AIRLINE ROUTE NETWORKS

A COMPLEX NETWORK APPROACH

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Als meus pares

ABSTRACT

Communication via air routes is an important issue in a world organized around a web-like city network. In this context, the robustness of network infrastructures, e. g. air transport networks, are a central issue in transport geography. Disruption of communication links by intentional causes (e. g., terrorist attack on an airport) or unintentional (e. g., weather inclemency) could be a serious drawback for countries, regions and airlines. Policymakers and the management of airlines and alliances should be able to reduce the effects of such interruptions in order to ensure good communication through air transport (i. e., maximize the robustness of their network at a reasonable cost). The literature review of the study of air transport route networks through an analysis of complex networks has highlighted a lack of contributions to the study of the topology and the robustness of such networks, which contrasts with advances undertaken for other transport networks or communication systems. The literature survey suggests areas in which research should be undertaken, based on the existing literature in other areas and from three different perspectives: global route networks, airline alliances and airlines. The aim of this research is to develop a better understanding of air traffic and, in particular, to be able to assess the potential damage of any airport being inoperative for a continent, country or airline.

This thesis analyzes the topology and robustness of 3 proposed levels of study characterized by different units of analysis: *global route networks*, *airline alliances route network* and *airlines route network*. The different levels do not only represent different network magnitudes in number of nodes (airports) and links (routes), but also represent different approaches. In Chapter 2 robustness of the global air transport network (L1) will be analyzed and criteria based on Bonacich power centrality will be presented in order to assess attack vulnerability of complex networks. One of the outcomes of this study will be a list of the most critical airports for the vulnerability of the entire air transport network. In Chapter 3 robustness of alliances route network (L2) will be assessed comparing the robustness of the three major airline alliances (Star Alliance, oneworld and SkyTeam). To perform this analysis, one new node selection criterion based on the efficiency of networks and one new method of assessing vulnerability will be presented. This analysis will lead also to a comparison of the robustness of the three alliances. Finally, in Chapter 4 robustness of 10 FSCs and 3 LCCs route network (L2) will be analyzed. The studied FSCs belong to the different airline alliances showed in Chapter 3 thus allowing the comparison among levels. This chapter outlines a comparison of the differences in robustness between FSCs and LCCs. In Chapter 5 a summary and discussion of conclusions obtained for each level will be carried out.

I pay no attention whatever to
anybody's praise or blame.
I simply follow my own feelings

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Gràcies a tots.

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ACRONYMS

AARN Airline Alliance Route Network

ATN Air Transport Network

FSC Full-Service Carrier

HS Hub-and-Spoke

IAS Inverted Adaptive Strategy

L1 Level 1

L2 Level 2

L3 Level 3

LCC Low-Cost Carrier

PP Point-to-Point

RN Random

SF Scale-Free

SW Small-World

Part I

INTRODUCTION

Communication via air routes is an important issue in a world organized around a web-like city network. In this context, the robustness of network infrastructures, e. g. air transport networks, are a central issue in transport geography. Disruption of communication links by intentional causes (e. g., terrorist attack on an airport) or unintentional (e. g., weather inclemency) could be a serious for countries, regions and airlines. Policymakers and the management of airlines and alliances should be able to reduce the effects of such interruptions in order to ensure good communication through air transport (i. e., maximize the robustness of their network at a reasonable cost). The literature review of the study of air transport route networks through an analysis of complex networks has highlighted a lack of contributions to the study of the topology and the robustness of such networks which, contrasts with advances undertaken for other transport networks or communication systems. This survey suggests areas in which research should be undertaken, based on the existing literature in other areas and from three different perspectives: global route networks, airline alliances and airlines in order to develop a better understanding of air traffic and, therefore, to be able to assess the potential damage of any airport being inoperative for a continent, country or airline.

1 AIR TRANSPORT NETWORKS

Air transport is one of the many networked systems that human societies depend upon, as they do on telecommunications, transportation, electricity, water, etc. [1]. These infrastructures, and particularly air transport, have contributed to the shift of the organization of the global economy from "spaces of places" to "spaces of flows" [2, 3]. This change may lead to a new organization of the global space around a "world city network" [4]. The current transport geography shapes and is shaped by the evolution of the network of large cities, mostly connected by the air transport network [5, 6, 7].

Therefore, the global economy has a growing dependence on network based infrastructures that can be described as a set of physical entities located on the surface of the earth. The functionality of these entities can be modelled as a set of nodes and edges connecting them [8]. One of the mentioned infrastructures is the air transport network, which can be schematically represented as a flight network. The flight network nodes are airports, which are connected when a direct flight is scheduled between them [9]. The assessment of the robustness of air transport networks when facing random errors and intentional attacks is, therefore, an important issue on the field of transport geography research. There is a growing concern in the transport geography community about the understanding of the operability and functionality of critical infrastructure systems [10] like the air transport network under severe disruption.

The investigation of complex networks began with the purpose of defining new concepts and measures that allowed to characterize the topology of real networks. The result was the identification of the principles of statistical properties of real networks. However, over the last decade new lines of research have emerged. On the one hand, to address the complexity of the network structure multiple types of networks have been defined and studied. Some examples of networks are weighted networks (i. e., networks with weighted links) [11] and spatial networks (i. e., networks with links that depend on the Euclidean distance between the nodes) [12]. On the other hand, the approach of the studies on this field has changed due to advances in the analysis of complex networks. Currently, the main interest lies in investigating the dynamic behavior of networks. The concepts of robustness, resilience, dynamic collective synchronization or propagation processes were coined as a response to the needs caused by this this new scenario [13].

The theoretical developments around complex networks has helped us to gain understanding around a large number of phenomena, from social networks, economy and communication to financial markets and computer science [14]. There have been a number of applications of complex networks theory to transportation networks, such as streets [15, 16], railways [17], subways [18] and the power grid [19]. Until recently, the analysis of the air transport network has dealt extensively with the study of the global air transport network's topology [20, 21, 22, 23, 24]. The insights gained on topology of real complex networks have allowed the application of techniques of analysis of robustness facing errors and attacks [25, 26].

A common feature of the studies mentioned above is that they are focused in methodology, rather than on organizational considerations. In order to gain insight on the structure and robustness of air transport networks, it can be argued that organizational considerations regarding air transport should be taken into account. In this chapter, it is proposed a framework to study the topology and robustness of the different air transport networks that takes into account the organizational complexities of this industry. The aim of this study is to introduce new lines of research resulting from the application of the complex networks methodology for studying the robustness of networks in the commercial aviation sector. This framework allows the definition of specific solutions for specific regions, airlines or alliances on the network structures the air routes should have in order to minimize the impact of an emergency on one or more of its airports. As a result, the most critical airports to fight against the complete disruption of the activity of a country or an airline can be identified.

Through the discussion of the existing literature, it will be introduced the main lines of research that could help to a better understanding of air traffic from different levels of analysis: *global route network*, *airline alliances*, *airlines* and *airports*.

1.1 THEORETICAL FRAMEWORK

1.1.1 *The air transport industry*

The airline industry has evolved from a mosaic of individual, protected companies to a liberalized system of global business organizations. In the last decade, changes in regulatory regimes in the air transport sector (e. g., the nine freedoms of the air [27]) have driven new strategies for airlines, which were already common in other sectors, such as alliances, mergers or takeovers. This is a consequence of the evolution of an industry that has been characterized by its low profitability and progressive increase of internal competition [28].

Until 1978, governments, national flag carrier airlines and national airports dominated international air transport. In 1979, the US domestic market began to liberalize. As a result Low-Cost Carriers began to appear, mergers occurred, charges fell, the *hub-and-spoke* structure emerged and demand rose [29]. Ten years later, Europe began deregulation with three packages (1988, 1990 and 1993) but it was not until 1997 that the deregulation was complete. The hub-and-spoke network was adopted by flagship carriers while new Low-Cost Carriers configured their routes as *point-to-point*. In this context, airline alliances began to appear. Airline alliances are the result of the need to consolidate traffic from several airports to undertake intercontinental routes, whose demand is growing due to economic globalization [30, 31].

Recently a new deregulation process has started, the Open Skies agreements [32]. On April 30, 2007, the first Open Skies agreement was set. It included the US and EU and allows flights by European or American airlines from anywhere in Europe to anywhere in the United States without restrictions. Currently, the US-EU agreement has new amendments (2010 and 2011) and other Open Skies agreements have been signed between US-Australia, US-Switzerland and US-Japan (2008). As it can be seen, the airline industry is in constant evolution and this affects its structure and characteristics. As a result of the deregulatory measures there are currently three business models in the aviation sector [33]: *Full-Service Carrier* (FSC), *Low-Cost Carrier* (LCC) and *Charter Carrier*.

Full-Service Carriers (FSCs) are the former national flag carriers, which as a result of the deregulatory processes have a business model based on a great variety of links (i. e., domestic, international and intercontinental) and services, hub-and-spoke networks, yield management, vertical product differentiation and the creation of *alliances*. These carriers are also known as traditional or legacy carriers.

The creation of alliances is crucial to the airlines as none of them has its own global network. The main reason for airlines to cooperate or form alliances is cost reduction [34, 35]. Being a member of a partnership is an important factor in both the routing strategy of the airline in the long term and the network configuration adopted by alliance partners and competitors. In 2012, the three major alliances (Star Alliance, oneworld and SkyTeam) accounted for 60 percent of global air traffic measured in available seat-kilometres for the total of scheduled passengers [36] and so their impact on market dynamics is important. Thus, airlines route network should be developed taking into account the continuous structural changes occurring to the global route network due to multiple new agreements on route sharing and mergers.

Due to the hub-and-spoke strategy followed by FSCs, the establishment of hubs is another very important point. Hubs are organized in order to allow airline flight connections by coordinating the scheduled arrival and departure of flights. The coordination of schedules should not only take into account flights operated by the airline but also all routes, including those operated by other airlines. To understand the strategy of the airlines in the design of connectivity between hubs and schedule coordination has been the objective of several empirical and theoretical studies [37, 38, 39, 40].

Low-Cost Carriers (LCCs) are airlines with a business model based on having a competitive cost advantage through the use of secondary airports, point-to-point networks, basic services, payment for auxiliary services and a single airplane model. Although it is not an implicit feature, LCCs tend not to establish any kind of alliance with other LCCs or FSCs. Finally, Charter Carrier airlines operate unscheduled flights based generally on specific consumer demand for tourist destinations.

The structure of the global route network can be seen as a complex transportation network consisting of various airline network structures (e. g., hub-and-spoke and mixed point-to-point, *multihubs*). Studies tend to focus on the analysis of hub-and-spoke and point-to-point typologies but it must be kept in mind that they do not represent the entire airline transport network. These typologies are not unique to air route networks, the hub-and-spoke network can be found in biological networks [41] and point-to-point networks in wireless networks [42].

1.1.2 *Topology and robustness of air transport networks*

The are different viewpoints in which one can study the network strategies followed by airlines. There are studies on the effect on prices deriving from the existing connections between airlines [34, 35] or on the connectivity levels and the competitive position of airports [43]. Another approach is the analysis of the route network architecture through complex network analysis [9, 21, 24].

Those studies that have characterized the topology of air route networks and those that have analyzed the network robustness under errors and attacks should be reviewed in order to asses the state of the art of air route networks in continents, countries and airlines.

As shown in Table 1.1, the literature is very recent and has been developed mainly in the field of methodology. The study of complex networks, as shown throughout this chapter, has been developed in parallel in other areas in greater depth. In particular, it must be highlighted the thorough literature analysis of complex networks conducted in [13] which has enabled the observation and comparison of different characteristics and properties between real networks in various fields, and the recent surveys of applications of complex network theory [14].

Guimerà and colleagues [20, 21] have studied the airport network structure across the world, finding that the degree and betweenness centrality distributions follow a truncated power law distribution, given that airports have limitations to the number of connections they can offer. To model the real network, the authors used a variant of the models from [12, 71]. Both of them include the standard growth mechanism for the addition of links between already existing nodes, the current base for studying route networks using complex networks. Only a model that includes geopolitical constraints, such as the fact that most cities are only allowed to make connections to other cities within the same country, can generate nodes with high and lower intermediation values, as observed in the real airport network [20, 21]. With the development of this comprehensive study, complex networks analysis has started to be used more frequently in the airline industry. In particular, most new studies have regional scope, as in the case of Italy [22], India [23], US [48] and China [24, 46, 57]. The intensive study of the topology of air route networks has shown different network structures. For instance, [21] obtained a scale-free network structure with a small-world property, [22] obtained a small-world network structure with a fractal small-world property and [23] obtained a small-world network.

Empirical research has found that FSCs route networks behave like scale-free networks [54] and random networks are useful for describing point-to-point connections [33]. LCCs

Year	Authors	Published in	Level
2003	Li-Ping et al. [44]	Chinese Physics Letters	L1*
2004	Barrat et al. [11]	Proceedings of NAS	L1
	Guimerà & Amaral [20]	The European Physical Journal B	L1
	Chi & Cai [45]	International Journal of Modern Physics B	L1*
	Li & Cai [46]	Physical Review E	L1*
2005	Guimerà et al. [21]	Proceedings of NAS	L1
2007	Guida & De Maria [22]	Chaos, Solitons & Fractals	L1*
2008	Bagler [23]	Physica A	L1*
	Hu & Di Paolo [47]	NICSO	L1
	Xu & Harriss [48]	GeoJournal	L1*
2009	Cento [33]	Contributions to economics	L3
	Han et al. [49]	Physica A	L3
	Lacasa et al. [50]	Physica A	L1*
	Reggiani et al. [51]	Networks, Topology and Dynamics	L3
	Zanin et al. [52]	23rd European Conference on MS	L1*
2010	Liu et al. [53]	Physics Procedia	L1*
	Reggiani et al. [54]	European Journal of Information Systems	L3
	Zhang et al. [55]	Physica A	L1*
2011	Wang et al. [24]	Journal of Transport Geography	L1*
	Dang & Li [56]	JTSEIT	L1*
	Liu et al. [57]	TRR: Journal of the Transportation Research Board	L1
	Mo & Wang [58]	Proceedings 2011 International Conference TMEE	L1*
	Wilkinson et al. [59]	Natural Hazards	L1*
	Zeng et al. [60]	JTSEIT	L1*
2012	Cai et al. [61]	Chinese Physics B	L1*
	Dang & Peng [62]	JTSEIT	L1*
	Grady et al. [63]	Nature communications	L1
	Jia & Jiang [64]	Physica A	L1*
	Lin [65]	Journal of Transport Geography	L1*
	Sawai [66]	IEEE Congress on Evolutionary Computation	L1
	Wang & Wen [67]	24th CCDC	L1*
2013	Zanin & Lillo [9]	The European Physical Journal Special Topics	L1
	Cardillo et al. [68]	Scientific Reports	L1*
	Fleurquin et al. [69]	Scientific Reports	L1*
2014	Zhang et al. [70]	Physica A	L1

Table 1.1: Literature study of air route networks as complex networks. * *Regional*

do not connect all their airports nor have a hub, but they rather base their route network structure on point-to-point routes. This network structure can only be used on short-haul routes due to the smaller size of their aircrafts and reduced flight time. The lack of hub airports should indicate fairly similar concentrations in all airports leading to a very different type of network to those of scale-free. However, the network model for point-to-point connections according to [47, 57] is described as a small-world network [72, 73].

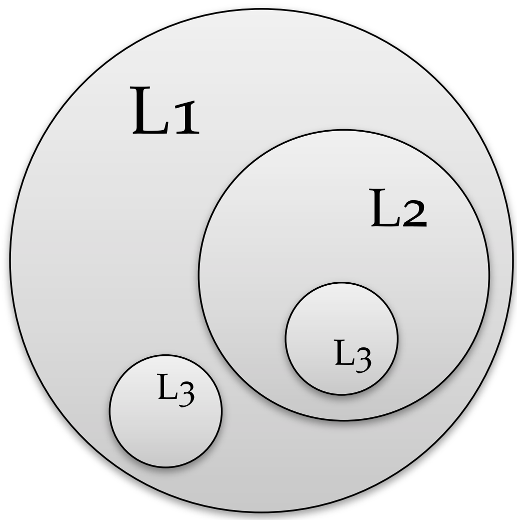
Recent studies have pointed out that the air transport network is a multilayer network, meaning that it is the result of the simultaneous presence of different subnetworks organized in separate layers [68]. From this point of view, the air transport network is the result of the aggregation of the route network of all the airlines. The analysis of the current literature studying air route networks as complex networks allows establishing different dimensions or levels of study characterized by different units of analysis. Therefore, and given that each level has different characteristics and properties, three levels of study are proposed: the *global route network* (L1), the *airline alliance network* (L2) and a particular *airline network* (L3) as shown in Figure 1.1. The different levels do not only represent different network magnitudes in number of nodes (airports) and links (routes), but also represent different approaches.

The study of the global route network –first level: L1– looks at the competitive environment for airlines and the general framework of air transport development. Due to the size of the global route network and that it is a spatial network (i. e., restricted by its geographical characteristics), the network must be analysed both globally and regionally. The literature contains examples of both global [21] and regional [23] analyses. The analysis of the robustness of networks at L1 can be of interest for policy makers whose objective is to increase the security of the air transport network, allowing the detection of critical airports to prevent major collapses of the network, which can have a significant impact in global economy. For instance, [59] have studied the impact of the eruption of the Icelandic volcano Eyjafallajökull on the global transport network, and [45] have analyzed the robustness of the US airport network to errors and attacks.

As indicated previously, air transport networks at the L1 are the result of several layers of airlines route network. Airlines network constitute the third level (L3) of the framework. In the study of an airline network (L3) the specific properties and characteristics of airlines can be appreciated [49, 51, 54], regardless of the competitive environment.

