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Route Networks within the Air Transport System

A comparative study of two European low-cost airlines using network metrics

Mark John Hall [1,2], Ranjit Ravindranath [1], Pablo Bermell-Garcia [1], Anders Johansson [2]

Airbus Group Innovations [1]. IC4, UK
University of Bristol [2], Systems Centre, UK

Abstract— **This paper presents a comparative analysis of the route networks of two European low-cost airlines in 2015. A case study is presented which highlights the key differences and similarities of their route network characteristics that they operate, aimed toward improving understanding of the current Air Transport System (ATS) for modeling and simulation purposes.**

Keywords— networks; air transport system; airlines;

I. INTRODUCTION

A. Why is the air transport system important?

Air transport networks are one of the key infrastructures of today's global economy [1]. Worldwide Airlines carry around 3.3 billion passengers per year. In order to do this they collectively operate more than 50,000 routes with approximately 25,000 aircraft, employing around 4 million staff and improving the mobility of world citizens [2]. It is evident that transport systems are fundamental elements of both our economies and societies [3].

An airline's route network is a complete set of direct flights provided by the company to cover its targeted destinations [4]. Route networks within the ATS have evolved organically over the last few decades with air transportation becoming the most popular mode of transport for distances over 750 miles [5]. These networks are part of the complex transport system, composed of routes in certain regions connected according to given laws, including airports, aircraft, etc [6]. The nature of the route systems has important implications for the performance of the ATS [7], which presents the need to understand this further.

B. How can understanding route networks improve the ATS?

With the advent of the 'network era' [8], the advances in the areas of statistical topology and kinetics of complex networks has made it possible to study air transport route networks [8]. Analysis of route networks and business models will enable more accurate simulations of various future scenarios to assess the value of new and disruptive technologies within the ATS.

Scenario modeling using techniques such as agent-based modeling offer a means of discrete event simulation of the ATS network in both time and space, and is gaining popularity in the modeling of transport systems [9] [10]. As a first step toward this, we need to understand current operations from which we can derive insights and accurate assumptions to inform any mathematical ATS models for simulation [9].

These insights and assumptions can be deduced from operational flight data. An inductive theory building approach can then be used from the quantitative analysis to improve the understanding of airline route networks.

This paper is organised as follows. Section II outlines the related work in this domain; Section III describes the method used for the case study to analyse the two European low-cost airlines; Section IV presents the results of the study; Section V discusses the findings in the content of the ATS; Finally, Section VI presents the concluding remarks and proposes future work.

II. RELATED WORK

A. What approaches have been taken before?

The advancement of complex network theory has generated an increasing body of literature on applications within transport systems [11]. A review was conducted in 2013 on the application of complex network theory to the ATS, showing that it can be used to characterise the structure of air transport and its dynamics [3]. This highlighted that most of the published works can be classified into three main families, namely (i) characterisation of the topology without considering evolution through time (ii) studies aimed at identifying and characterising the transition between point-to-point to a hub-and-spoke architecture (iii) the dynamics of networks [3]. The work presented within this paper is based on the topological and metric properties of flight networks, where nodes represent airports, and links correspond to route journeys.

There are several aspects of network analysis that could be conducted on airline route networks. They could be typically classified as Topology Criteria, Concentration Criteria, and Connectivity Criteria. The various measurements used for each criteria are discussed in Reggiani et al. [12]. In this study, only network topology criteria is considered. Topology [13] looks at the network purely from a non-geographical perspective. Common topology criteria metrics include: degree, diameter, density, modularity, connectedness centrality, clustering coefficients. A similar study conducted by Bounova et al. [14] considers topology of several Chinese airlines, and rewires the networks by optimisation methods based on reducing number of aircraft changes, and maximising passenger throughput. This study addresses more network topology optimisation parameters than studied by Bounova et al., which could be used to populate ATS models.

B. What is the contribution of this study?

Studies have been previously undertaken related to using a complex network approach. However, this prior work falls into one or more of the following categories:

- They are not recent, e.g. [12], especially given that the airline industry is in constant evolution and this changes its structure and characteristics [1], so an updated understanding is necessary.
- They are related to the spatial or dynamic elements of the route networks, not the topological aspect.
- They are based on non-European regions, e.g. China [11] [14] and the US [15], so a scoped study on representative airlines within Europe is required.

The unique contribution of this paper is in presenting the results of a case study of two European low-cost airlines to analytically compare their current route network characteristics. This is aimed at improving the understanding of airline operations based on recent empirical flight data, whilst also informing future ATS assumptions and models.

