |
| NA_AK | 687 | 3,168 | 9.208 | 0.013 | 13 | 3.760 | 0.911 | 0.705 | 53.443 | 0.319 |

Table 1: Descriptive measures of GRANs

Figure 1: Cumulative degree distribution of Asia (AS), Europe (EU), Latin America (LA) and North America (NA) global regions

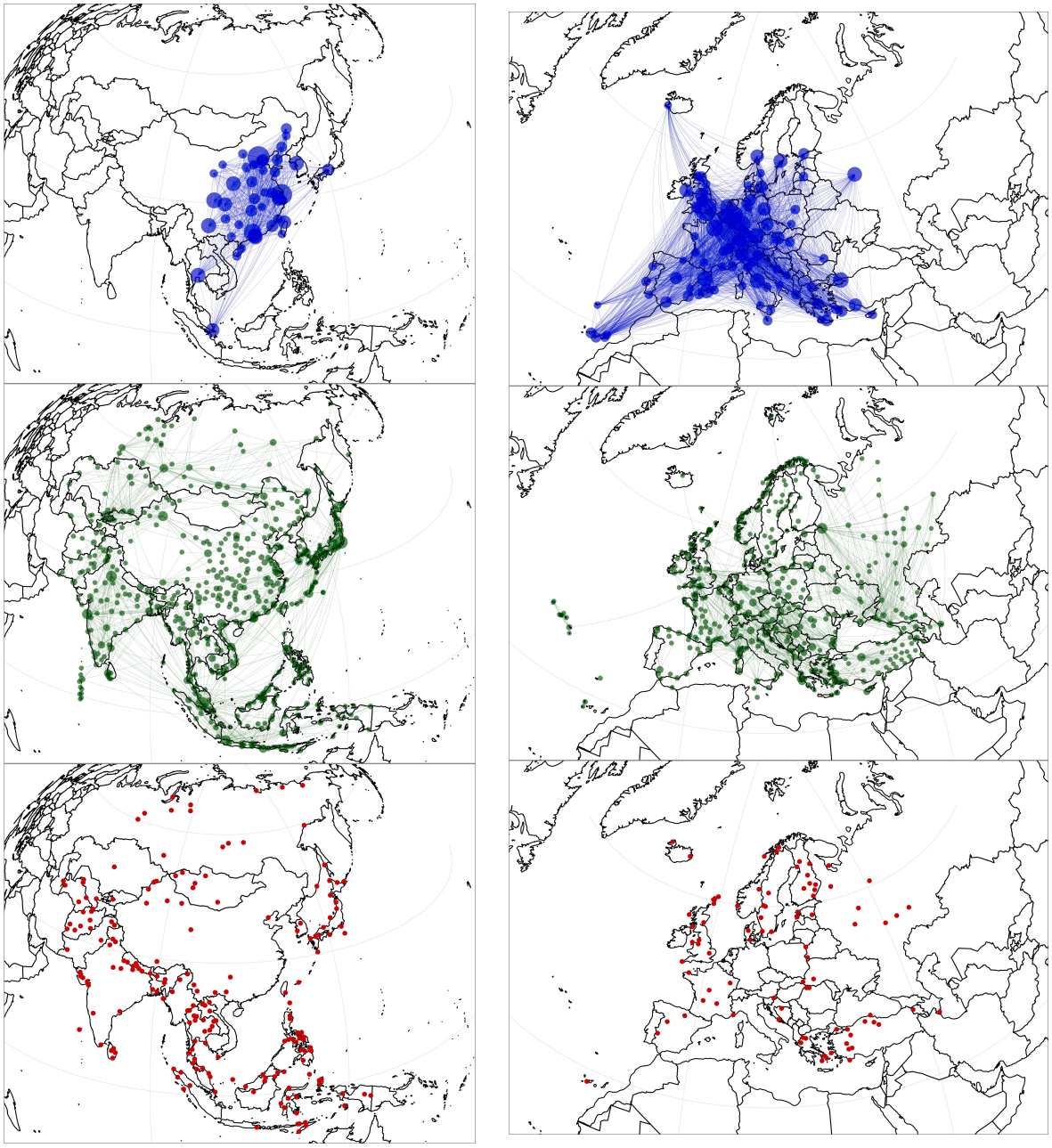


the differences of slope between the two regimes are more salient in Europe, the network with the largest number of connections.