The air networks of alliances constitute the second level (L2) of the framework. The participation on alliances can contribute to an improvement in network robustness for the member airlines thanks to the resulting codesharing agreements. The network of an airline alliance is the route network operated by its members and the routes of other airlines with which they have codesharing agreements. Therefore, L2 networks are also multi-layered, since they are an aggregation of L3 networks. As shown in Table 1.1, this level has not been developed in any study using complex networks although airline alliances have been extensively studied in the literature on air transport management [31, 34, 35]. This level represents the network structure of airline alliances and enables us, as in the case of airlines

Figure 1.1: Study levels



(L3), to determine the properties of an organizational network. The analysis of robustness of L2 and L3 networks can be of interest for airline management, of companies and alliances. The increase of the reliability and security of airlines and alliances network can help these organizations to maintain and increase their levels of profitability in the long run. Finally, the classification in different levels will allow to link characteristics for each level and to study the effects that exist between them.

1.1.3 *Models of real networks and robustness*

To study the transport network of airlines they have to be modelled as complex networks. In order to construct the model it must, firstly, be taken into account that the network topology determines the dynamics of complex connectivity [41] and, secondly, that it is a network in which the relationships are influenced by the Euclidean distances between airports. Therefore, the air route network or airport network is a *spatial network* as its nodes (i. e., airports) occupy a position in Euclidean space and its links (i. e., routes) are real physical networks. Spatial networks are strictly constrained by their geographical features [74]. Some important examples in the study of spatial networks include networks of information/communication [75, 76], networks of ants colonies [77], electric power networks [78], neural networks [79] and transport networks. The analysis of transport networks is a prime example on where to find studies on urban networks [16], trains and subways [18] and airports and air routes [21, 24].

Another important feature is that networks can be considered either *weighted* or *unweighted*. On weighted networks, a real number (i. e., the weight) is associated to each link [13]. Together with a complex topological structure, many real networks show a considerable heterogeneity in terms of capacity and strength of their connections, which would go unnoticed if they were modeled as an unweighted network. Examples of this are the existence of strong or weak ties between individuals in social networks [80, 81], irregular flows in metabolic reaction pathways [82], varying transmission capabilities of electrical signals in neural networks [80, 83, 84] or the inequality in traffic via the Internet [75].

Ignoring this diversity in such interactions would mean overlooking most of the information on complex networks, which is in many cases, available and useful for its characterization. By way of example, it is very different to study an airline's route network by only considering the transit links between airports or to study the route frequency between these airports. These cases represent unweighted and weighted networks respectively. In the study of air routes networks there are examples of analysis of both unweighted networks [54, 57] and weighted networks [11, 20, 21, 46].

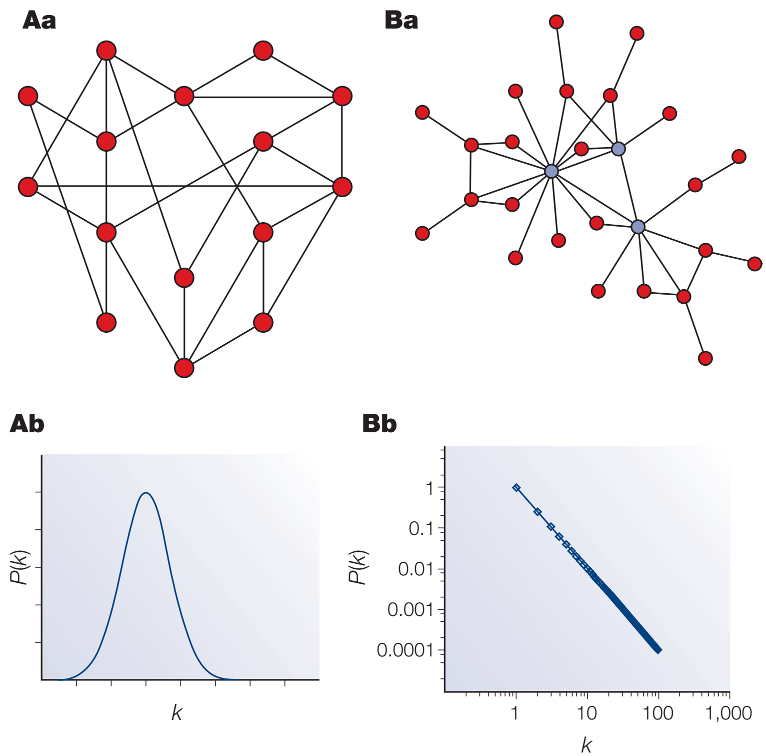
Complex networks analysis has found a common feature of topology of interactions in systems as diverse as communications systems [75, 85] social [72, 86, 87] and biological [41, 88, 89, 90]. The behavior of most communication systems, including air transport networks can be modelled with the scale-free (SF) network [91]. These and most of real networks usually have the *small-world* (SW) property (i. e., a low average path length) [72, 73].

During the growth of complex networks, new nodes tend to connect to existing nodes that are well connected [72]. Consequently, the hubs (i. e., well connected nodes) tend to reinforce themselves leading to a *scale-free* (SF) network (see Figure 1.2.Ba). The SF network, introduced in [91], incorporates two mechanisms in which many real networks have proven to be based: *growth* and *preferential attachment*. Growth explains the dynamic nature of the networks which grow through the addition of new nodes. Preferred attachment explains how new nodes enter the network by connecting to those nodes with most links (i. e., high degree). As a result, in SF networks the degree k (number of connections of each node) has a power law $k^{-\gamma}$ distribution (see Figure 1.2.Bb).

The exponent value γ depends on the attributes of the individual systems and it is crucial in detecting the exact topology of the network, in particular the existence of hubs. As [41] highlighted, the hub-and-spoke model corresponds to a SF network when $\gamma = 2$, while $2 < \gamma \leq 3$ indicates a hierarchy of hubs. When $\gamma > 3$, the SF network behaves as a random network and the effect of the hubs in the network is diluted. In the case of different typologies of air route networks, when $\gamma = 2$ we would find a pure hub-and-spoke network and when $\gamma > 3$ we would find a point-to-point network. Following the definitions of FSC and LCC, the FSCs network should have lower values of γ than LCCs.

Finally, there is a third widely studied and developed network model introduced in [92], the *random* (RN) network (see Figure 1.2.Aa). Its main difference to a scale-free network is that in a random network any connection between two nodes is equally likely to occur.

Figure 1.2: Random (**A**) and scale-free (**B**) networks. **Aa**: Graph of RN network. **Ba**: Graph of SF network where the grey nodes represent hubs. **Ab**: Degree distribution of a RN. **Bb**: Degree distribution of a SF network (graph log-log). Source: [41]



An RN network cannot be considered a real network model [13] but rather a standard model studied in mathematical graph theory. In contrast to SF networks, RN networks show homogeneous patterns, dispersed and without clusters. Their degree distribution, unlike SF networks, follows a Poisson law (see Figure 1.2.Ab). In air transport, RN networks can be useful to describe point-to-point connections [33]. In an ideal point-to-point route structure, all airports would be linked to most of the others so the diameter would be reduced, which would make the SW property appear.

Topology analysis will help understand the network's characteristics and properties that will influence its dynamic behavior. This may allow the study of phenomena such as robustness, resilience, collective synchronization dynamics or propagation processes [13]. The literature on the dynamic behavior of air transport networks, while limited, has focused its attention in the study of robustness. [47, 57] used robustness in their application of the genetic algorithm to optimize an airline's route network. [50] made a more detailed study of jamming transition phenomena in the European route network. More recently, [69] has analyzed the problem of delay propagation in the US airport network and [70] has applied a dynamic fluctuation model that quantitatively describes and reproduces the real airport network.

Air traffic is part of a dynamic environment, where airports and routes can be closed temporarily for various reasons such as environmental accidents, security alerts, strikes or terrorist attacks, etc. resulting in high costs for airlines and countries. For example, in 2010 the strike by air-traffic controllers in Spain is estimated to have cost airlines $134m [93] whereas snow and strikes cost easyJet £31m in the same year [94]. The alternative for airlines, depending on the cause of the malfunction, could be to seek a replacement route for their clients, using other airlines' routes or waiting for the route or airport to be operational again.

The analysis of *robustness* in air transport can evaluate the effect of errors (e. g., inclement weather) or attacks (e. g., terrorism) on a route network. The study of the robustness enables the evaluation of the capacity for networks to avoid a malfunction when some fraction of its components is damaged [13]. In this way, we can analyze network resilience, tolerance to attacks and congestion caused by any malfunction. Therefore, and due to its applications to aviation, we will focus on the analysis of robustness.

The study of a network's robustness facing random failures and intentional attacks was one of the first issues to be explored in the literature on complex networks [25, 26]. The problem can be explored in two different ways. The first, known as static robustness, is the action of isolating nodes without the need to redistribute any quantity transported by the network. This is the case, for example, of a social network in which relations between individuals in the system are cut. The second, dynamic robustness, takes into account the dynamics of flow redistribution. As an example, when an Internet router goes down, the packets it should transmit are diverted through alternative routes. The two types of robustness are similar, but while the first can be treated analytically, for example, by using tools of statistical physics such as percolation theory [95], the analytical process in the second case is more complex and in almost all cases numerical simulation has to be used.

As discussed, static robustness ignores flow redistribution as nodes or links are eliminated in the network. Tolerance to static errors is defined as the capacity of the system to maintain its connectivity features following some random disconnection of nodes or links. Furthermore, we refer to an attack as when the removal process is directed at a particular class of nodes or links, for example, well connected nodes. As well as numerical simulations [25, 26] a number of analytical approaches have been proposed [95, 96, 97, 98] to study tolerance to errors and attacks in complex networks.

Furthermore, dynamic robustness is more complex, since the links or nodes may have restrictions on their capacity and the load is often highly variable in space and time. Current studies in other fields have dealt, using dynamic effects, with the problem avalanches of broken nodes [99, 100] and congestion in communication systems [90, 101], providing indications for actions that can be taken to decrease undesirable effects [13].

As previously explained, the topology of networks must be known in order to analyze their dynamic behavior. [26] studied how Internet properties changed when some of its nodes were disconnected from a sample of the World Wide Web. On the World Wide Web the giant component remains unchanged despite high random removal rates of nodes, while, if the nodes are isolated as an attack, the size of the resulting fragments decreases rapidly. Furthermore, [102] simulated a series of attacks on a SF network showing that such attacks would cause the system to collapse. In these examples, the response to attacks or failures of an SF network is quite different than the response of a RN graph of the same size and average degree. For random failures, in SF networks the size of the largest component decreases slowly and no threshold is observed, contrarily to RN networks. On the other hand, the response of SF networks to attacks is similar to the response to attacks and failures in the RN network, with a lower critical value than the value observed in the RN graph. As in the case of [26], for the analysis of the route network the network topology must be taken into account in order to understand the effects that errors or attacks might have.

1.2 DISCUSSION AND FUTURE LINES

The study of network route robustness has been a recurring study topic in recent years. However, there is an approach that has had limited analysis: the airline management approach (L2 and L3) and the government policy approach (L1). In the levels described above, it can be seen how levels L2 and L3, alliances and airlines, focus their attention on companies or organizations. As shown in Table 1.1 the study of the alliance network (L2) has not been developed yet. On the other hand, some research has been carried on the airlines (L3), in companies such as Lufthansa [51, 54] and other European airlines [33, 49]. The analysis of business networks (i. e., companies or alliances) robustness could influence the decisions to open new routes or negotiate new codesharing agreements. On the other hand, the analysis of the robustness of route networks in a specific region (L1), whether they are continents or countries, would help to make better decisions at the policy-making level. For instance, European policymakers could be interested to know which airports are the most important in maintaining stable air communication. It might also be known which non-European airports could pose a problem for the flow of their air routes.

Because the current literature is mainly focused on complex network theory development, the studies conducted up to the present date have used the global air route network as a special case of a complex network. Since the aviation route network can be modelled and adequately characterized as a complex network, it can be argued that it is time to apply complex network analysis on aviation organizations: alliances and airlines. The analysis of topology of these networks can help to see how the airlines' own networks and alliances are made up, allowing for the evaluation of their characteristics (e. g., robustness) and their influence on these companies. These developments can be of vital importance at all levels of study, from those studies centred on airlines to those focusing on the overall policy environment. Consistent with the literature review, future lines of research will be formulated following the levels outlined.

1.2.1 *L1: Global route network*

The global route network has been the most studied network. This network consists of all currently active airports. Studies have examined network topology, but some criteria of analysis have had less or limited treatment. An increased knowledge of the airline routes network topology would enable to assess more completely the influence of different airports in the robustness of the global network and their impact on the connection of different regions. In other complex networks, this analysis has been carried out through centrality studies. Concepts such as the number of nodes to which a particular node is connected (degree centrality), the number of links to reach the rest of nodes (closeness centrality) or how intermediary a node is (intermediation centrality) in a network are some of the most widely used due to their ease of interpretation. However, [33] introduces network concentration measurements such as the Gini index or others used in the social media such as Freeman's centrality index and Bonacich's centrality. Along these lines there is still a long way to go on the implementation of new measures of complex networks used elsewhere.

Some of the examples seen in social networks are the intermediation flow centrality and Bonacich's power. The focus of flow centrality expands the notion of intermediation. It assumes that nodes will use all routes that connect them rather than only geodesic routes. Lets suppose that an airline wants to offer a route between two distant points, but an intermediary airport blocks the geodesic path between them. If another route exists, the two nodes will probably use it, even if it is longer or less efficient. Such behavior can be effectively modelled through flow centrality. Bonacich [103] proposed that both the notions of centrality and power are functions of node's links to its environment. A node will have high Bonacich centrality if connected to nodes of high centrality, and high Bonacich power when connected to low power nodes. Note that Bonacich's power should not be confused with Bonacich's centrality.

The robustness analysis of the global network should be carried out taking into account the characteristics of spatial networks, through a detailed study of the global network and its regions. On one hand, this study would provide great value for the analysis of complex networks, and on the other hand, it could be assessed how the different countries or regions studied would be affected by airport closures. As an example, the closure of London's airspace might not have the same impact on European air traffic as the closure of Barcelona's airspace. It would also be shown which airports, in case of an error or a deliberate attack, would affect the global network most. Following this a debate would ensue about whether these airports should have greater controls or if their route volumes should be reduced in order to alleviate the inherent risk.

1.2.2 *L2: Airline alliances network*

Currently, there are three airline alliances (i. e., Star Alliance, oneworld and SkyTeam). These three alliances accounted for 60% of global air traffic in 2012. The main activities within the alliance are creating codesharing agreements and buying fleet and fuel in bulk. The aim of an alliance is that the whole network of the member airlines appears to be an extension of each partners' routing system [104]. Through codesharing agreements the airlines work in order to provide a continuous service, so passengers cannot distinguish between making an interline flight with one or more airlines. This is achieved by the already mentioned coordination of flight schedules to reduce downtime, ensuring the proximity of gates at airport transfers and merging the alliance partners' frequent flyer programs.

With the extensive use of this practice, codesharing agreements have become the hallmark of the alliance revolution in the commercial aviation industry [34]. Coordination among member airlines of the alliance and the adequate control of their routes leads to a significant increase in the scope and frequency of the routes offered to customers. In Table 1.1 it can be seen that at this level there have been no studies of complex networks, whereas alliances and codesharing agreements have been studied from other approaches [34, 35].

Therefore, it is interesting to study the topology of what might be considered "mega-airline carriers" in the same way as there have been in the study of airlines (L3). The network of an airline alliance is defined as the route network operated by its members and the routes of other airlines with which they have codesharing agreements. In this way, the real route network offered by alliances is taken into account, not only those routes operated by alliance members. The topology study may offer insight into the properties of networks as to, for example, assess whether the networks of individual members are complementary or redundant.

At this level, the study of route network robustness takes a business stance. How robust is the network of each alliance? Do members of these alliances see their route network increase in robustness thanks to their membership, and to what extent? Alliances route network analysis can provide a lot of information about the position of its members in such networks. Through previous analysis of the topology of these networks it can be determined how these alliances are constructed and evaluated, among other things, whether belonging to an alliance increases the robustness of the airline route network.

As an example, if members of the alliance were selected only to increase the total range of their routes, and codesharing agreements among its members were only on routes not operated by them (i. e., complementary routes), the alliance would not provide robustness to its members; but if on the other hand, members do not close similar routes and codesharing arrangements are also made on routes operated by the airlines (i. e., redundant routes), robustness could be seen to increase as well as its relevant benefits. This would only be an example because, as explained above, these characteristics depend on various network attributes.

1.2.3 L3: Airlines network

The last proposed level of analysis is individual airlines network. Consistent with alliances network (L2), airline network can be defined as the route network the airline operates and routes of other airlines with which it has codesharing agreements. At this level, [51, 54] have undertaken a case study of Lufthansa. Also, [33, 49] evaluated the structural properties of various European airlines through complex networks analysis.

In order to assess the robustness of airline routes and thus ensure their stable traffic development, the airline's topology should be analyzed first. If it is taken into account that the network topology of a FSC network is hub-and-spoke, its network topology should be SF. Similarly, an LCC, due to its network typology being mainly point-to-point, might be considered RN or an SF with a low preferred connection (i. e., a high γ). These assumptions should be analyzed in order to determine the influence of the closure of a major or a secondary airport on airline operations.