III. METHOD

A seven-day sample of flight data for two European low-cost airlines was used to analyse their typical route networks over that period. This data consisted of all of the flights for every aircraft within the fleet of Airline A and B, which was used as a basis for comparison. The flight data was typical of that provided by Flightradar24 [18] and contained the date, airport origin, airport destination, flight number and times for each flight for each aircraft in the two fleets:

This flight data was firstly prepared to transform it into a usable format for network analysis. This pre-processing was undertaken within *Microsoft Excel* which involved data cleaning, re-formatting and aggregating. The data was exported as a .csv file for each respective airline. These files contained the aggregation of all flights for the airline over a seven-day period in September 2015.

The analysis was then undertaken based on their overall fleet, key airports and key routes. The data was then analysed to derive network statistical measures to identify each airline's route network characteristics. The network software *Gephi* [18] was used for the statistical analysis and visualisation.

It is important to note the following limitations of this study. *The data is a representative sample*. The comparison is of two low-cost European airlines and is only a representative sample of this type of airline. The seven-day timeframe shows the airline's typical operations, but this is a relatively small time period. The route networks are also likely to differ with seasonal variation [6], so the data only provides a comparative snapshot of the airline's operations. *There may be inaccuracies within the original datasets*. Whilst steps were taken to check for errors within the raw data, it is possible that inaccuracies exist which were beyond these checks, which would influence the results somewhat.

IV. RESULTS

The results of the analysis are shown below in terms of fleet overview, key airports, key routes and network statistics.

A. Fleet Overview

Table 1 shows the breakdown of the total flight data for each airline. The *no. of airports* shows the total number of unique airports that the airline flew from/to, either as origin or destination. The *unique journey legs* shows the total number of routes that were flown in one direction, i.e. an airline route is considered as two (return) journey legs. *Total flights* is the sum of all flights during the week for the airline.

Table 1: Overview of flights over 7 day period

	Airline A	Airline B
No. of Aircraft Utilised	216	321
No. of Airports Used	130	185
Unique Journey Legs	1,168	2,535
Total Flights	8,989	12,510

B. Key Airports

Table 2 and Table 3 shows the top five ranked airports for both airlines based on their importance within the network and the total flights associated with each airport. The PageRank statistic is used as the measure of importance, or how central an airport (node) is within the network. The underlying assumption is that more important airports (nodes) are likely to have more flights (edges) from other airports (nodes). PageRank is a link analysis algorithm and it assigns a numerical weighting to each element, with the purpose of measuring its relative importance within the set. The probability is expressed as a numerical value between 0 and 1. The measure of the *percentage of total flights,* show the proportion of overall flights that are from/to the airport.

Table 2: Airline A – Top 5 Airports

		Importance in Network (PageRank)	Total Flights (from/to airport)	Percentage of total flights from/to airports	Percentage of total flights to/from airports
1	London (LGW)	0.1444	2,516	28.0%	61.5%
2	Milan (MXP)	0.0510	1,025	11.4%	
3	London (LTN)	0.0382	772	8.5%	
4	Paris (CDG)	0.0301	636	7.1%	
5	Berlin (SXF)	0.0283	577	6.4%	

Table 3: Airline B – Top 5 Airports

		Importance in Network (PageRank)	Total Flights (from/to airport)	Percentage of total flights from/to airports	Percentage of total flights to/from airports
1	London (STN)	0.0924	2,280	18.2%	
2	Dublin (DUB)	0.0450	1,286	10.3%	
3	Milan (BGY)	0.0359	1,061	8.5%	48.5%
4	Barcelona (BCN)	0.0248	722	5.8%	
5	Brussels (CRL)	0.0283	721	5.8%	

Figure 1 and Figure 2 visually shows the distribution of the top 25 ranking airports for each airline, based on frequency of flights and importance within the network.
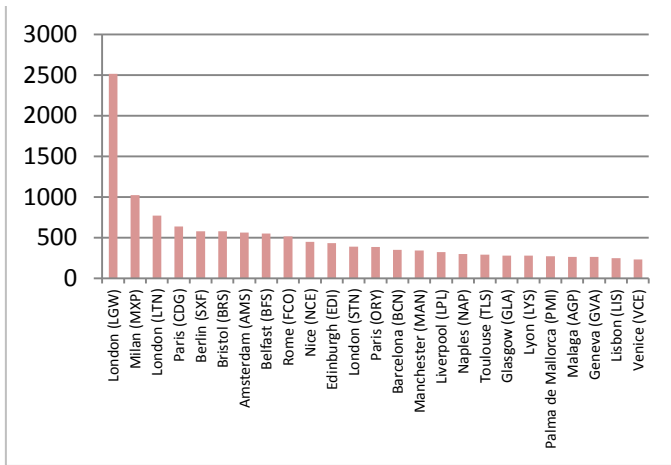