## 3. Detecting core cities through multilevel structure

We have used $k$-core decomposition to detect which cities of each GRAN belong to each core, bridge and periphery. A $k$-core or core of order $k$ of a graph $G$ is a subgraph $H_k \in G$ whose nodes have degree equal or larger than $k$ (Batagelj and Zaversnik, 2003). As cores are nested (the core of order $k$ contains all $i$-cores $H_{i<k}$) any network can be considered as a set of successively enclosed $k$-cores (Dorogovtsev et al., 2006). The core with the highest value of $k$ is the main core, and includes the most cohesive subset of nodes of the network. We consider *core cities* of an airport network the ones included in the main core. Core cities are strongly interconnected and therefore may play a relevant role in the regional economy. On the other extreme, the nodes that are included only in the 1-core constitute the *periphery* of the network, and the remaining cities are included in the *bridge*. Following the heuristic reported in Batagelj and Zaversnik (2003), we have obtained the core, bridge and periphery of each GRAN. The obtained core of all GRANs is a connected graph, providing evidence of the homogeneity of global regions. Information about the core, bridge and periphery decomposition of the four largest GRAN can be seen in Figures 2 (Asia and Europe) and 3 (Latin and Noth America). In Table 2 is listed the number of cities included in the core, bridge and periphery of each region.

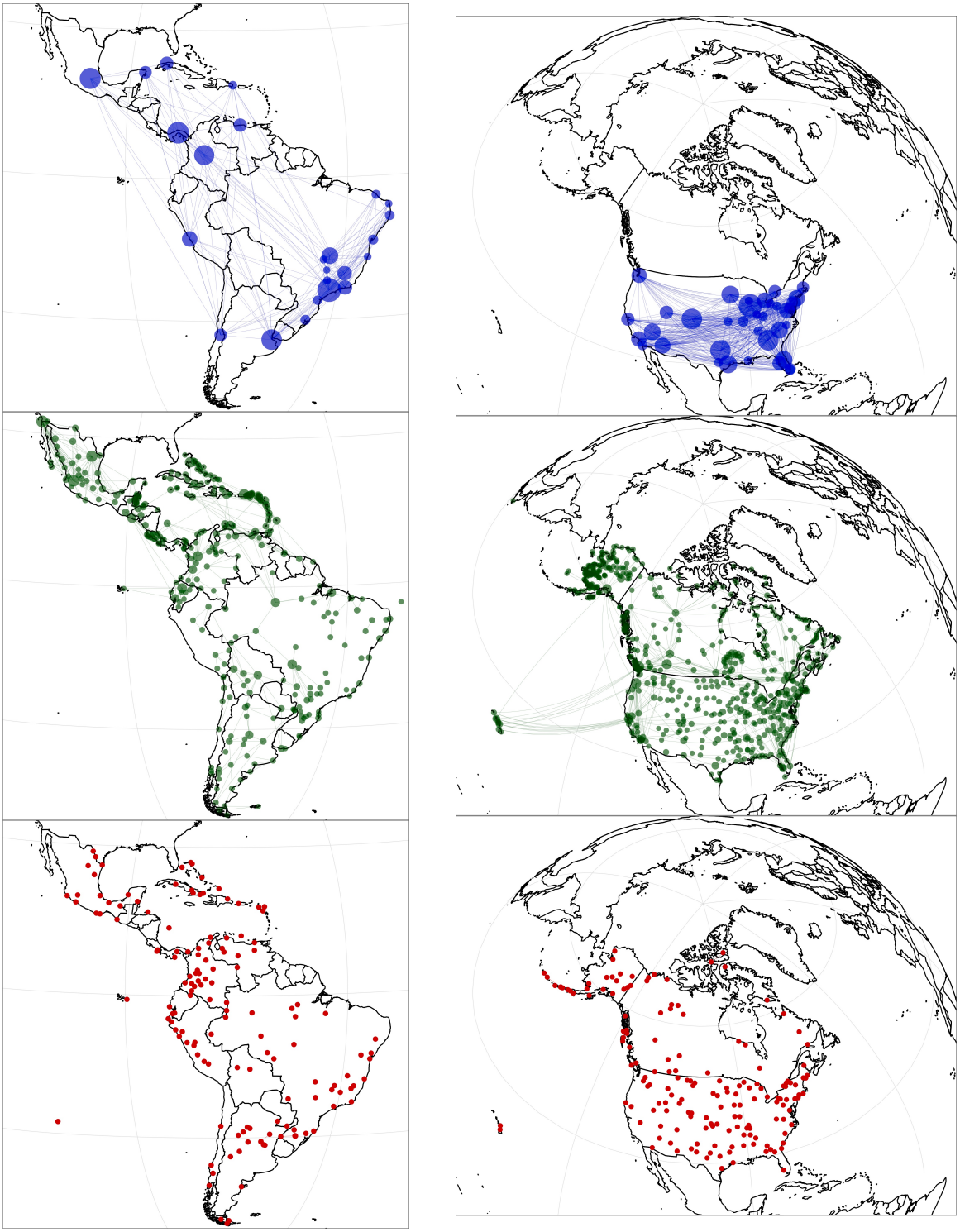
Results show remarkable differences in the multilevel structure of large GRANs. The most polar cases are Europe and North America. Figure 2b