Finally, the study of robustness would allow airlines to resolve questions such as: Are LCCs, those airlines which do everything possible to keep the aircraft in the air, protected against failure or an attack on their network? If they are compared with FSCs, is their network more robust than FSCs as part of an alliance or not? Do FSCs and LCCs adopt the same network structures regardless of their geographical base? Previously, the airlines' network topology should be examined because, if the FSCs network are SF with a higher preferred connection than LCCs, current studies of complex networks would indicate that FSCs would have a less robust network structure against attacks than LCCs.

1.3 CONCLUSIONS

Air transport networks are one of the critical infrastructures of today's world economy, and there is a need to better understand the functioning of these networks under severe disruption events [10]. This work has identified the main research areas in air transport geography derived from the study of robustness of complex networks. The literature review has shown that in recent years air route networks have begun to be modelled and analyzed as complex networks but from a very theoretical point of view. In this review three levels of study are presented through two new applied approaches: the airline management focus (airline alliances L2, and airlines L3) and the government policy focus (global air transport network L1).

These approaches help to see and structure important practical implications inherent to the dynamic analysis of air route networks. As with the study of robustness, the effect that either terrorist attacks or inclement weather may have on the proper operation of an airline or the aviation relations between two regions can be assessed. Consequently, a line of research has been proposed which follows the lead taken in other areas where the study of complex networks has been more extensive (e. g., neural network study) but within the field of air transport geography.

This approach represents a first step in the study of complex networks applied to air transport and will allow for better understanding of air route network structures. This will make possible to evaluate and enable a restructuring of the system of air transport with the aim to avoid serious collapses, both at the airline level as in the regional level, when faced by errors or attacks at airports in an increasingly crowded market.

Part II

ROBUSTNESS ANALYSIS

The robustness analysis of each level shows how vulnerable and fragile the global, alliance and airline network are when facing unintentional errors and intentional attacks. Several approaches has been considered introducing new concepts from other areas and new ones self-developed.

2 L1: ROBUSTNESS OF THE AIR TRANSPORT NETWORK

2.1 ABSTRACT

The assessment of the impact of disruption of the air transport network by intentional (e. g., terrorist attack on an airport) or unintentional causes (e. g., weather inclemency) is crucial for the management of the global transportation system. The potential impact of air traffic disruptions will be assessed through an analysis of the vulnerability of the global air transport network (ATN). The behavior of the ATN against intentional airport closure depends on its topological properties. The aim of this research is to analyze the impact of the closure of a sequence of airports on the reliability of the entire ATN. That analysis can provide insight about how to reduce the effects of such disruptions in order to ensure good communication through air transport (i. e., maximize the robustness of the global network).

2.2 INTRODUCTION

The air transport network (ATN) is one of the most important and critical infrastructures of today's global economy. Together with the Internet, which has lowered dramatically the costs of dissemination of knowledge, the continuing expansion of the air transport has contributed to the globalization of the economy, and has increased the possibilities of mobility of people and merchandises worldwide. ATN is responsible of the mobility of millions of people every day: from November 2011 to November 2012 24,848 commercial connections between 3,712 airports were scheduled (source: SRS database). But in spite of its critical importance, the ATN can be vulnerable to incidents with some airports at the brink of failure.

Failures or inefficiencies on flight operation cause high economic costs. Some minor incidents, such as low clouds, can lower landing rates as much as 28% [21]. The eruption of the Icelandic volcano Eyjafallajökull on March 14, 2010 caused serious restrictions on European air traffic, causing 10 million delays in European airports [105], with estimated losses for affected companies of $1.7b [106]. The cost for airlines of the 2010 controllers strike in Spain have been estimated to be of $134m [93]. Disruptions of the ATN can be the source of huge losses, and can affect seriously global mobility.

The ATN is the result of concurrent actions of airline companies and alliances trying to maximize their profit, and also of a sequence of events arising from geographical, political and economic factors. Therefore, in spite of the potential consequences of ATN disruptions, it has not been designed to be resilient facing unintentional errors (e. g., bad weather) and intentional attacks (deliberate actions trying to disrupt ATN connectivity). The analysis of the ATN can benefit from the results of extant research on complex networks. This literature has defined generic models for real networks, such as *Erdős-Rényi random* (RN) graphs [92], Watts-Strogatz *small-world* (SW) network [72] or Barabási-Albert *scale-free* (SF) networks [91].

Extant research has examined the reliability facing errors and attacks (i. e., the ability of a system or component to perform its required functions under stated conditions) not only of complex network models, but also of real networks. Tolerance to *static errors* is defined as the capacity of the system to maintain its connectivity following some random node isolation (i. e., disconnection of all connections to a particular node) or link disconnection. On the other hand, in an *attack* isolation process is directed at a particular class of nodes or links, for example, well connected nodes.

Numerical simulations [25, 26] as well as a number of analytical approaches have been proposed [95, 96, 97, 98] to study tolerance to errors and attacks in complex networks. Several studies [45, 107] have investigated how some network properties such as size of giant component, clustering coefficient C, average shortest path length L and global efficiency E are affected when a fraction f of the nodes is isolated.

In homogeneous networks, such as in the RN model, there is no significant difference in the behavior of the network as to whether the nodes are selected randomly or according to a preference criterion (e. g., degree or betweenness centrality). But in heterogeneous networks, such as the SF model, network properties deteriorate dramatically when they are subjected to attacks [107]. The fraction of the nodes to be disconnected in an attack to observe a significant network disruption can vary according to the preference criterion adopted in network isolation. In air transportation, [47] and [57] used robustness analysis as in their application of the genetic algorithm to optimize an airline's route network. [50] made a more detailed study of jamming transition phenomena in the European route network. More recently, [108] measured the weighted network robustness of Virgin America by computing the algebraic connectivity.

As the global ATN is a SF network with SW property [21], it can be possible to alter effectively its connectivity properties with the isolation of a reduced fraction of airports. In this study, the effectiveness of several criteria of node selection to attack effectively the ATN will be assessed. The criteria of selection can be defined in terms of decreasing order of several measures of centrality (*degree*, *betweenness* or *Bonacich power*), or with alternative strategies based on the assessment of the critical *damage* caused by the disconnection of a node [76] or by node parameters obtained through *modal analysis* [19]. Such analysis can reveal the airports whose isolation would affect ATN connectivity. Following this a debate would ensue about whether these airports should have greater controls or if their route volumes should be relaxed in order to alleviate the inherent risk.

2.3 METHODS

The static robustness of the ATN under attacks will be analyzed isolating airports using an adaptive strategy. First, the airport to be isolated is the one with the highest value of a particular measure. Once the airport is disconnected, the measure is recalculated for all airports of the resulting network to find the new airport to be disconnected. It should be noticed that all the connections of the airport will be disconnected, but neither the airport nor the passengers will disappear [109]. Based on extant research, the effectiveness (measured in terms of reduction of the size of the giant component) of attacks based on five different measures: *degree*, *betweenness*, *modal analysis*, *damage* and *Bonacich power* has been compared. The first two measures, degree and betweenness, are two standard measures of node centrality. The *degree* k_i of a node i is the number of edges incident with the node, and is defined as:

$$k_i = \sum_j a_{ij} \tag{1}$$

where a_{ij} corresponds to the elements of the graph adjacency matrix $\mathcal{A}$. For each pair (i, j) of airports connected by at least one route the corresponding element a_{ij} equals 1, and 0 otherwise. The *betweenness* b_i of a node i is the number of times that a node appears between the shortest paths of two other nodes quantifying the importance of a node [13], and is defined as:

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

where n_{jk} is the number of shortest paths connecting j and k, while $n_{jk}(i)$ is the number of shortest paths connecting j and k and passing through i. In the context of the ATN, degree can be seen as a measure of connectedness, and betweenness as a measure of the centrality of each airport. The third measure, *modal analysis*, was proposed in [19], where is reported that this measure is more effective to attack the power grid than degree or betweenness. Modal analysis is based on the analysis of the eigenvalues of the graph Laplacian. [19] defines the modal connectivity matrix Γ as:

$$\Gamma = L'\Phi \tag{3}$$

where L' stands for the transposed Laplacian and Φ is a matrix composed of the Laplacian eigenvectors. Modal contributions to each node are determined as:

$$w_i = \sum_j |\gamma_{ij}| \tag{4}$$

where γ_{ij} corresponds the modal connectivity matrix Γ elements. The modal contribution is a measure of the load each node receives, thus the modal contribution w_i can be used to rank the nodes according to their busyness [19]. The fourth measure, *damage* was introduced in [76]. The critical damage of a node i is the reduction of the giant component obtained when i is disconnected. Finally, the fifth measure the *Bonacich power* analysis for assessing attack vulnerability of complex networks is introduced. Bonacich [103] proposes a family of centrality measures as:

$$c_i(\alpha, \beta) = \sum_j (\alpha + \beta c_j)\mathcal{A}_{ij} \tag{5}$$

where $\mathcal{A}$ is the adjacency matrix. α is a scaling constant and β reflects the effects of the centrality of its neighbors on a node's centrality. Considering λ as the $\mathcal{A}$'s largest eigenvalue, when $|\beta| < 1/\lambda = \kappa$, the matrix solution to 5 is:

$$c(\alpha, \beta) = \alpha(I - \beta\mathcal{A})^{-1}\mathcal{A}1 \tag{6}$$

where I is an identity matrix and "1" is a column vector of ones. This family of measures allows us to analyze two types of network status just varying the parameter β that reflects how the status of a node is affected by the status of its neighbors [103]. On the one hand, for access to information, popularity, or social status this effect would be positive, sometimes named as collaborative networks. For $\beta = +\kappa$ the measure is the same as the eigenvector centrality. On the other hand, for networks with a power-dependence orientation, having weak neighbors with no alternative exchange partners is a source of power [110], sometimes named competitive networks. Knowing that the ATN is a power-dependence network, it has been considered the Bonacich power of the network for $\beta = -\kappa$.

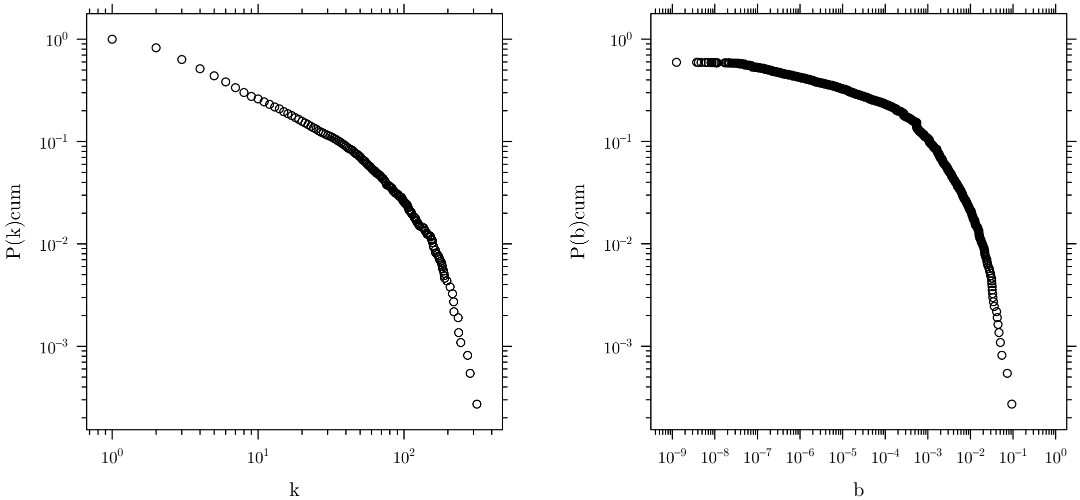
2.4 THE GLOBAL NETWORK OF AIRPORTS

The global ATN has been analyzed in [20, 21], where the nodes are the cities with airports, and two cities are connected if at least one non-stop commercial airline route between them exists. It had been found that ATN defined in that way is a SF network with SW property, i. e. a low average path length and a high clustering coefficient. The ATN had also a multi-community structure, whose emergence can be explained in terms of geographical and geopolitical factors. The network properties of the ATN make it resilient to errors, but specially vulnerable to intentional attacks.

Attacks to the global network of airports will be simulated in this work. Airports are considered as nodes rather than cities, given that airports are the likely target of an intentional attack. To define the network, all connections between airports from November 2011 to November 2012 have been retained from the SRS database complied by IATA. This leads to a network of $N = 3,712$ airports, with $24,848$ connections between them. As the vast majority of connections are reciprocal, the airport ATN is treated as an undirected network [21]. It has been also considered as an unweighted network because the purpose of this study is to assess the effect of a total disconnection of an airport from the global network. This network has an average shortest path length of $L = 3.94$, and a clustering coefficient of $C = 0.64$. These values are of the same order as the ones obtained by [21] for the cities ATN in 2000. So the airport ATN 2012 like the cities ATN in 2000, has a low value of L having the SW property, together with a high value of C.

In Figure 2.1 are depicted the degree and betweenness cumulative distributions of the ATN. The degree distribution (i. e., the probability that the degree of a given node has value k) follows a truncated power-law distribution, similar to the distribution reported in [21] for the network of cities. The betweenness distribution has a starker truncation than

Figure 2.1: ATN degree (k) and betweenness (b) cumulative distributions



the one reported in the network of cities, revealing the existence of a small subset of airports with anomalously large values of betweenness centrality.

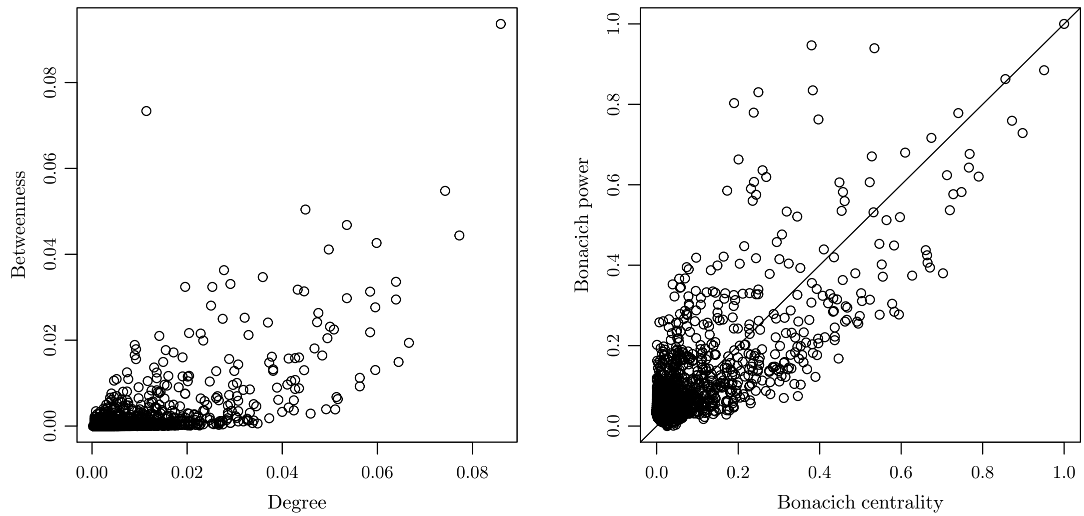
Figure 2.2 shows the existence of nodes with high values of betweenness (i. e., central nodes) and with low values of degree (i. e., low-connected nodes). This phenomenon is even more evident if Bonacich centrality is used as a measure of connectedness, and Bonacich power as a measure of centrality. This is a distinctive feature of the ATN, and a result of the socioeconomic, geopolitical [21] and operational factors that have determined ATN evolution. That fact shows that ATN has a multicommunity structure, with communities defined on the grounds of geographical and geopolitical constraints [21].

2.5 RESULTS

Figure 2.3 shows the variation of the size of the giant component of the ATN as a function of the number of airports isolated for the network for each criterion (it is also provided the % of the global network that represents the global airports). It has also been assessed the behavior of the ATN when suffering errors, i. e. random isolation of airports. A simulation of the behavior of the ATN facing errors has been run $5,000$ times, and in Figure 2.3 it is also reported the average size of the giant component as a function of the number of airports isolated.

Unsurprisingly, taking into account the degree distribution reported in Figure 2.1, the ATN is much more resilient to errors than it is to attacks. The random isolation of the 13% of airports of the network reduces the size of the giant component by 22%. The same

Figure 2.2: Betweenness as a function of the degree and Bonacich power as a function of the Bonacich centrality for the ATN. *Note*: all measures are normalized



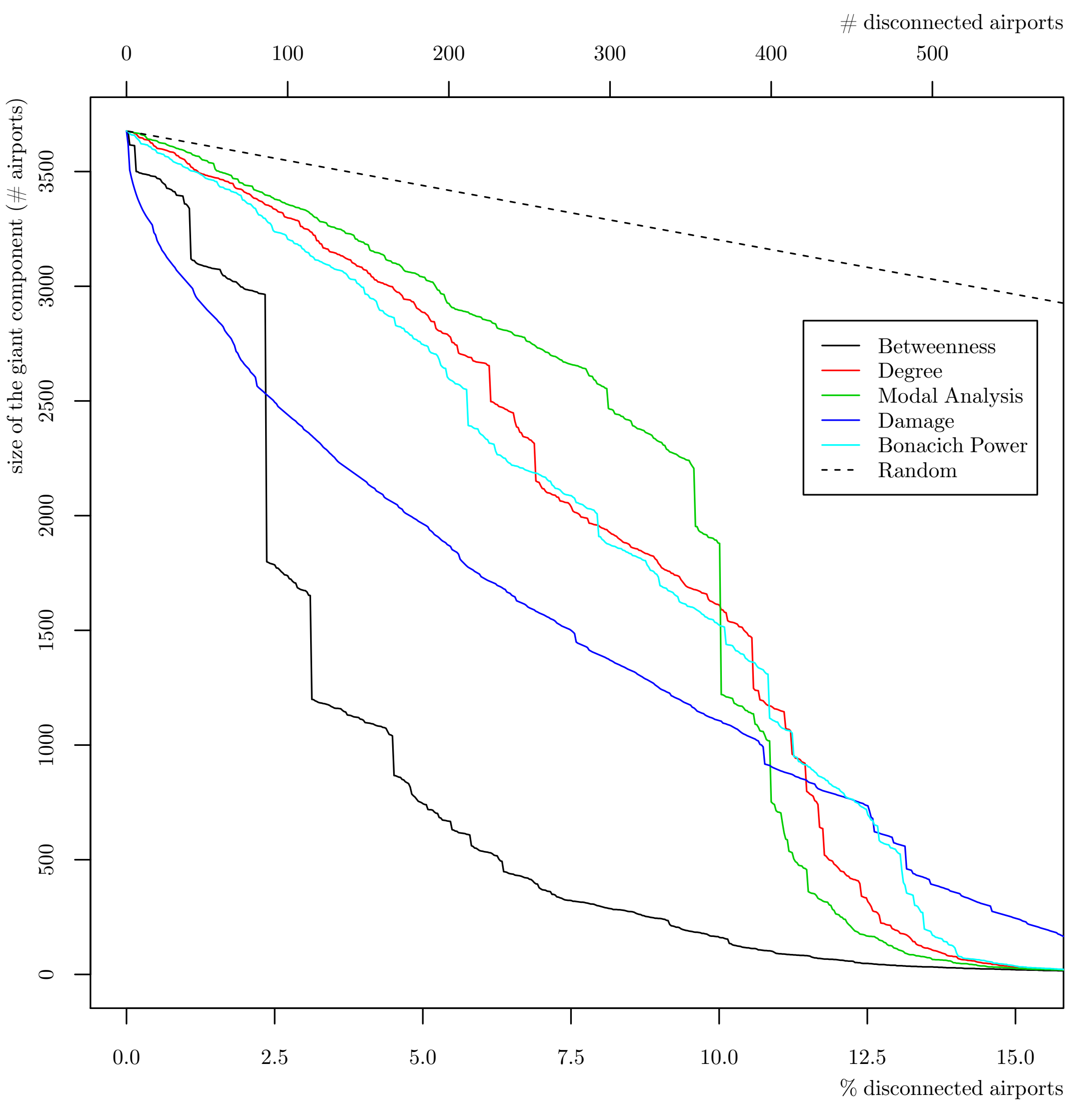
number of airports can be enough to disconnect completely the whole ATN, as can be seen in Figure 2.3 for betweenness disconnection. With 3,200 airports operative, the size of the largest network connected has decreased from 3,677 to just 40 airports.

A distinctive feature of the ATN is that the betweenness criterion is more effective than the degree to reduce the size of the giant component. In fact, Figure 2.3 shows that when the 2.5% of airports are isolated with the betweenness criterion, a steep fall of the size of giant component occurs. From that value of f on, betweenness is the most effective criterion. For values of $f < 0.025$, the damage criterion is the most effective to reduce the size of giant component. But while this criterion starts being the most effective, it ends up being the worst one for high values of f.

To compare damage and betweenness, in Table 2.1 are listed the 15 first airports to be disconnected following both criteria and plotted on Figure 2.4. Only the ANC and FAI airports are present in both damage and betweenness lists. These two airports are in Alaska, depicted in black in Figure 2.4, and are the only two hubs that connect Alaska to the rest of the world. If these two airports were disconnected, Alaska would be almost completely isolated to the entire ATN.

The damage criterion tends to select airports that act as hubs of relatively isolated networks of airports. A clarifying example of it could be that PPT, HIR and MNL (i. e., 4th, 5th and 9th on damage disconnection) are in fact the hubs of French Polynesia, Solomon Islands and Philippines respectively. None of them has a deep impact on the ATN core. It is assumed that the ATN core includes the largest geopolitical air transport networks:

Figure 2.3: Vulnerability of ATN



	Betweenness		Damage	
Top	Airport	Giant size	Airport	Giant size
1	FRA	3,674	ANC	3,619
2	ANC	3,616	FAI	3,506
3	CDG	3,615	SEA	3,475
4	AMS	3,614	PPT	3,447
5	DXB	3,613	HIR	3,423
6	FAI	3,500	BOG	3,401
7	PEK	3,499	KTM	3,381
8	LAX	3,494	YVR	3,364
9	LHR	3,493	MNL	3,348
10	YYZ	3,490	PER	3,333
11	NRT	3,489	THR	3,320
12	ICN	3,488	YQQ	3,308
13	PVG	3,486	MAO	3,297
14	HKG	3,485	AEP	3,287
15	BKK	3,481	ALG	3,277

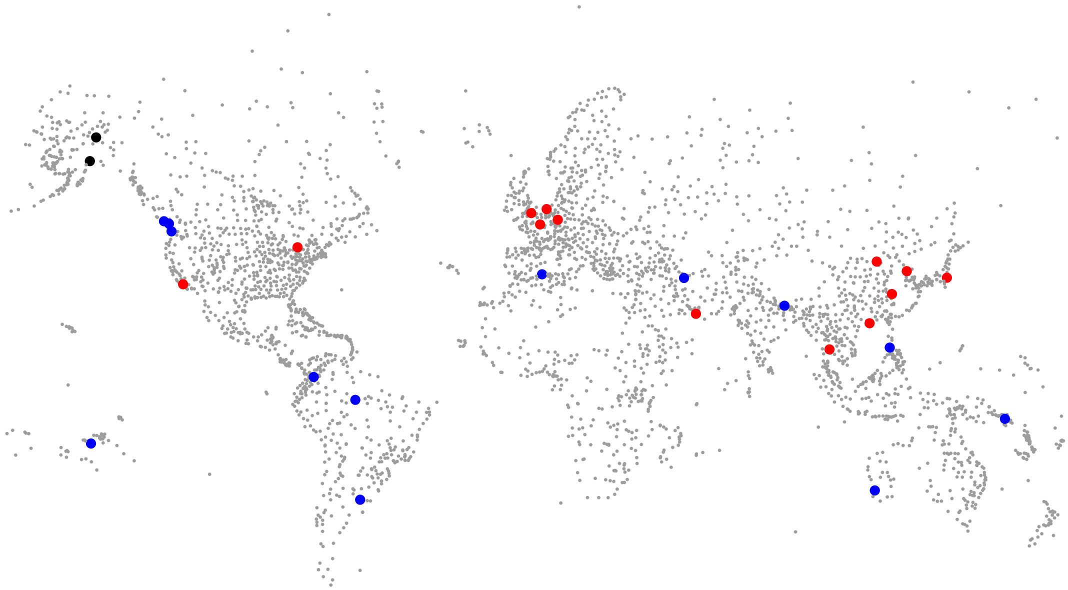
Table 2.1: Top 15 disconnections for betweenness and damage measures. Airports (IATA code) and size of the giant component

US, Europe and China. Therefore, critical damage criterion tends to select airports that link relatively unconnected groups of airports (and that might be the reason why it is more effective for low values of the fraction of isolated airports f), while the betweenness criterion is more effective selecting airports that disconnect the entire ATN, therefore being the most effective for higher values of f.

In Figure 2.5 it can be observed that the evolution of the characteristic path length (L) as a function of f is quite different for the damage and betweenness criteria than to the other three. While damage and betweenness tend to reduce the giant component isolating network communities, the other criteria perform a global attack of the network: that is the reason why in the degree, Bonacich power and modal criteria L peaks to a high maximum for values of f around 0.1, falling dramatically afterwards. The difference between damage and betweenness can be seen through the average degree $\langle k \rangle$ vs f graph. The value of $\langle k \rangle$ falls slower with damage than for other criteria, because damage tends to choose small hubs, whose disconnection isolates small communities.

On the other hand, betweenness takes advantage of the multicommunity structure of the ATN to select strategic, important hubs, disconnecting large regions from the giant component faster than other criteria. Finally, the efficiency E decreases with a similar rate

Figure 2.4: Top 15 disconnections for betweenness (*blue*) and damage (*red*) measures. Overlapped top 15 airports (*black*) and the rest of them (*grey*)



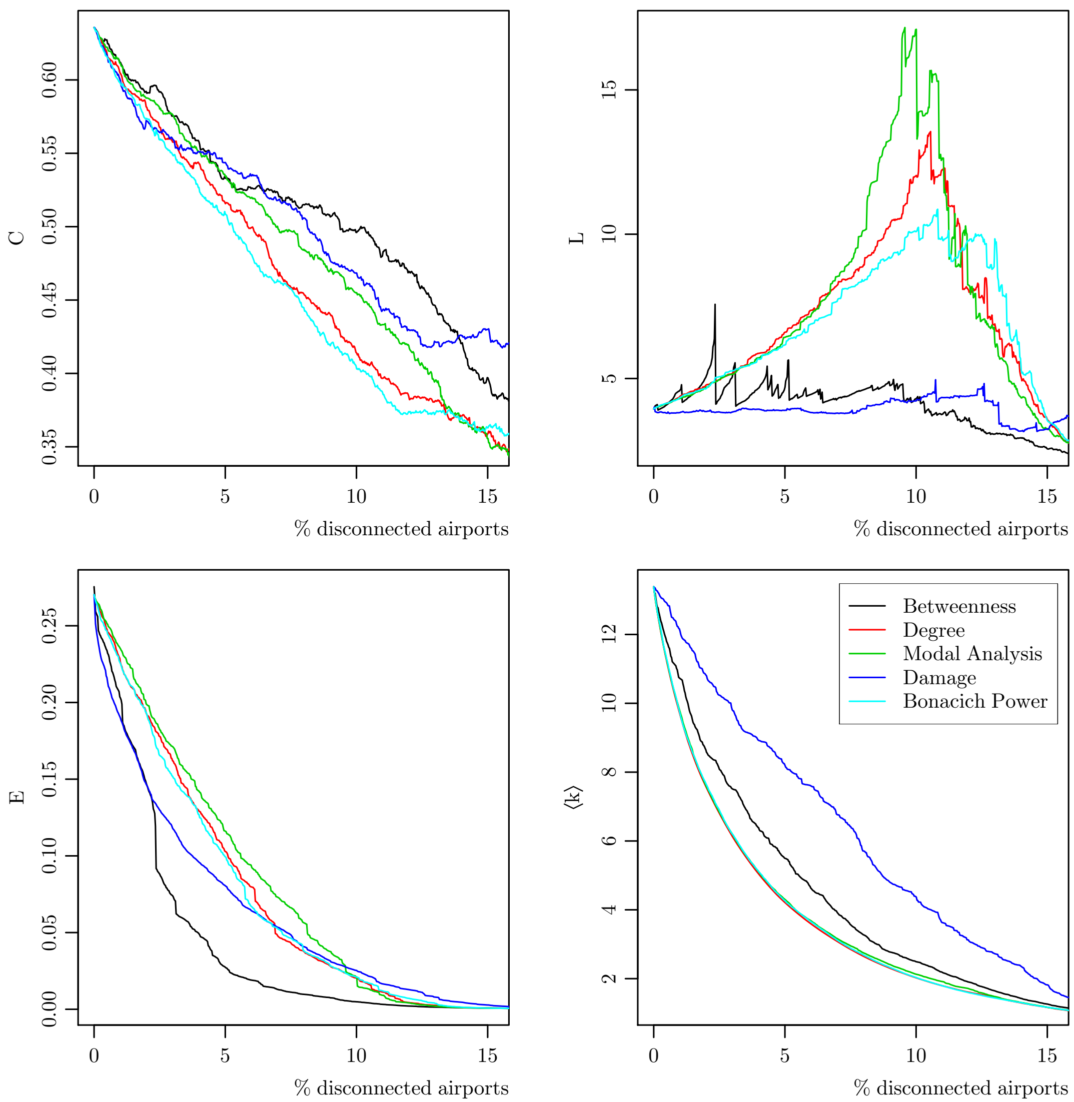
for all criteria. It is interesting to note that, for most values of f, the criteria most effective in reducing giant component size are the ones with lower efficiency.

2.6 CONCLUSIONS

In this study, the resilience of the ATN facing intentional attacks has been assessed. This network is resilient facing unintentional errors (i. e., random isolation of nodes), but has proven to be fragile facing intentional attacks. The isolation of a small fraction of selected nodes can cause serious problems to the functioning of the global ATN. This behavior can be explained by the characteristics of the ATN. The ATN is a SF network, with a truncated power-law distribution, thus less resistant to attacks than homogeneous networks. Furthermore, the ATN has additional properties that make it different to other SF networks, such as the presence of central airports with a reduced number of connections. The presence of these airports can be explained by the socioeconomic and political factors [21], and also by operational reasons (for instance, the adoption of hub-and-spoke route configurations by Full-Service Carriers).

It has been assessed the effectiveness of five criteria of node selection to simulate attacks using an adaptive strategy, in terms of reduction of size of giant component as a function of the fractions of isolated nodes. In Figure 2.3 can be seen that the damage criterion is

Figure 2.5: Evolution of network basic characteristics. Quantities measured are: clustering coefficient C, characteristic path length L, efficiency E, average degree $\langle k \rangle$



the most effective for $f < 0.025$, and that the betweenness criterion overcomes damage for higher values of f. The list of the first airports isolated with each criterion (see Table 2.1 and Figure 2.4) shows that while the betweenness criterion selects airports belonging to the ATN core (i. e., US, Europe and China), damage criterion selects airports belonging to more peripheral communities of the ATN.

It has also been introduced the Bonacich power criterion to select the nodes to isolate in an intentional attack. Although it is not the most effective criterion to disconnect the ATN, for most of the values of f beats the degree criterion. The Bonacich power criterion needs to be tested on other networks to determine its true potential. For instance, it would be interesting to apply this criterion to simulate attacks to networks where the degree criterion is more effective than betweenness, e. g. the power grid analyzed in [19]. The modal analysis criterion has proven to be the most effective to attack power grid networks [19], but it is not so effective when used in the ATN. It just proven to be effective when more of the 10% of airports are disconnected. This fact shows that different SF networks can have different properties regarding its strength facing intentional attacks.

The results of the comparison of effectiveness of criteria of node selection to attack the ATN shows that this network has a multicommunity structure where central airports (i. e., airports with the highest betweenness centrality) are the most critical infrastructures of the network in terms of its resilience facing attacks. This structure has emerged due to not only socioeconomic and geopolitical factors, but also for operational reasons. The most central airports are the hubs of Full-Service Carriers, whose routes have a hub-and-spoke structure.

The study of ATN robustness can help to improve its reliability, since it can help to detect the critical airports in the ATN structure. It can also help to devise strategies to increase network robustness, using improvement analysis techniques [76]. This research also suggest new directions to research ATN robustness. It would be interesting, for instance, to asses the dynamic robustness in the ATN. The closure of a set of airports may not cause a big damage *per se*, but the need to relocate the flights using other airports can cause the closure of these, thus provoking a cascading effect. There is evidence of this to happen, for instance in the case of the eruption of the Eyjafallajökull volcano [59]. Studies of static and dynamic robustness can also be of interest for airlines as it will be shown in Chapter 4. The use of the hub-and-spoke network configuration by Full-Service Carriers can make these airlines particularly easy to attack and they might consider to organize their route networks on a multihub-and-spoke basis to gain resilience facing intentional attacks.

3 L2: ROBUSTNESS OF AIRLINE ALLIANCES ROUTE NETWORK

3.1 ABSTRACT

The aim of this study is to analyze the robustness of the route network of the three major airline alliances (i. e., Star Alliance, oneworld and SkyTeam). Firstly, it is proposed a normalization of a multi-scale measure of the vulnerability in order to perform the analysis in networks with different sizes (i. e., number of nodes). It is also proposed an alternative node selection criterion to study robustness and vulnerability of complex networks, based on the efficiency of a network. And lastly, it is described a new procedure –the inverted adaptive strategy– for sorting the nodes in order to anticipate the breakdown of a network. Finally, the robustness of the three alliances network is analyzed with (1) the normalized multi-scale measure of the vulnerability, (2) the adaptive strategy based on four different criteria and (3) the inverted adaptive strategy based on the efficiency criterion. Results show that Star Alliance has the most resilient route network, followed by SkyTeam and oneworld. Besides, the inverted adaptive strategy based on the efficiency criterion –inverted efficiency– shows a great success on quickly breaking networks similar to betweenness criterion but with even better results.

3.2 INTRODUCTION

The coordination of airline activities in alliances has been one of the major traits of this industry since the beginning of the 90s, and in the last decade most of the Full-Service Carriers and regional airlines have participated in an airline alliance. Airlines can join alliances for several reasons. First, alliance members can benefit from economies of scale and density: without increasing the investment in aircrafts, alliance members can extend their route network and offer a wider range of frequency to customers in selected routes. Furthermore, alliance members can explore more easily ways to collaborate with other members through codesharing, joint-ventures or even merger and acquisitions [111]. Finally, alliance members can benefit from the joint offering benefits to customers (e. g., frequent-flyer programs) or from the joint purchase of supplies such as fuel. In respect to consumer welfare, airline alliances lower the fares of interline flights, which compensates the fare raises in interhub flights [34, 35]. Though, It must be noted that competence of alliance members in coordinating routes and fares is an important requirement for passengers benefits to materialize [112].

When an airline joins an alliance, the reliability of the services offered to customers depends not only on the flights the airline operates, but also on the operations of the rest of alliance members, since most of the routes offered by alliances are operated on a hub-and-spoke basis. Then, although airline alliances have been formed for operational and competitive reasons, the ascription to an alliance can determine the robustness of the incumbent airline networks.