(a) Asia (AS)

(b) Europe (EU)

Figure 2: Core, bridge and periphery of Asia (AS) and Europe (EU)



(a) Latin America (LA)

(b) North America (NA)



Figure 3: Core, bridge and periphery of Latin America (LA) and North America (NA)

Table 2: Number of cities belonging to the core, bridge and periphery of each region

| | AF | AS | EU | LA | ME | NA | SW | NA-AK |
|---|---|---|---|---|---|---|---|---|
| core | 15 | 42 | 89 | 24 | 14 | 36 | 14 | 36 |
| bridge | 257 | 569 | 423 | 314 | 62 | 636 | 222 | 465 |
| periphery | 75 | 194 | 86 | 140 | 14 | 166 | 83 | 137 |
| total | 347 | 805 | 598 | 478 | 90 | 838 | 319 | 638 |

shows that Europe has by far the largest and more connected core, including up to 89 cities scattered mainly across central and western Europe. Eastern European cities belong mainly to the bridge, suggesting that air travel market is less developed in these countries than in the rest of Europe. The presence in the European core of Azores and Canary Islands suggests a developed leisure air travel industry connecting northern European cities with southern leisure destinations.

The multilevel structure of the North American region is quite the opposite of Europe. While Europe has 14.88% of cities included in the core, North America has only 4.29%, being these the largest and lowest values for all regions. In Figure 3b can be seen all cities included in the core but one (Toronto, in Canada) belong to the United States, and none of them is Alaskan. The core of North America includes the main cities of the East and West Coast, and the main hubs of North American airlines, shaping a core of 35 cities. Canadian and Alaskan cities (with the mentioned exception of

Toronto) belong to the bridge, indicating that the Alaskan subregion is less tightly connected that the core of the main cities in north America.The Latin American region has a proportion of core nodes similar to North America. Figure 3a depicts core cities of Latin America include the most relevant capital cities of the region (interestingly, Havana is included in the core), and several Brazilian cities.

Asia's core includes mainly Chinese, Korean and Southeast Asian country cities, including also Tokio. Japanese (except Tokio), Indian and Indonesian cities belong to the bridge of this region. Asia's core structure suggests that the Chinese airport network is the one most tightly connected in the region, and shows the intensity of relationships between China and Korea, Japan,Thailand and Singapore (see core of Figure 2a).

## 4. Detecting critical cities through robustness analysis

One of the interesting properties of complex network is their robustness to errors (disconnection of nodes chosen at random) and attacks (disconnection of nodes chosen to maximize the deterioration of network connectivity). Robustness can be assessed through the evolution of the size of the giant component (the connected component of the graph with maximum number of nodes) as a function of the fraction of disconnected nodes $f$ (Lordan et al., 2014b).