The aim of the present study is to analyze the vulnerability of the *airline alliances route network* (AARNs) to errors (i. e., random isolation of an airport) and attacks (i. e., isolation of well-connected airports with the aim of causing the maximum damage to the route network). This assessment is performed by two different approaches: first, using a multi-scale measure of vulnerability [109], and second, examining the effect of the disconnection of a fraction f of well-connected nodes on the size of the giant component. This study can shed light on the robustness of real networks, not only for the special case of airline alliances, but also for networks sharing similar topological properties.

3.3 METHODS

3.3.1 *Vulnerability*

In [109], Boccaletti and colleagues developed a multi-scale measure of the vulnerability of a graph G introducing the coefficient p at the characteristic formula of the average edge betweenness as:

$$b_p(G) = \left(\frac{1}{|E|} \sum_{l \in E} b_l^p \right)^{1/|p|} \tag{7}$$

where $|E|$ is the number of edges, and b_l is the betweenness of the edge l calculated as:

$$b_l = \sum_{i \neq j} \frac{n_{ij}(l)}{n_{ij}} \tag{8}$$

where $n_{ij}(l)$ is the number of geodesics (i. e., shortest paths) from node i to node j that contain the edge l, and n_{ij} is the total number of shortest paths.

If one wants to compare the vulnerability of two networks G and G' with similar structural properties, one first has to compute b_1. If $b_1(G) < b_1(G')$, then G is more robust (less vulnerable) than G'. If $b_1(G) = b_1(G')$, then one has to compute b_p for values of $p > 1$ until $b_p(G) \neq b_p(G')$. Then, the network with the least value of b_p will be the most robust one. In general it has to be considered the full multi-scale sequence of betweenness coefficients $(b_p(G))_{p \geq 1}$ in order to get a sharp approach to the robustness of the network [109].

This procedure can be used to assess differences in vulnerability between airline alliance route networks (AARNs). As has been shown in Table 3.1, AARNs have a really different number of nodes and edges, so the measures of vulnerability have to be normalized in order to be able to compare graphs. One possible normalization procedure can be defined using the graphs of N nodes with minimum and maximum vulnerability: the complete and the string graphs, respectively. A complete graph of N nodes is a fully connected graph where each node has $N-1$ edges. It is easy to see that the complete graph is the graph with the minimum vulnerability, being $b(G_{complete}) = 1$. On the other hand, a path graph of N nodes can be defined as a string of nodes attached to its neighbors. Each node has two edges excepting the two end nodes of the string that just have one. This graph has the maximum vulnerability among all graphs of N nodes. With this graphs, [113] proposed a normalization for $b(G)$ as:

$$b_{nor}(G) = \frac{b(G) - b(G_{complete})}{b(G_{path}) - b(G_{complete})} = \frac{b(G) - 1}{\frac{N(N+1)}{6} - 1} \tag{9}$$

This normalization can be extended for other scales of vulnerability where $p \neq 1$. Considering the multi-scale approach on a complete graph, one can easily see that $(b_p(G_{complete}))_{p\geq 1} = 1$. For the path graph, although it is known that $b_1(G_{path}) = \frac{N(N+1)}{6}$, this simplification cannot be extended for $p > 1$. Despite of that, it is easy to see that $b_p(G_{complete}) \leq b(G) \leq b_p(G_{path})$. As a consequence, the normalization of the multi-scale measure of the vulnerability of a graph is defined as:

$$b_{p_{nor}}(G) = \frac{b_p(G) - b_p(G_{complete})}{b_p(G_{path}) - b_p(G_{complete})} = \frac{b_p(G) - 1}{b_p(G_{path}) - 1} \tag{10}$$

where G_{path} and $G_{complete}$ have the same number of nodes than G.

3.3.2 *Size of giant component*

An alternate method to assess robustness is to examine the decrease of the size of the giant component when a fraction f of nodes is isolated. To select the nodes to isolate, several node selection criteria can be adopted. In this study, the robustness to intentional attacks for each AARN attacks will be analyzed using six different node selection criteria: *degree*, *betweenness*, *modal analysis*, *damage*, *Bonacich power* and *inverted efficiency*. For the first five criteria, an adaptive strategy is adopted: each time a node is isolated, the measure for node selection is recalculated for all still connected nodes, and the node with the highest value is selected to be disconnected in the following step. These five criteria have been described in Chapter 2. In this analysis, a new way for analyzing the robustness of a network is used, the *inverted efficiency*. For this purpose, two new features are introduced altogether: the use of the efficiency for assessing the robustness of a complex network and how to invert the adaptive strategy.

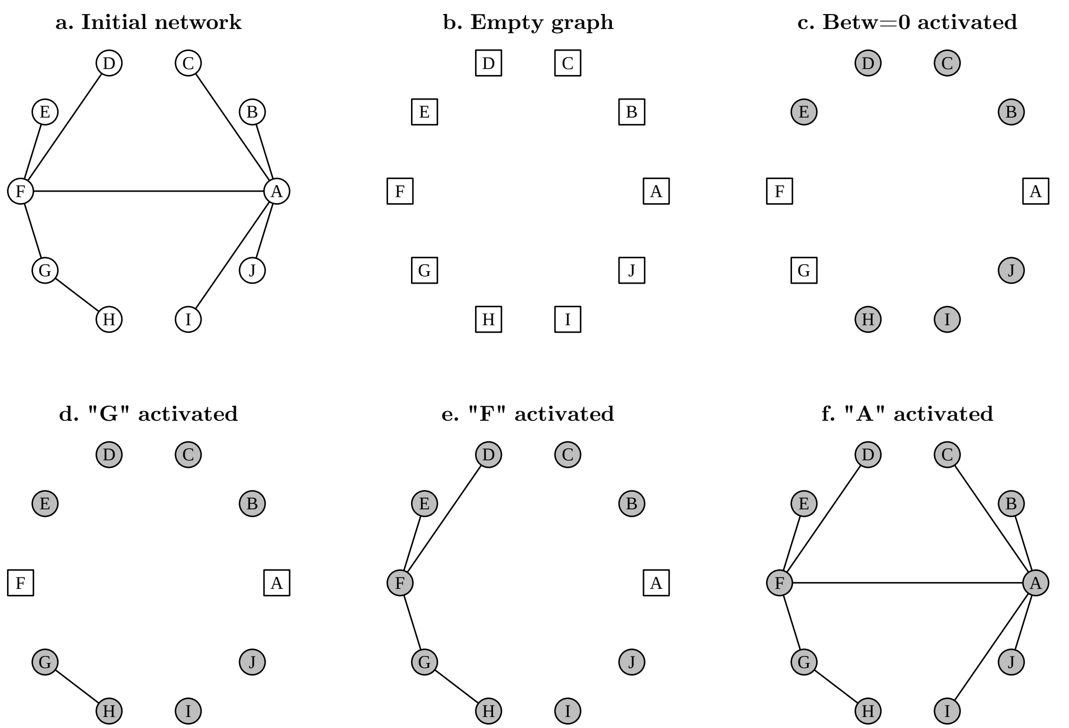
3.3.2.1 *Efficiency*

Latora and colleagues [80, 83] introduced the efficiency of a network as an indicator of its own traffic capacity as:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{11}$$

In the analysis carried in Chapter 2, it can be observed that the decrease of the efficiency of the network has an evolution similar to the decrease of the size of giant component. Therefore, a promising criterion of node selection for maximizing attack effectiveness could be selecting the node whose disconnection causes the maximal decrease of efficiency. If an adaptive strategy is used, the decrease of efficiency caused for the isolation of each of the remaining nodes must be recalculated for the next iteration. Note that efficiency, as damage criterion, is a network measure, while the other criteria are based in node measures. While for damage criterion the node to be selected is the one whose isolation maximizes this measure, for the efficiency criterion is the one that minimizes it.

Figure 3.1: Example of the inverted adaptive strategy. *Grey circles*: activated; *white squares*: desactivated



3.3.2.2 *The inverted adaptive strategy: Inverting the procedure*

When following an adaptive strategy, the usual (direct) procedure to attack a network consists on starting with the connected network, and then disconnecting nodes one by one –selected following a criterion recalculated for each disconnection– that might bring a decrease of the size of giant component as large as possible, recalculating the value of the criterion for all remaining nodes each time a node is isolated. For each criterion it is possible to construct an inverted procedure, beginning with an isolated network and adding –*activating*– nodes keeping the giant component as small as possible. The edges considered for computing the size of the giant component are those between activated nodes, and the process ends when all nodes of the original network are activated. The direct adaptive strategy starts with the original network and wants to disconnect *as soon as possible* the most central or important nodes, while the *inverted adaptive strategy* (IAS) presented starts from an empty network and wants to connect the most important nodes *as late as possible*.

A good starting point for an IAS is to compute the betweenness centrality for the nodes of the whole network, and select for activation the nodes with betweenness centrality equal to zero. These nodes are among the last ones to be disconnected with the usual direct procedures, and the network obtained considering the edges linking these nodes should have a giant component of value zero or one. The node selection procedure will be different for criteria based on node measures and on network measures:

- *Node measures*: for node measures such as degree or betweenness, the node to be selected in each step is the one that, when activated, has the smallest value of the measure among the non-activated nodes.
- *Network measures*: in the straight version of the network measures criteria, the node to be disconnected is the one that whose disconnection either maximizes (e. g., damage) or minimizes (e. g., efficiency) the chosen measure. For the IAS, the node to be activated will be the one whose activation minimizes (e. g., damage) or maximizes (e. g., efficiency) the chosen measure, respectively.

In the first activations of the IAS there can be a lot of draws between nodes. A possible criterion for breaking draws is to select the node with the lowest value of betweenness centrality in the initial network. For illustrating purposes, Figure 3.1 exemplifies this procedure, showing each step of an IAS based on the degree criterion. The graph of study is the one showed in Figure 3.1a. The first step is to take its nodes and generate an empty graph (see Figure 3.1b), where all of them are deactivated. To initiate the process, the betweenness for all nodes of the original graph is calculated: $b_i = (26, 0, 0, 0, 0, 25, 8, 0, 0, 0)$. Then, all nodes with zero betweenness are activated (see Figure 3.1c).

Following the IAS, in each iteration the non-activated node with *minimum* degree has to be activated. For instance, in the first iteration the non-activated nodes are A, F and G (see Figure 3.1c). If A were activated, its resulting degree would be 4 with A-B, A-C, A-J and A-I connections. In the same way, the degrees of F and G would be 2 (F-E and F-D) and 1 (G-H) in this iteration, respectively. As G is one of the nodes with minimum degree, it is the node to be activated in the first iteration (see Figure 3.1d), only adding the the connection G-H.

For the second iteration, the non-activated nodes are only A and F. If activated, A would have a degree of 4 and F a degree of 3. Therefore, F is the node to activate in the second step (see Figure 3.1e). Finally, there is just A left to activate (see Figure 3.1f), and the process ends since all nodes have been activated.

3.4 RESULTS

3.4.1 *Topology of alliances route networks*

The three current global airline alliances (Star Alliance, SkyTeam and oneworld) have been included in the study. These three alliances offer around 9,136 routes, which represents a 36% of the routes of the global ATN (see Chapter 2). It must be said, though, that the routes offered by alliances represent around two-thirds of total industry capacity [111]. Therefore, routes operated by alliances are among the most important, in terms of passengers and revenue, of the whole airline industry.

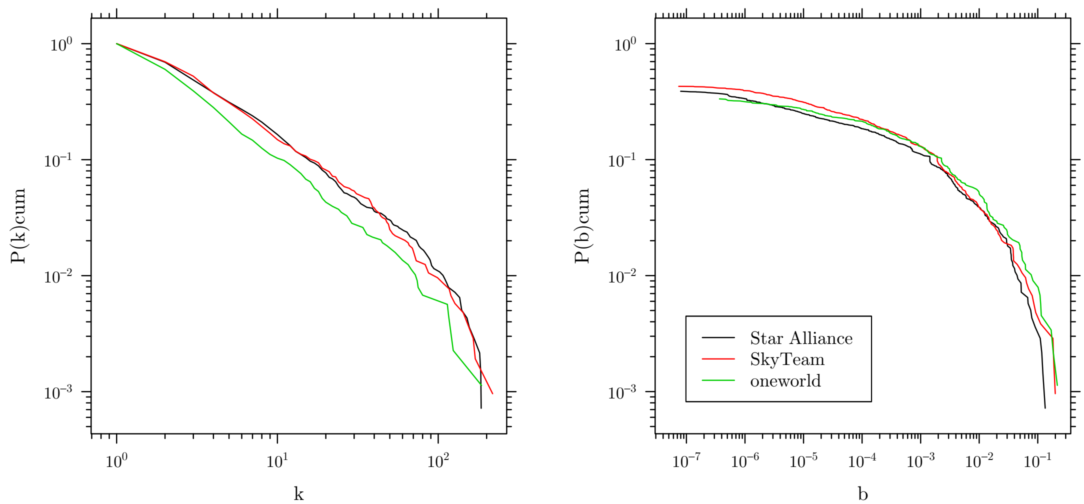
An AARN has been constructed for each alliance, in which the edges are the routes where at least one of the alliance members acts as marketing airline, and the nodes are the airports covered by the set of routes. Codesharing flights have been included considering that alliances are formed by airlines from all around the world and it would be difficult to find some area where they would not been operating. Therefore, it has been considered that alliances have no spoke airports that depends from an intermediate hub. Airports are selected as nodes rather than cities, given that airports are the likely target of an intentional attack. The set of marketed routes is the route portfolio that the alliance offers to customers, therefore it makes more sense to assess the robustness of this set instead of the smaller set of operated routes.

	N	E	$\langle k \rangle$	L	C	ν
Star Alliance	1,150	4,240	7.37	3.24	0.77	< 0
SkyTeam	896	3,226	7.20	3.13	0.74	< 0
oneworld	741	1,670	4.51	3.28	0.71	< 0

Table 3.1: Main topological properties of AARNs. The quantities measured are: number of vertices N, number of edges E, characteristic path length L, clustering coefficient C, average degree $\langle k \rangle$, and type of correlations.

To define the network, it has been considered a time horizon that lasts from November 2011 to March 2012 as all alliances have a stable number of members. In this period had taken place three changes of alliance membership: Ethiopian Airlines (ET) became member of Star Alliance in December 2011; in April 2012 bmi British Midland (BD) left Star

Figure 3.2: Degree (k) and betweenness (b) cumulative distributions for each alliance

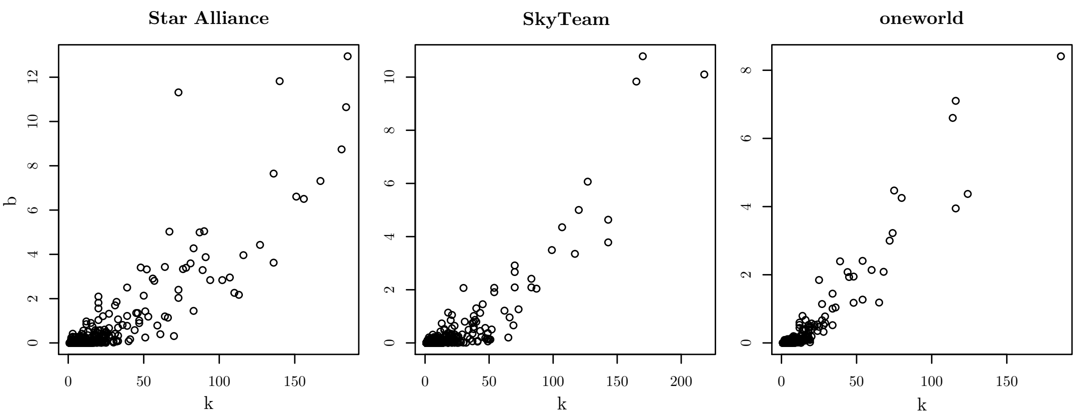


Alliance; and Air Berlin (AB) entered oneworld. Therefore, routes marketed by each AARN between December 2011 and March 2012 define the edges of each network that link the airports operated. These routes are obtained from the SRS database complied by IATA. As the majority of connections are reciprocal, the three alliance networks have been treated as an undirected network [21]. The AARNs have been considered as unweighted networks, since the purpose of this research is to assess the effect of a total disconnection of airports from the alliance network.

Table 3.1 reports the values of the main topological properties for the three alliances. When compared with the global ATN, the AARNs have smaller values of average path length and L and higher values of clustering coefficient C (as reported in Chapter 2, the ATN has $L = 3.94$ and $C = 0.64$). Thus, all the AARNs have the small-world property and also a high clustering coefficient.

Figure 3.2 reports the degree and betweenness cumulative distributions for each AARN, in a log-log scale. The three AARNs have a similar cumulative degree distribution (that is, the probability that a given node has a degree of value k), which follows a truncated power-law distribution, but with a less stark truncation than the obtained for the global ATN. Similarly, the cumulative betweenness distribution is similar for the three AARNs, and also follows a truncated power-law distribution, thus showing the presence of a subset of airports with high values of betweenness centrality for each alliance. Degree and betweenness cumulative distributions of alliances can be smoother than the ones for the global ATN for two reasons: on the one hand, a large set of airports with low degree (i. e., with few connections) present in the global ATN are not covered by airline alliances, and

Figure 3.3: Betweennes (b) as a function of degree (k) for each alliance



on the other hand, each alliance has a subset of airports with high number of connections and high betweenness centrality, as compared with the global ATN which includes all of them.

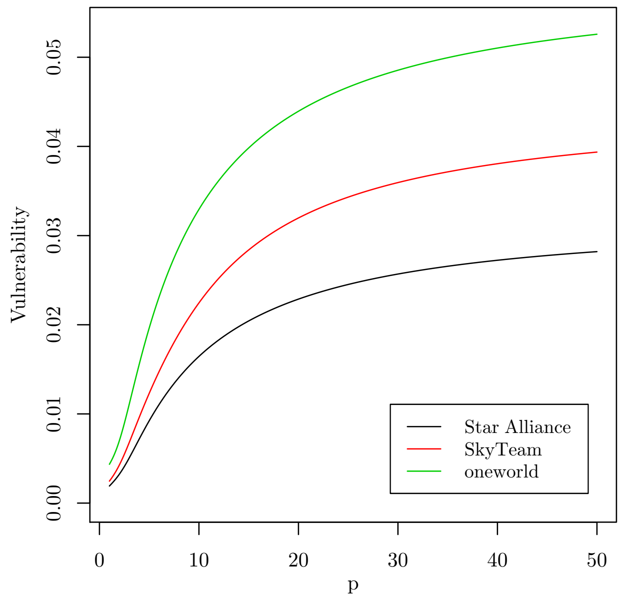
A distinctive feature for Star Alliance is shown in Figure 3.3, which compares the betweenness and the degree of each airport for each alliance. The graph of Star Alliance shows a similar pattern to the on observed for the global ATN (also considering nodes as airports, like in Chapter 2, or nodes as cities link in [21]): the appearance of nodes with a high value of betweenness and a low value of degree. In the other two graphs, though, it can be observed a strong correlation between degree and betweenness, with no airports showing the pattern of low degree and high betweenness. On the other hand, Star Alliance has a more continuous distribution of degree and betweenness, while the other two alliances have airports with values of degree and betweenness much higher than the rest (i. e., one in the case of oneworld and three for SkyTeam).

3.4.2 *Robustness of airline alliances route network*

Figure 3.4 depicts the multi-scale vulnerability measures for the three alliances for values of p ranging from 1 to 50. In order to compare the vulnerability of each alliance, the values of the multi-scales measures have been normalized following the procedure described in Section 3.3.1. The results show that Star Alliance is the alliance with lowest values of vulnerability, followed by SkyTeam and oneworld, respectively. Therefore, according to this measure, oneworld seems to have the most vulnerable network and Star Alliance the most robust one.

Figure 3.5 shows an alternative assessment of the robustness of the alliances route network: the evolution of the size of the giant component when a fraction f of the nodes is

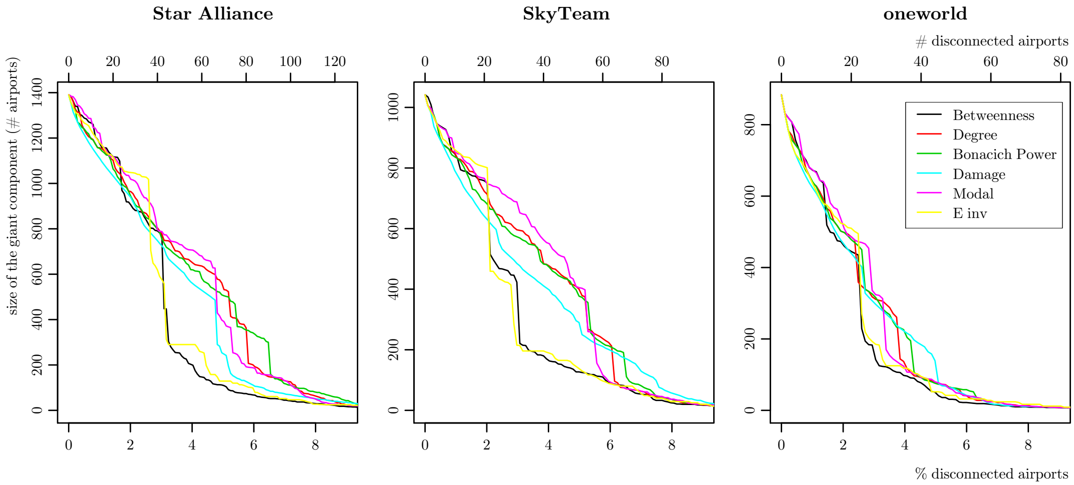
Figure 3.4: AARNs multi-scale vulnerability comparison



isolated. The criteria used to select the nodes are the ones described in Section 3.3.2: *betweenness*, *degree*, *Bonacich power*, *damage*, *modal analysis* and *inverted efficiency*. As all node criteria disconnect the networks for $f > 9\%$, this value has been adopted as the threshold for Figure 3.5. At a first glance, it can be seen that while node selection criteria give different results for Star Alliance and SkyTeam, the results of all criteria are quite similar for oneworld. A possible explanation of the behavior of oneworld comes from its topological properties: Figure 3.3 shows that oneworld is the alliance whose betweenness and degree are most correlated as all nodes with high degree have also high betweenness. It can also be observed that oneworld appears as the least robust network, as for $f \simeq 2.5$ the giant component has decreased significantly.

As for Star Alliance and SkyTeam, node selection criteria offer different results, with a similar pattern than the one obtained for the global ATN in Chapter 2. The most effective criteria to select nodes to attack Star Alliance and SkyTeam networks turn out to be betweenness and inverted efficiency (see Figure 3.5). In fact, it can be observed that inverted efficiency anticipates the significant falls of size of giant component obtained with betweenness. For values of f around 2% and 2.5% inverted efficiency is the most effective criteria in both networks. The greater performance of betweenness in front of the rest of criteria, except inverted efficiency for Star Alliance and SkyTeam can also be explained in terms of the degree vs betweenness graphs in Figure 3.3. Figure 3.6 shows the detailed decrease of the size of giant component for $f \leq 2\%$. For low values of f, damage is the most effective

Figure 3.5: Vulnerability of AARNs $f \leq 9\%$



way of attacking all AARN. More precisely, in all cases damage overcomes the rest of node selection criteria until the first break is obtained through betweenness of inverted efficiency.

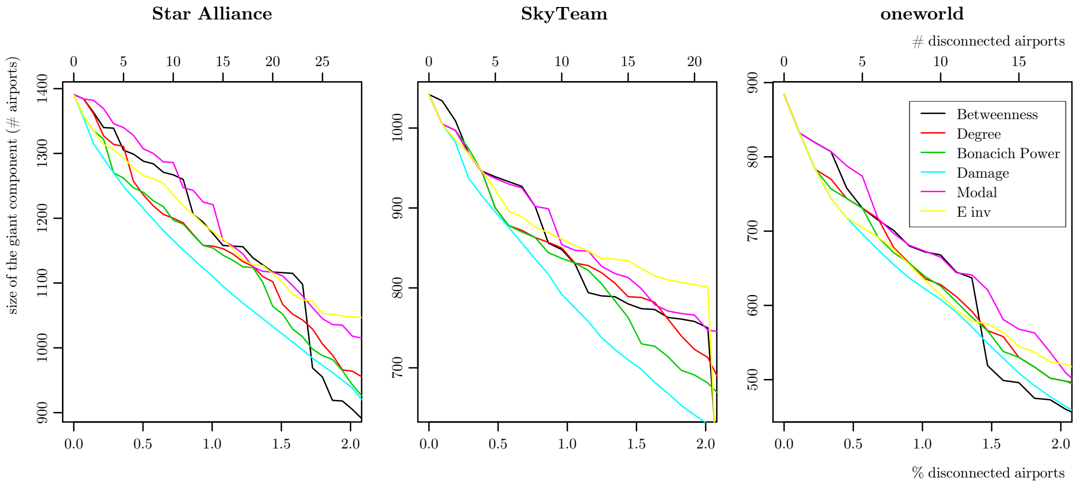
The topology of Star Alliance replicates, to some extent, a property observed in [21] for the global ATN: the existence of central (i. e., high betweenness), low-connected (i. e., low degree) nodes. This property is less salient in the case of SkyTeam, but nevertheless thus alliance has also a multicommunity structure where there are some central airports with a connectedness lower than expected, considering its network centrality.

From the results of the analysis reported in Figure 3.5, the most robust AARN to intentional attacks is the Star Alliance network, followed by SkyTeam and oneworld. Using the betweenness or inverted efficiency node selection criteria, the first network break –a significant decrease of the size of giant component– occurs for values of $f \simeq 1.5\%$ for oneworld, of $f \simeq 2\%$ for SkyTeam and $f \simeq 2.5\%$ for Star Alliance (for the first two alliances, the first break can be observed in detail in Figure 3.6). When attacked, the size of giant component of Star Alliance falls abruptly with one single break, while for the other alliances the disruption of the giant component occurs in two steps. Interestingly, the results of ranking the robustness of alliances by decrease of size of giant component are the same of the standardized multi-scale vulnerability (see Figure 3.4).

3.5 CONCLUSIONS

The airline alliances are an idiosyncratic mode of coordinating airline operations that allows airlines to provide customers worldwide mobility through collaboration with other airlines. The routes marketed by any of the members of the alliance define the airline al-

Figure 3.6: Vulnerability of AARNs. Detail: $f \leq 2\%$



liance route network, or AARN. Although any alliance covers all the global air transport network (ATN), all of the three alliances have global reach and their routes are among the most important of the ATN, in revenue and passengers transported. The AARNs are networks with a truncated power-law distribution, the small-world property (i. e., low average path length) and high clustering coefficient. The Star Alliance network is the most similar to the global ATN, since it includes central airports (i. e., airports with high betweenness centrality) with low connectedness (i. e., with low degree). For SkyTeam and oneworld is observed a strong correlation between node degree and betweenness.

The robustness of AARNs has been analyzed through two methods: the multi-scale measure of vulnerability, defined in [109], and the study of the effect on the size of giant component of the isolation of a fraction f of the airports covered by the alliance following several node selection criteria. In order to allow network vulnerability comparison, a normalization procedure has been defined for the multi-scale vulnerability. To perform the later analysis, the inverted adaptive strategy (IAS) for defining node selection criteria has been defined. Rather than starting with the connected network and trying to disconnect it *as soon as possible*, IAS starts with a disconnected network, and adds new nodes in order to connect the original network *as late as possible*. From the results of the robustness analysis of the global ATN in Chapter 2, it has been considered convenient to define a IAS in the analysis based on reducing network efficiency.

Both methods of assessing network vulnerability coincide in that the most robust AARN is the Star Alliance route network, followed by SkyTeam and oneworld. In all cases, the node selection criterion based in damage is the most effective for low values of f (around 2%), while betweenness and inverted efficiency are the most effective for higher values of

f (between 2% and 9%). The later criteria disconnect the networks through breaks (abrupt reductions of giant component). In fact, betweenness and inverted efficiency are the most effective for values of f when the first break occurs. The merit of the inverted efficiency criterion is that breaks appear before the betweenness criteria, therefore the former being the most effective for some ranges of f. Interestingly, Star Alliance has a single break of the giant component for $f \simeq 2.5\%$, while in the other two AARNs two breaks occur, of a relative size half of the value of the break of Star Alliance.

Airline alliances have appeared for economic and operational reasons, since they allow airlines benefit from economies of scale and density. A deeper insight of how AARNs are formed can include criteria based on robustness in the decisions shaping alliance evolution. Airlines seeking in which alliance participate should take into account the gain or loss of robustness of their marketed route network after joining the alliance. On the other hand, alliances seeking partners should balance the gain of coverage of the network with the variation of robustness of their AARN.

The results of the analysis reported in this study allow to compare the results of the robustness of the alliance route networks with the global ATN, analyzed in Chapter 2. As indicated in Chapter 1, the next step is to assess the robustness of individual airlines route network. It must be noted that individual airlines have features that should make their network different from the AARNs and the global ATN. First, airlines route networks do not have the global scope of alliances, and it must also be considered that the airline route network could depend on the business model adopted by each airline.

4 L3: ROBUSTNESS OF AIRLINES ROUTE NETWORK

4.1 ABSTRACT

Network strategies adopted by airline carriers have been a recurring subject in air transport research. Disruption of communication via air routes by intended causes (e. g., terrorist attack on an airport) or unintended (e. g., weather) could be a serious drawback for the operations of the affected airlines. Airlines should be able to reduce the effects of such interruptions in order to ensure good communication through air transport (i. e., maximize the robustness of their network at a reasonable cost). To do this, a complex network approach provides a network robustness analysis. As showed in Chapter 1, the literature review of the study of air transport route networks through an analysis of complex networks has highlighted a lack of contributions to the study of the dynamic behavior of such networks. This behavior, however, has been analyzed for other transport networks or communication systems. Since airline carriers have different network strategies –especially considering the use of hub airports where traffic intensifies and therefore exists greater risk to an attack on the hub– the aim of this research is to study how airline carriers respond to intended and unintended airport closures depending on their network configurations.

4.2 INTRODUCTION

The air transport industry is one of the most dynamic industries in the global economy and with one of the toughest competition. The liberalization of the airline sector [114] has produced very distinct business models among the airlines [115], being the design of their route networks a strategic factor, in addition to others such as the cost structure and principal services.

Most of the times the airlines make the election of operating a route based on the existing supply and demand volumes. The robustness of its network is considered of secondary importance, although it can provide great improvement to the stability and security of the operation of the carrier. Many domestic airlines are often associated with the image of a country or region and produce a huge economic impact on its national and international economy. Collapse or critical error of airline network can produce high financial costs for the airline and all its geographical area of influence [20].

The examination of flight networks (i. e., networks where the airports act as nodes connected if at least one direct route between them exists) through complex networks techniques can provide a deeper understanding of the behavior of airline networks when facing random errors and intentional attacks. Recent articles have analyzed the topology of the air transport network in order to understand their distribution and characteristics. These studies have assessed the behavior of both global and regional air traffic networks [21, 22]. Other studies have analyzed the robustness of the air transport network in order to determine which airports can be critical if they cease operations [47, 50, 57]. However, airlines (the main users of such airports) have been rather unnoticed in the literature with just a few studies [33, 54]. Currently, there are two predominant business models: *Full-Service Carriers* (FSC) and *Low-Cost Carriers* (LCC). These types of carriers are characterized by having, respectively, hub-and-spoke (HS) and point-to-point (PP) network configurations, although in the last case the model has size limitations due to network route density issues [116]. Given the differences in network topology their behavior in front of the malfunction of airports, its robustness, should be quite different.

The aim of this study is to study the robustness of airline networks when facing attacks and errors. In order to compare the robustness of the point-to-point and hub-and-spoke network configurations, the set of airlines to be studied will include Full-Service Carriers and Low-Cost Carriers.

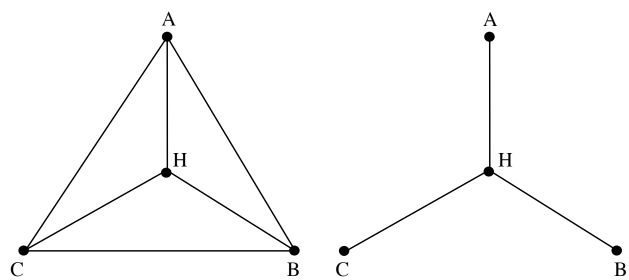
4.3 ROBUSTNESS OF CONFIGURATIONS OF AIRLINE NETWORKS

The business models and strategies of airlines strongly define their network structure. Traditional airline network analysis measures its topology variables depending on traffic distribution or concentration of frequencies [117, 118, 119]. One objective of these studies is to relate, compare and resemble an airline network to the HS and PP configurations. LCC adopt a PP network configuration because they connect city pairs that offer high load factors and therefore optimize their operability. On the other hand, FSC often develop a HS configuration, offering more destinations by using one or more strategic hubs where large passenger flows concentrate. This allow FSC to get a profitable load factor on routes applying economies of scale [120].

Both HS and PP configurations can be described schematically through a network of four nodes, as shown on Figure 4.1. The HS configuration is represented on the right. It consists of a central node or hub H connected to the other nodes, thus only three routes are needed to bond the four destinations. The PP configuration is shown on the left and it uses a total of 6 routes to connect all possible node pairs. Generalizing these concepts for n airports to connect all their destinations, the PP configuration requires $n(n-1)/2$ routes while the basic HS configuration works with only $n-1$ [120]. It is also important to consider the temporal distribution of each model, a fact directly related to the schedule of flights for each airline. The hub of the HS configuration concentrates a high traffic density in space and time [119].

In the scheme proposed on Figure 4.1, the HS configuration concentrates a larger volume of flights and passenger traffic in the switching times. For example, for being able to go from B to A and from C to A one must call at H. Therefore, it is necessary to coordinate the arrivals of the first section and the exit of the second at the hub. This would give enough time to operate the connection without hindering the operability of the airline. The PP traffic model is temporally and spatially more dispersed because airlines adopting this configuration often operate from airports where planes sleep. The reasons for this strategy are both economic and political due to the lack of volume of demand on certain routes, the absence of slots at airports and rotation need to optimize the operational fleet [120].

Figure 4.1: HS and PP configurations. Source: [120]



However, the design of an airline network is a complex process adapted to maximize the profitability of the airline. Thus it is not surprising to verify that the FSC and LCC business models evolve depending on market opportunities. For example, in 2006 Iberia created Clickair as a LCC following a multi-brand strategy to maintain product differentiation. That same year Aer Lingus was redefined as a LCC because of the major survival threats it was facing [33]. But robustness issues, although not usually considered in airline network development, can affect seriously airline profitability in the long term, and have a relevant impact in the economy.