To assess the robustness of GRANs to errors, 5,000 simulations of isolation of nodes at random have been carried out for each network. The reported value is the mean of all simulations for each value of $f$. The robustness of GRANs to attacks has been tested using several adaptive strategies of node

disconnection. Three particularly effective measures (Lordan et al., 2014b) were selected as selection criteria: degree, betweenness and damage. The *degree* $k_i$ of node $i$ is the number of edges incident to the node:

$$k_i = \sum_{j=1}^{n} a_{ij} \tag{1}$$

The *betweenness* $b_i$ of a node $i$ is defined as:

$$b_i = \sum_{i \neq j \neq k \in \mathcal{N}} \frac{n_{jk}(i)}{n_{jk}} \tag{2}$$

where $n_{jk}$ is the number of shortest paths between any pair of nodes $j, k$, and $n_{jk}(i)$ is the number of shortest paths between $j$ and $k$ including $i$. In the context of airport networks, nodes with high degree represent well connected cities, while nodes with high betweenness are associated with central cities. *Damage* of a given node is defined as the reduction of size of giant component when the node is disconnected (Latora and Marchiori, 2005). For each iteration, the adaptive strategy disconnects a node with the maximum value of the measure. Once the node is disconnected, the measure is recalculated for all nodes before selecting the node of the next iteration. The output of the analysis for each selection criterion is a plot of size of giant component as a function of the fraction of disconnected nodes $q$. The resulting plots of the robustness analyses for each of the eight GRANs are depicted in Figure 4. It can be observed that, for all GRANs, the network is resilient to errors but breaks down fast when attacked. This behaviour is consistent with real world scale-free complex networks, and quite different to the behavior of random

networks, which are equally resilient to errors and attacks (Barabási, 1999). This behaviour has been also previously observed for regional (Chi and Cai, 2004) and global airport networks (Lordan et al., 2014b; Verma et al., 2014).

As for the node selection criteria regarding attacks, the degree criterion is the least effective to reduce the size of giant component. In most cases, damage performs better than betweenness for small values of the fraction of disconnected nodes $q$, but betweenness performs better for larger values of $q$. The most critical nodes of the network, in this case the critical cities, will be the first ones to be isolated in the robustness analysis following a node selection criterion. In Table 3 are listed the critical cities obtained by damage criterion for the largest GRANs: Asia, Europe and North America. We have reported cities selected by damage criterion as this is the most effective when the fraction of nodes to remove is low, as can be seen in Figure 4. We have also added the critical cities of North America excluding Alaska, as they are especially relevant in this context.

The case of North America is especially illustrative about the role of critical cities. While in North America the first critical cities are Alaskan (Anchorage and Fairbanks), the exclusion of Alaska fosters the rank of cities with a large connection network like Denver, Vancouver and Minneapolis. Interestingly, Seattle/Tacoma (the main hub of Alaska Airlines) third critical city in North America, drops from the list once Alaskan cities are removed. Stockholm and Helsinki play a similar role in Europe, acting as gateways for a large number of Scandinavian cities. As for Asia, In Asia, the isolation of Bangkok, Manila and Cebu may disconnect the Thai and Philippine cities. A similar phenomenon occurs in Southwest Pacific, where the most critical

Figure 4: Size of giant component vs fraction of disconnected nodes for the GRAN (dotted: random isolation, red:degree, blue:damage, black:betweenness)

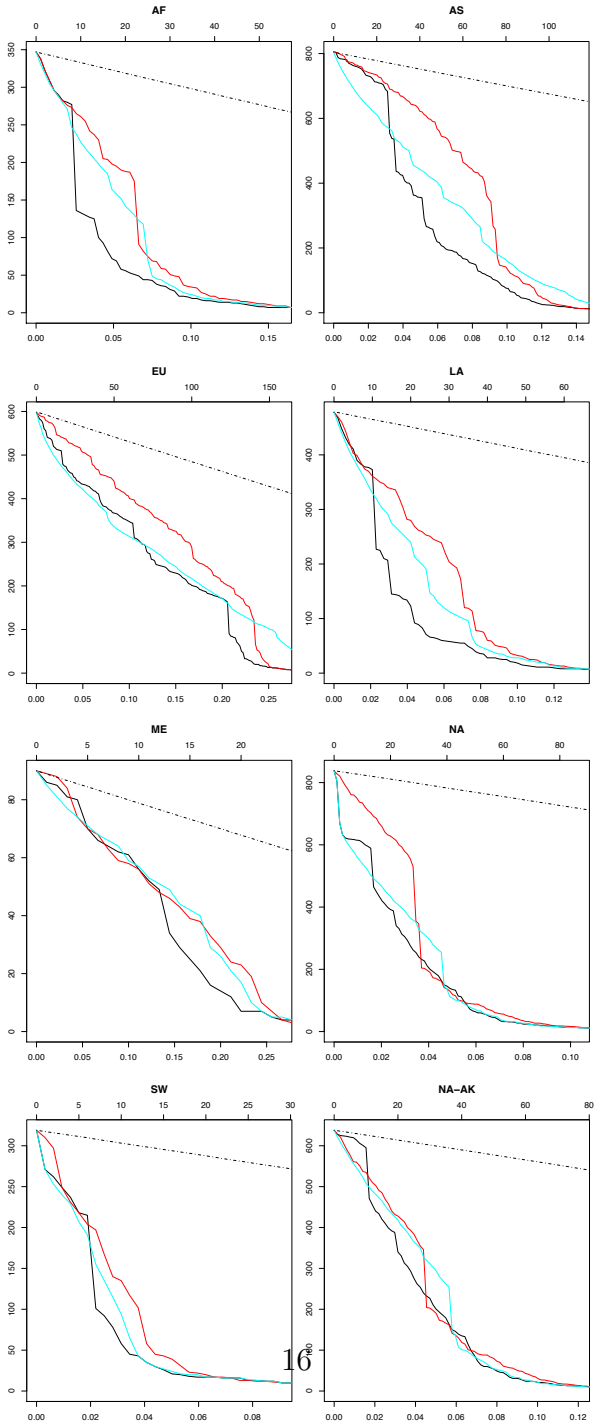


Table 3: Critical airports of largest RAN obtained by damage criterion

| AS | EU | NA | NA-AK |
|---|---|---|---|
| Bangkok | Stockholm | Anchorage, AK | Denver, CO |
| Manila | Helsinki | Fairbanks, AK | Vancouver |
| Cebu | Istanbul | Seattle/Tacoma, WA | Minneapolis, MN |
| Kabul | Ankara | Denver, CO | Dallas, TX |
| Tokyo | Athens | Vancouver | Chicago, IL |
| Colombo | Glasgow | Minneapolis, MN | St. Louis, MO |
| Kathmandu | Moscow | Dallas, TX | Detroit, MI |
| Bombay | Orkney | Chicago, IL | Houston, TX |
| Delhi | St. Petersburg | St. Louis, MO | Atlanta, GA |
| Rangoon (Yangon) | Adler/Sochi | Detroit, MI | Charlotte, NC |

cities are Papeete and Honiara, followed by Perth. What these cities have in common is that act as gateways for relatively isolated regions of each regional network: Alaska in North America, Scandinavia in Europe, Thailand and Philippines in Asia and Polynesia in Southwest Pacific. These relatively isolated sub-networks belong to the bridge, while critical cities usually belong to the core. These results suggest that regional networks have relatively isolated sub-networks belonging to the bridge, connected to the core networks by critical cities. These critical cities can be considered as regional hubs, which has been pointed out in Bagler (2008) in the analysis of the Indian airport network as a complex weighted network, or by Xu and Harriss (2008) in their analysis of the U.S. intercity passenger network, play an important role in network connectivity.

Another interesting result coming from this analysis is the differences in robustness between regional networks, measured by the $R$ parameter (Schneider et al., 2011):

$$R = \frac{1}{N} \sum_{Q=1}^{N} s\left(Q\right) \tag{3}$$

where $N$ is the number of nodes and $s\left(Q\right)$ is the fraction of nodes in the largest connected component after removing $Q = qN$ nodes. Using the normalization factor $1/N$ ensures that the robustness of networks with different sizes can be compared. The value of this index varies from 0 to 1/2, and larger for robust networks. As extant research considers that robustness behaviour is mainly influenced by degree distribution (Albert et al., 2000), all GRANs may yield similar values of $R$.

We have calculated the values of $R$ for each GRAN performing robustness analysis using betweenness criterion. Contrarily to expectations, GRANs have quite diverse robustness behaviour. While Europe $R_{EU} = 0.121$ and Middle East $R_{ME} = 0.143$ have relatively high values of robustness, North America ($R_{NA} = 0.028$) and Southwest Pacific ($R_{SW} = 0.029$) have low values (North America's $R$ goes up to $R_{NA-AK} = 0.043$ when removing Alaska).