The global air transport network is responsible for the movement of thousands of people daily. Considering its magnitude, any failure and inefficiency on flight operations causes a high economic cost for many business sectors. The volcanic eruption of Eyjafallajökull on March 14, 2010 in Iceland restricted the European air traffic and left areas out of operation for 30 days [105]. It caused about 10 million delays on the operating airports. Economically, the revenue loss of the affected companies was estimated to be about \$1.7b [106]. The consequences of Hurricane Sandy on the US East Coast, an area that holds major hubs connecting to Europe, resulted in 17,000 cancelled flights and a loss of \$0.5b in airlines revenue [121]. The cost for the airlines of the 2010 Spanish controllers strike is estimated to be \$134m [93]. That same year snow and strikes cost easyJet £31m [94]. These examples show the large economic consequences that affect both states and airlines themselves. Therefore, the robustness of an airline network and its response to intended attacks or errors in its airports is vital for the proper development of the sector.

4.4 METHODS

A total of 10 FSCs and 3 LCCs (see Table 4.1) route network have been analyzed.

During the summer period, and more precisely in August, there is a higher passenger traffic affecting directly on passengers relocation, being this period the one with the highest contribution margins for the airlines. The route networks of scheduled flights of August 2013 have been chosen for the analysis in order to be able to assume this analysis as static without taking into account the relocation of passengers. The graph of the route network in this period for each airline has been constructed. In the graph the vertices represent airports and the edges represent the operated routes scheduled between them. Airports are selected as nodes rather than cities, given that airports are the likely target of an intentional attack. Table 4.2 shows the list of selected airlines together with the number of airports (N), number of connections (E) and other topological properties of their network. The network will be treated as undirected since just a small number of flights follow a "circular" pattern [21].

	Airline Name	Alliance	Region
LH	Lufthansa	Star Alliance	Europe
UA	United Airlines	Star Alliance	North America
US	US Airways	Star Alliance	North America
AB	airberlin	oneworld	Europe
AA	American Airlines	oneworld	North America
BA	British Airways	oneworld	Europe
AF	Air France	SkyTeam	Europe
MU	China Eastern	SkyTeam	China
CZ	China Southern	SkyTeam	China
DL	Delta	SkyTeam	North America
FR	Ryanair	LCC	Europe
U2	easyJet	LCC	Europe
WN	Southwest Airlines	LCC	North America

Table 4.1: Airlines analyzed by IATA code

Only flights that are operated for the selected airlines are being considered thus dismissing the flights operating under codesharing agreements. The aim of this study is to analyze the robustness of the airline so adding codesharing flights could blur the results. For example, by considering the codesharing flights on the network of British Airways, Dallas/Fort Worth would appear as the airport with the highest degree, followed by London Heathrow, O'Hare, Miami and London Gatwick airports. However BA is actually not allowed to flight a route from Dallas/Fort Worth to another American destination. If this airport had been selected the resulting robustness would have been miscalculated. Disconnecting their real hubs (i. e., London Heathrow, London Gatwick and London City) BA would not have been able to flight any route from Dallas/Fort Worth nor O'Hare nor Miami airports.

The sample of airlines includes FSC belonging to the main three current airline alliances (i. e., Star Alliance, oneworld and SkyTeam) analyzed in Chapter 3, fulfilling the requirements of maximum number of airports, maximum number of passengers per year and/or maximum income within their alliance as published respectively on their annual report for 2012 [122, 123, 124]. Nevertheless, it must be noticed that airberlin was defined as a LCC before becoming part of oneworld but in this study has been considered as a FSC. This is because it belongs to an airline alliance and cooperates with other airlines, a feature uncommon for a LCC. The 3 selected LCC are those that operate a higher number of flights per year.

	N	E	$\langle k \rangle$	L	C	ν
LH	209	395	3.78	2.18	0.93	< 0
UA	362	933	5.15	2.57	0.91	< 0
US	203	408	4.02	2.26	0.96	< 0
AB	119	361	6.07	2.31	0.51	< 0
AA	272	523	3.85	2.3	0.94	< 0
BA	186	223	2.4	2.87	0.15	< 0
AF	178	258	2.9	2.42	0.46	< 0
MU	182	571	6.27	2.5	0.55	< 0
CZ	178	576	6.47	2.45	0.62	< 0
DL	328	882	5.38	2.38	0.88	< 0
FR	178	1,396	15.69	2.16	0.44	< 0
U2	131	601	9.18	2.19	0.39	< 0
WN	86	507	11.79	1.97	0.72	< 0

Table 4.2: Main topological properties of airlines route network. The quantities measured are: number of vertices N, number of edges E, characteristic path length L, clustering coefficient C, average degree $\langle k \rangle$, and type of correlations.

The static robustness analysis in air transport can evaluate the effect of errors (e. g., weather inclemencies) or attacks (e. g., terrorism) in a route network. Network robustness can be assessed through the effect of the isolation of a fraction f of nodes on the size of the network's giant component. The network will be robust when the size of giant component decreases little for relativelt high values of f [19, 113]. The study of the robustness allows to evaluate the capacity of a network to avoid a malfunction when a fraction of its components is damaged [13]. Thus, the network resilience (i. e., the tolerance to attacks and congestion caused by any malfunction) can be analyzed. Although there is a lack of robustness studies on the air transport field, the study of the robustness of a network was one of the first issues to be explored in complex networks literature [26].

In this study the network resilience to random failures and intentional attacks is analyzed. For the analysis of random failures, 1,000 iterations of random airport closures for each airline were simulated. Regarding the study against attacks, the established methodology has been to determine the order of importance of each airport according to a measure of centrality, and simulate an isolated attack on the airport with the highest value of that centrality. After each airport is disconnected the centralities are recalculated so that the next attack strikes the new most central airport. The centralities used are the degree (i. e., number of connections of each node) and betweenness (i. e., number of times a node is in the shortest path between two nodes). These are two of the standard measures of node centrality that have been used in Chapter 2 and Chapter 3. With each airport offlined the largest connected component, or giant component, will be observed in order to see how the network fragmentation evolves.

4.5 RESULTS

4.5.1 *Topology*

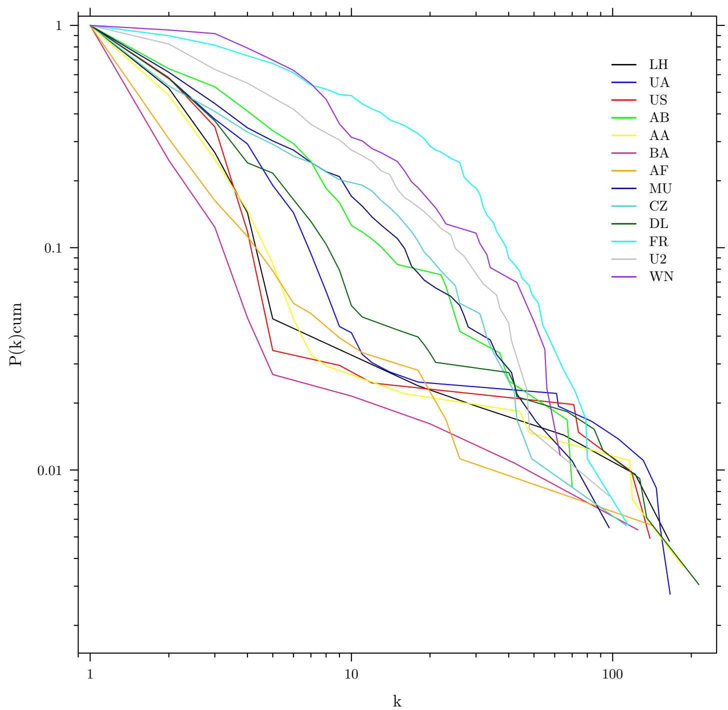
Considering the impact of network topology on robustness, an analysis of degree distributions of the airline network of the selected airlines has been conducted. Figure 4.2 shows the cumulative degree distribution plotted in double-logarithmic scale where $P(k)cum$ is the cumulative probability for a node to have degree k. There are three different behaviors present, and none of them follows a Poisson distribution as it would be expected for random graphs. This simple interpretation allows a distinction of the topological differences of the business models.

On the top of Figure 4.2 there are the curves for FR, WN and U2. They have the lowest initial gradient and a concave shape. This means that these carriers will have a more uniform network connection distribution. This shallow slope highlights the presence of a high number of airports with 10 or more connections. This is the characteristic behavior of the PP configuration. Although having this configuration, LCC also have operating airport bases with a high number of connections that they use for operating and maintenance purposes. For instance, Ryanair has around 50% of its airports with ten or more connections while already having 115 connections in London Stansted.

The next set of airlines, AB, MU, CZ follow a more linear distribution in the double-logarithmic scale that responds to a power-law degree distribution. airberlin, China Eastern and China Southern have the highest values of mean degree $\langle k \rangle$ right below the first set of airlines, all of them LCCs (see Table 4.2). These carriers have an intermediate behavior between the LCCs and the remaining analyzed FSCs.

Finally, the remaining carriers are FSCs. They have a steeper fall as a response to a slightly increase of the degree. This underlines the existence of many airports with 1 to 5 connec-

Figure 4.2: Cumulative degree distribution plotted in double-logarithmic scale



tions and very little with over 100 connections. For instance, the network of British Airways consists of 186 airports spread over the five continents being London Heathrow airport the node with the largest degree with 125 destinations followed by London Gatwick with 42 and London City with 20. The connections of the rest of the airports are drastically lower, having more than a 75% of its airports with just one connection.

Through this, one can observe that FSC seem to have a clearly differentiated topology from LCC. There are also the carriers with an intermediate behavior, airberlin or some Chinese carriers such as MU and CZ. As discussed earlier on, airberlin was a LCC before becoming part of oneworld. Therefore, this airline can have a hybrid behavior, with a business model blending low-cost traits with those of full-service carriers [125]. The behavior of Chinese carriers can be explained by the fact that most point-to-point flights are operated from a few important airports.

4.5.2 *Robustness*

For the first five criteria, an adaptive strategy is adopted: each time a node is isolated, the measure for node selection is recalculated for all still connected nodes, and the node with the highest value is selected to be disconnected in the following step.

In order to assess the network robustness of the airlines in study, the behavior of each one has been analyzed after the progressive closure of airports as a consequence of errors and attacks. To evaluate the robustness to intentional attacks, two adaptive strategies based on degree and betweenness centralities have been tested. In an adaptive strategy, each time a node is isolated, the centrality measure is recalculated for all still connected nodes, and the node with the highest value is selected to be disconnected in the following step. It has also been assessed the behavior of the airlines route networks when suffering errors, i. e. random isolation of airports. A simulation of the behavior of the airlines facing errors has been run $5,000$ times, and the average size of the giant component as a function of the number of airports isolated has been retained. The evolution of the decrease of size of giant component of each airline for the three tests (degree- and betweenness-based attacks and errors) can be found on Figure 4.3. The number (up) and percentage fraction f (down) of disconnected airports are depicted on the x axis.

As a consequence of the analysis of the robustness of airlines network against errors or unintended causes, it can be concluded that there are no major differences between the behavior of FSC and LCC (see point-dotted line in Figure 4.3). The decrease of the giant component against errors caused by the disconnection of a fraction of airports equal to $f = 0.05$ ranges from 5 to 10% of the initial size. This means that the network is not particularly vulnerable to unintended attacks. Although there are not major differences between FSC and LCC behaviors against errors, some minor differences can be observed. Reviewing the decrease caused by a $f = 0.05$ disconnection, LCC ranges $5 - 5.5\%$ while FSC ranges $7 - 10\%$. FSC are a little less resilient than LCC against unintended attacks.

The conclusion of the study on the response in front of intended attacks is that, overall, the best method of attack is the betweenness criterion as shown in Figure 4.3. In most of the cases, however, there are small differences between the degree and betweenness criteria attacks because of the network size and its structure. These are networks not as large as the ones previuosly analyzed in Chapter 2 and Chapter 3. Their size is between 86 to 362 airports (see Table 4.2), where the airport that has the largest number of routes is usually the busiest. For Lufthansa, US Airways, American Airlines and British Airways the giant component variation is completely identical for both criteria. The most significant changes are observed in the curves of China Eastern and Ryanair. It can be observed that they are the airlines with the most distinct degree and betweenness curves. The maximum differences on the curves occur on China Eastern, for a given $f = 0.104$ with a corresponding size of the degree attack that exceeds in 31 airports the equivalent betweenness attack. And for Ryanair, the maximal difference are 21 airports for a $f = 0.270$.

A comparison of the robustness of the airlines is shown both with an almost total range of f (see Figure 4.4a) and in more detail for low values of f (see Figure 4.4b) to achieve better insight in the reduction of the size of the giant component after disconnecting the first airports. Since the betweenness criterion has turned out to be the best elimination criterion it will be the one considered from now on to compare the network robustness of the selected airlines. According to airlines network behavior, the selected airlines can be grouped in three different categories.

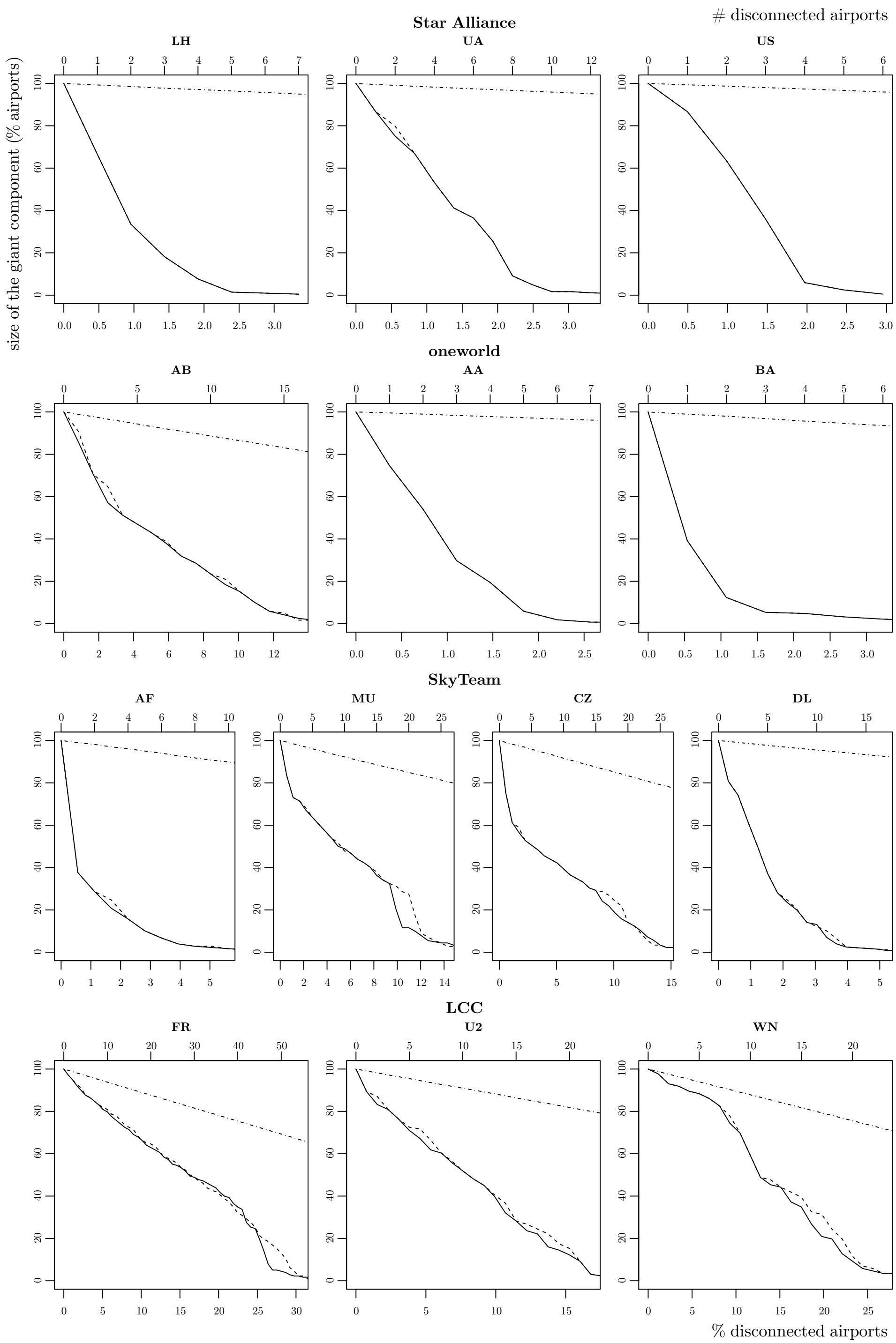
On Figure 4.4a it can be observed that LCC are much more robust and have a higher tolerance to attacks than FSC. For LCC, to have less than 5% of the network connected is necessary to disconnect up to a routes fraction of 0.28 for Ryanair (FR) and 0.26 for Southwest Airlines (WN). For Easyjet (U2) the fraction of nodes to disconnect lowers to 0.17. One can also observe that at the start of the disconnection process (see Figure 4.4b) the LCC also behave with a higher robustness. After isolating a fraction of nodes $f = 0.04$, the giant component of the network of WN, FR and U2 still have the 91%, 84% and 70% of the initial size, respectively. Given that WN is the airline with a network with the lowest number of airports and under this perspective the initially most robust one, it can be concluded that the robustness of the network of an airline is not proportional to its size but to its intrinsic structure. As explained earlier, the three airlines have a PP route network configuration and therefore this configuration is more resilient against attacks than HS configuration.

In consequence with Figure 4.4a it is considered that WN and FR fall into the first of the three categories introduced above. As shown on Figure 4.4a, WN is initially more robust than FR but around of the 11% of the airports disconnected in their route networks. Despite the fact of also being a LCC, U2 has a clearly different behavior against this kind of attacks and is necessary to group it with the second set category of airlines, i. e. China Eastern (MU), China Southern (CZ) and airberlin (AB).

According to what has been exposed on the degree distribution section, MU, CZ and AB show a particular behavior as FSC both on the medium (see Figure 4.4a) and low (see Figure 4.4b) values of f. In order to have the network almost disconnected, i. e. just to a 5% of its original giant component size, these airlines must have a fraction of their airports disconnected closer to U2 than to the other FSC: $f = 0.13$ for MU, 0.14 for CZ and 0.12 for AB. For $f = 0.04$ the network size is much higher than it is for the carriers of the previous category, being 56%, 46% and 48% respectively. This can be interpreted as a result of a network structure laying somewhere in between the PP and HS. Although it is true that each airline has one or two central airports both in degree and in betweenness measures, Shanghai and Kunming for MU, Dusseldorf and Berlin-Tegel for AB and Guangzhou for CZ, the rest of the network has a structure similar to a PP. This means that the decrease of the size of the giant component against attacks is substantially more gradual than in the HS configuration.

The last category of airlines includes the FSC carriers: Lufthansa (LH), United Airlines (UA) and US Airways (US) from Star Alliance; American Airlines (AA) and British Airways (BA) from oneworld, and Air France and Delta (DL) from SkyTeam. Those are the airlines

Figure 4.3: Error and attack vulnerability of each airline transport networks. Plain line: betweenness attack; Dotted line: degree attack; Point-dotted line: error



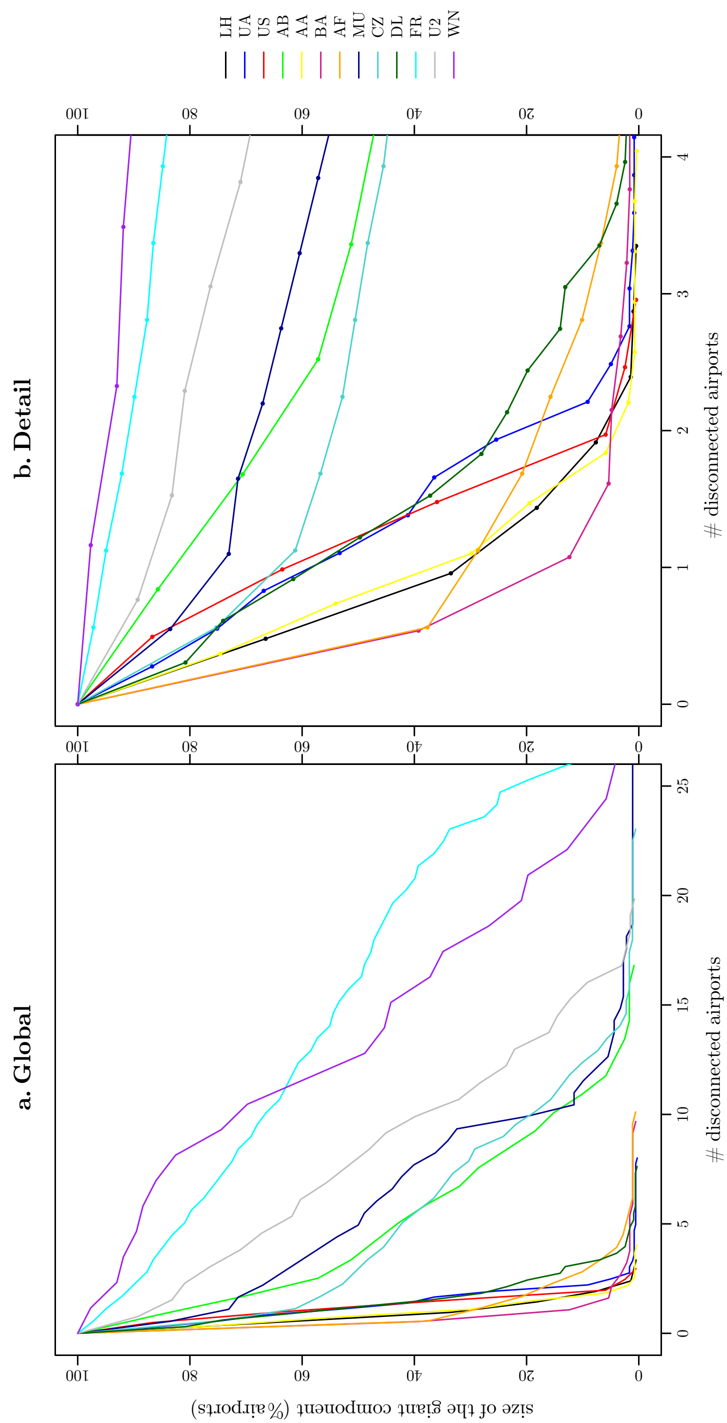
where first attacks have a greater impact. After attacking around $f = 0.04$, the size of their network's giant component plunges to under a 5% of the initial size generating a severe state of lack of operation capability (see Figure 4.4a). This behavior can be associated to the HS structure because once the most central nodes are attacked, the network is almost completely disconnected. Given the fast pace of network breakage, in this case it is important to assess the damage to lower fractions. For $f = 0.01$, the decrease of its size is not uniform and varies in relation to the existence of a single hub or more (i. e., multi-hub-and-spoke configuration).

From the results, it can be concluded that the FSC have a network configuration that makes them weak against intentional attacks. For example, Charlotte-Douglas, Phoenix and Philadelphia are the three main airports of US. They are followed by a less central airport but with a big difference of centrality from the fifth, the Washington-National. After attacking the first two ($f = 0.01$) the size of the giant component is reduced to 64%, maximum robustness of this category, but after attacking the third and fourth ($f = 0.02$) it is reduced to just 6%. On the other extreme there is BA which, as discussed above, centralizes its operations at Heathrow, followed by Gatwick and London City. By disconnecting only a fraction of $f = 0.01$, i. e. the first two airports, the size of its giant component falls to the 12% of its initial value, the minimum robustness of this category. For $f = 0.02$, after closing the third and forth airports, the size drops to 5%. By also considering that an attack against Heathrow would suppose the closure of the nearby airspace and consequently all the airports in London, the network of British Airways would be virtually disconnected and practically inoperative with a single attack.

It is also noteworthy the response to attacks of DL, the airline with the highest number of airports in its network. After disconnecting its four most central airports, Atlanta, Minneapolis St.Paul, Detroit and New York JFK its network still has half of its nodes connected. Atlanta stands out significantly in terms of degree and betweenness while the other three airports, with lower indices, share similar values. After the attack on the next three airports reaching $f = 0.02$, the size falls to 23%. AF shows a somewhat different behavior. After the disconnection of its main hub Paris-Charles De Gaulle ($f = 0.01$) the size of its giant component is lowered to 38%. However, subsequent attacks to Paris-Orly and the other airports downsize the giant component on a much more gradual way, since the degree and betweenness indices decrease with a significantly lower rate than the other airlines. The network that remains after isolating Paris-Charles De Gaulle has a structure similar to a PP configuration, thus having a network structure similar to AB, MU and CZ but with a much more prominent central hub.

Such considerations can determine that the damage caused by intentional attacks to networks with HS configuration is higher than to those with a PP configuration. The less hubs the airline has, the more severe the damage is. The fact that the hubs are located closer geographically can increase the potential damage, because of the damages associated with the disconnection of the nearby airspace as exemplified in [59].

Figure 4.4: Betweenness attack vulnerability of airline transport networks. **a**. Global ($f \leq 25\%$). **b**. Detail ($f \leq 4\%$)



4.6 CONCLUSIONS

In this chapter the analysis of the network robustness of thirteen airlines based on error and attack simulation is performed. This simulation is run to verify if there is any difference on the behavior of FSC and LCC business models.

The analysis has confirmed that FSC are more sensitive to intentional airport closure than LCC. That is, disconnecting the FSC hubs causes a bigger harm than the disconnection of the base airports of a LCC. On top of it, WN and FR, the most important LCC at the moment turned out to be the most robust against attacks. Within the set of FSC there are three airlines with a peculiar behavior. These are the Chinese MU and CZ, the only ones in a region outside of Europe or North America, and AB, which was a LCC before it joined oneworld, which explains its differentiation.

Whereas Figure 4.4b grants a more realistic approach of an individual attack approach, Figure 4.4a allows to evaluate the consequences of attacking a higher number of airports. Comparing the robustness of the set of studied airlines, it can be concluded that it is possible to attenuate the consequences of attacks by means of disposing of a multi-hub-and-spoke network. This network should be built by hub airports strategically disposed distant from each other in order to avoid larger problems related to airspace closure. This distance would allow an homogenization of the importance and centrality of the network without neither losing operability, nor the possibility of applying economies of scale. A second action to increase robustness would be to schedule PP connections on the less central airports to connect them if one of their hubs fails, achieving with this an structure somewhere between HS and PP. This second solution should take into account the supply and demand of each route in order not to hinder the profitability of the airlines.

It is worth mentioning that these considerations are based on topological criteria applied to complex networks. In the day to day of the airlines there are many other aspects that define airline strategies [126], that can have an impact on route structure and network strategy. Therefore the application of the proposed solution has to be evaluated deeply and in detail. In future studies the passenger flux could be taken into account and as a result an interpretation of the traffic loss that supposes the closure of airports may arise. Nevertheless a similar result should be expected because the most central airports are those that concentrate a higher volume of aerial traffic in terms of flights and passengers. Despite these considerations, further studies on this area will suppose a complement for the evaluation of the protection, stability and safety of each airline network according to their business model.

Part III

CONCLUSIONS

5 CONCLUSIONS

Currently, the literature analyzing air route networks through a complex network approach seems to be focused on the study of the topology of regional or global route networks as shown in Chapter 1. The literature review has allowed the definition of different dimensions or levels of study characterized by different units of analysis. Therefore, and given that each level has different characteristics and properties, three levels of study have been proposed: the *global route network* (L1), the *airline alliance network* (L2) and a particular *airline network* (L3). They can be separated in two different approaches: the airline management approach (L2 and L3) and the government policy approach (L1).

The study of the global route network (L1) looks at the competitive environment for airlines and the general framework of air transport development. On the other hand, alliances and airlines network studies (L2 and L3, respectively) focus their attention on companies or organizations and it allows to determine the properties of organizational networks. The analysis of business networks (i. e., airlines or alliances) robustness could influence the decisions to open new routes or negotiate new codesharing agreements while the analysis of the robustness of route networks in a specific region (L1), whether they are continents or countries, would help to make better decisions on air route development at the policy-making level. This thesis has analyzed the topology and robustness of these 3 proposed levels.

In Chapter 2, the resilience of the first level proposed L1 –the global air transport network (ATN)– facing errors and intentional attacks has been assessed. This network is resilient facing unintentional errors (i. e., random isolation of nodes), but has proven to be fragile facing intentional attacks. The isolation of a small fraction of selected nodes can cause serious problems to the functioning of the global ATN. This behavior can be explained by the characteristics of the ATN. The ATN is a scale-free (SF) network, with a truncated power-law distribution, thus less resistant to attacks than homogeneous networks. Furthermore, the ATN has additional properties that make it different to other SF networks, such as the presence of central airports with a reduced number of connections. The presence of these airports can be explained by the socioeconomic and political factors [21], and also by operational reasons (for instance, the adoption of hub-and-spoke route configurations by Full-Service Carriers).

Chapter 2 has assessed the effectiveness of five criteria of node selection to simulate attacks using an adaptive strategy, in terms of reduction of size of giant component as a function of the fractions of isolated nodes f. The damage criterion is the most effective for $f < 0.025$, and that the betweenness criterion overcomes damage for higher values of f. The list of the first airports disconnected with each criterion has shown that while the betweenness criterion selects airports belonging to the ATN core (i. e., US, Europe and China), damage criterion selects airports belonging to more peripheral communities of the ATN. The security and performance of the most critical airports found in both criteria –FRA, ANC, CDG, AMS, FAI, SEA, PPT, etc. (see Table 2.1)– should be properly reviewed due the great impact that a possible malfunction would have on the entire ATN.

It has also been introduced the Bonacich power criterion to select the nodes to isolate in an intentional attack. Although it is not the most effective criterion to disconnect the ATN, for most of the values of f it has beaten the degree criterion. The Bonacich power criterion should need to be tested on other networks to determine its true potential. For instance, it would be interesting to apply this criterion to simulate attacks to networks where the degree criterion is more effective than betweenness (e. g., the power grid). The modal analysis criterion has proven to be the most effective to attack power grid networks [19], but it has not been so effective when used in the ATN. It has just proven to be effective when more of the 10% of airports were disconnected. This fact shows that different SF networks can have different properties regarding its strength facing intentional attacks.

The results of the comparison of effectiveness of criteria of node selection to attack the ATN shows that this network has a multicommunity structure where central airports (i. e., airports with the highest betweenness centrality) are the most critical infrastructures of the network in terms of its resilience facing attacks. The most central airports are the hubs of Full-Service Carriers, whose routes have a hub-and-spoke structure.

Descending one level to L2, Chapter 3 has analyzed the airline alliances route network (AARNs). It revealed that the AARNs are networks with a truncated power-law distribution, the small-world property (i. e., low average path length) and high clustering coefficient. The Star Alliance network has been the most similar to the global ATN, since it includes central airports (i. e., airports with high betweenness centrality) with low connectedness (i. e., with low degree). For SkyTeam and oneworld has been observed a strong correlation between node degree and betweenness.

The robustness of AARNs has been analyzed through two methods: the multi-scale measure of vulnerability, defined in [109], and the study of the effect on the size of giant component of the isolation of a fraction f of the airports, covered by the alliance following several node selection criteria. In order to allow network vulnerability comparison, a normalization procedure has been defined for the multi-scale vulnerability. To perform the later analysis, it has been defined the inverted adaptive strategy (IAS) for defining node selection criteria. Rather than starting with the connected network and trying to disconnect it *as soon as possible*, IAS starts with a disconnected network, and adds new nodes in order to connect the original network *as late as possible*. From the results of the robustness analysis of the global ATN in Chapter 2, it has been considered convenient to define a IAS in the analysis based on reducing network efficiency.

Both methods of assessing network vulnerability has coincided in that the most robust AARN is the Star Alliance route network, followed by SkyTeam and oneworld. In all cases, the node selection criterion based in damage is the most effective for low values of f (around 2%), while betweenness and inverted efficiency are the most effective for higher values of f (between 2% and 9%). These results are comparable with ATN robustness results, where betweenness was the most effective criterion although damage criterion had better performance for lower airports disconnected. In fact, for AARNs, betweenness and inverted efficiency has been the most effective for values of f when the first break had occured. The merit of the inverted efficiency criterion is that breaks appeared before the betweenness criteria, therefore the former being the most effective for some ranges of f. Interestingly, Star Alliance had a single break of the giant component for $f \simeq 2.5\%$, while in the other two AARNs two breaks occured, of a relative size half of the value of the break of Star Alliance.

Finally, reaching the last level L3, Chapter 4 has analyzed the network robustness of thirteen airlines based on error and attack simulation. This simulation has been run to verify if there is any difference on the behavior of FSC and LCC business models. The analysis has confirmed that FSC are more sensitive to intended airport closure than LCC. That is, disconnecting the FSC hubs causes a bigger harm than the disconnection of the base airports of the LCC. On top of it, Southwest Airlines and Ryanair, the most important LCC at the moment turned out to be the most robust against attacks. Within the set of FSC there were three airlines with a peculiar behavior. These were China Eastern and China Southern, the only ones in a region outside of Europe or North America; and airberlin, which was a LCC before it joined oneworld, which explains its differentiation.

Following these results it would be possible to attenuate the consequences by means of disposing of a multi-hub-and-spoke network. This network should be built by hub airports strategically disposed distant from each other in order to avoid larger problems related to airspace closure. This distance would allow an homogenization of the importance and centrality of the network without neither losing operability, nor the possibility of applying economies of scale. A second action to increase robustness would be to schedule PP connections on the less central airports to connect them if one of their hubs fails, achieving with this an structure somewhere between HS and PP. This second solution should take into account the demand of each route in order not to hinder the rentability of the airlines.

As seen in Chapter 1, the study of air transport networks through complex network theory is in an early phase of development, and is a stream of research valued for the scientific community. This thesis has contributed to the literature defining three levels of analysis for air transport networks, analyzing the topology of examples of these networks, and performing a study of static robustness to errors and attacks of air route networks at these three levels. Some of the contributions of this thesis, such as the inverted adaptive strategy and the normalized multi-scale measure of vulnerability defined in Chapter 3, or the node selection criteria based on efficiency and Bonacich centrality introduced in Chapter 3 and Chapter 2, respectively, can be tested on other real-world networks. This could bring to the scientific community a deeper understanding of the determinants of static robustness of complex networks. Future studies on static robustness can take into account the passenger flux through airports, to get a more realistic interpretation of the traffic loss that supposes the closure of airports of high traffic. Nevertheless, a similar result than the one obtained in the performed analysis should be expected, since the most central airports are those that concentrate a higher volume of aerial traffic in terms of flights and passengers.

An avenue of further research could be the assessment of dynamic robustness of air route networks, analyzing phenomena such as cascading failures, congestion or jamming (e. g., [50, 127]). When studying these phenomena, it should be taken into account that the disconnection of the first airports could increase network damage (e. g., the closure of an airport could cause the congestion of others), or its reduction (e. g., passengers could be relocated in flights to secondary airports).

Therefore, the study of air transport networks through complex network theory is an interesting and relevant research field. Further studies on this area will transfer findings obtained in complex network theory to air transport research, and they will be for sure an important contribution for the protection, stability and safety of passengers, airlines and the rest of stakeholders of the air transport sector.

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