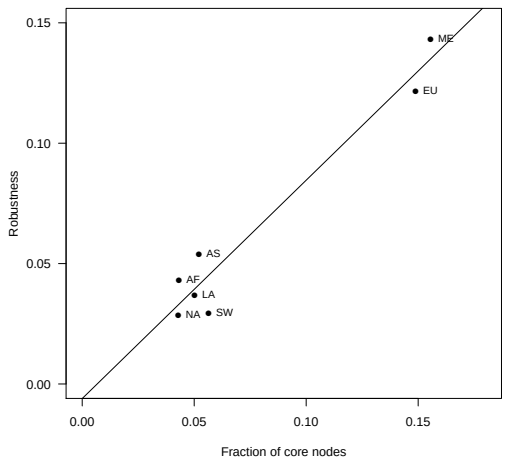
These differences in robustness can be explained by multilevel structure. Considering the large GRANs, Europe (see Figure 2b) has a larger core than North America (Figure 3b). In Figure 5, where is plotted the robustness parameter $R$ as a function of normalized core size, it can be seen that these relationship is maintained also for small networks: the Middle East GRAN behaves like to Europe, and Southwest Pacific like North America.

Therefore, the differences of resilience to targeted attacks between GRANs can be explained by their multilevel structure. Evidence shows that a large number of core cities enhances network robustness, as a larger fraction of nodes should be isolated to disconnect the network. This finding adds another explanatory variable to robustness for airport networks.

## 5. Conclusions

In order to find determinants of network robustness in airport networks, for each GRAN a multilevel and a robustness analysis has been performed. The multilevel analysis divides network nodes in core, bridge and periphery (see Figures 2 and 3 for maps for each level of the largest GRANs, and Table 2 for results for all GRANs). We have defined *core nodes* as the ones

Figure 5: Network robustness as a function of normalized core size ($r = 0.9849$)




contained in the main core obtained through $k$-core decomposition. Robustness analysis consists of assessing the evolution of the size of the largest connected component as a function of the fraction of isolated nodes. This analysis has been performed simulating errors (isolation of nodes at random) and attacks (isolation of nodes following adaptive strategies based on damage, node degree and node betweenness). The results of this analysis can be seen in Figure 4.

Performing a robustness analysis for a set of GRANs allows comparing their behaviour, finding differences and similarities. As for similarities, all GRANs are more resilient to errors than to attacks. The most effective criterion of selection of important nodes is damage for a small fraction of isolated nodes, replaced by betweenness as the fraction of removed nodes increases.

Therefore, the first cities isolated by the damage criterion are the *critical cities* of each GRAN (see Table 3) This behaviour is similar to the predicted theoretically for networks with truncated power-law distributions (Albert et al., 2000) and to the observed empirically for the world airport network (Lordan et al., 2014b). Differences appear when robustness to attacks is compared across GRANs, examining differences of robustness through the $R$ parameter (Schneider et al., 2011) or examining the fraction of nodes that disconnects the network in Figure 4. As demonstrated in Figure 5, differences of robustness across GRANs can be explained by the number of core cities, normalized by the total number of nodes. This finding helps to explain the behaviour of airport networks in episodes of isolation of important nodes: airport networks with a large main core of densely knit cities (e.g., Europe or Middle East) are more resilient to isolation of critical cities than networks with a smaller core (e.g., North America or Southwest Pacific). This result adds up to evidence of previous research indicating that network robustness does not depend only on degree distribution, but also on other structural properties.

A prescription to enhance airline operations and the robustness of the system would be to plan airline operations to enlarge the size of the main core. Nevertheless, evidence shows that the multilevel structure of GRANs depends of socio-economic and geographical processes. For instance, the absence of many Central and Eastern Europe cities from the core of the European region shows that these economies are still transitioning from socialist command to market demand economies (Jorgenson et al., 2014). The core of the Asian region shows the growing relevance of China as the main Asian economy, as

well as differences of economic development between Chinese regions (Liao and Wei, 2016). A longitudinal examination of the multilevel structure of airport networks can be an effective tool to help to define policies regarding long-range planning of regional networks, in order to reduce the impact of incidents of critical cities in airline operations.

The results of this research suggest that networks showing (at least apparently) similar structural properties can present significant differences in behaviour. As recent research suggests Broido and Clauset (2018), rather than looking for an unifying theme in network science, it can be more fruitful to look for similarities and differences in behaviour in and across network domains.

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