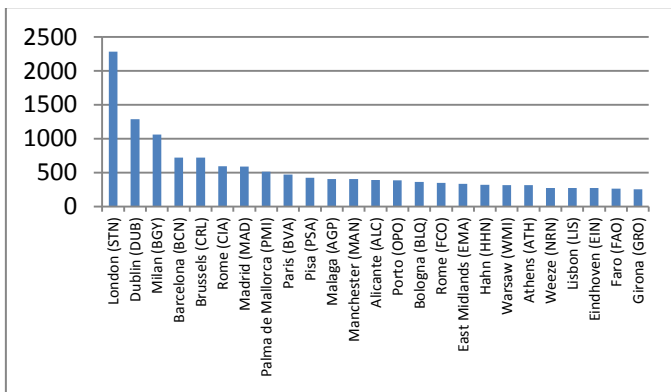**Figure 1: Airline A – Top 25 Key Airports (total flights)**

Figure 2: Airline B – Top 25 Key Airports (total flights)

C. Key Routes

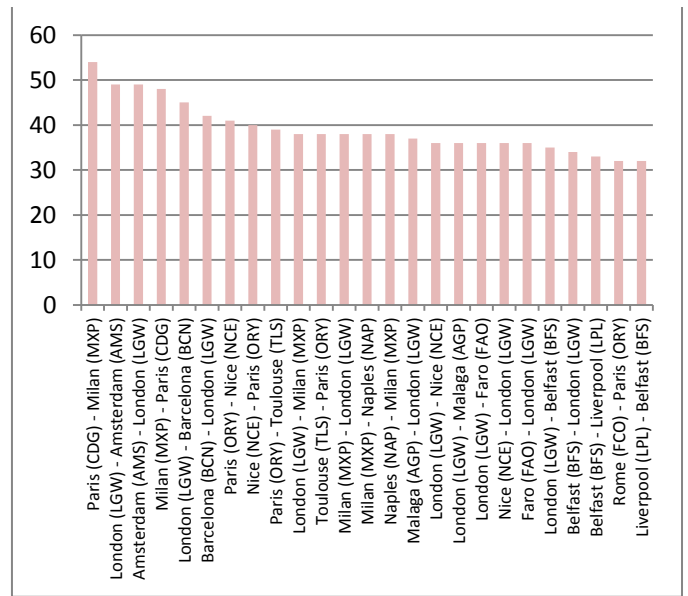Figure 3 and Figure 4 show the most frequent 25 routes of the airlines based on frequency within the seven-day period.
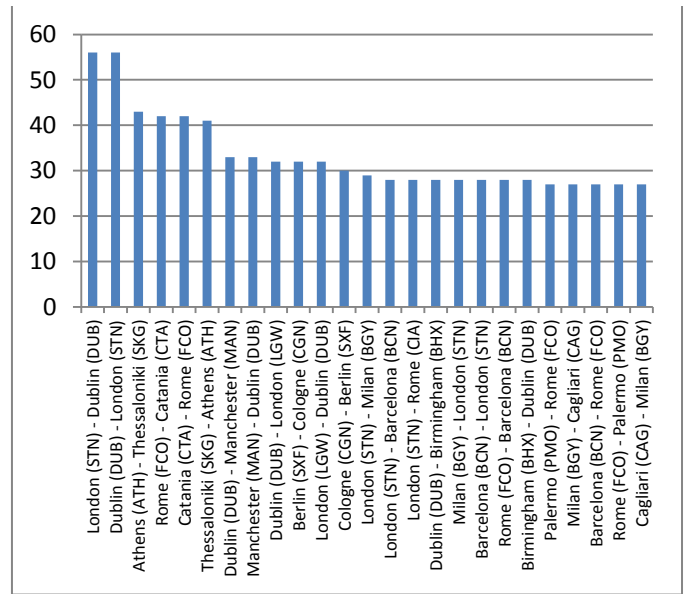

Figure 3: Airline A – Top 25 Key Routes

Figure 4: Airline B – Top 25 Key Routes

D. Network Statistics

Table 4 presents the statistical measures for the network characteristics of each airline. These measures are explained and interpreted in relation to the ATS in Section IV.

Table 4: Network Characteristics

Statistical Measure	Airline A	Airline B
Average Degree	8.985	13.703
Avg. Weighted Degree	69.131	67.622
Network Diameter	4	4
Graph Density	0.070	0.074
Modularity	0.216	0.259
Connected Components	1	1
Avg. Clustering Coefficient	0.393	0.373
Avg. Path Length	2.140	2.185

Figure 5 graphically shows the two airline route networks. The network shows the airports as nodes and the edges as unique journeys (flights). The upper visualisations show the routes without any weighting applied to represent the volume of flights for each journey or route. The lower visualisations highlight the key hub airports toward the centre, whereby the node size represents the number of flights and the colour as the PageRank measure of importance. The less operated routes are positioned toward the outside, which demonstrates a hub-and-spoke architecture for routes for both airlines at the fleet level.
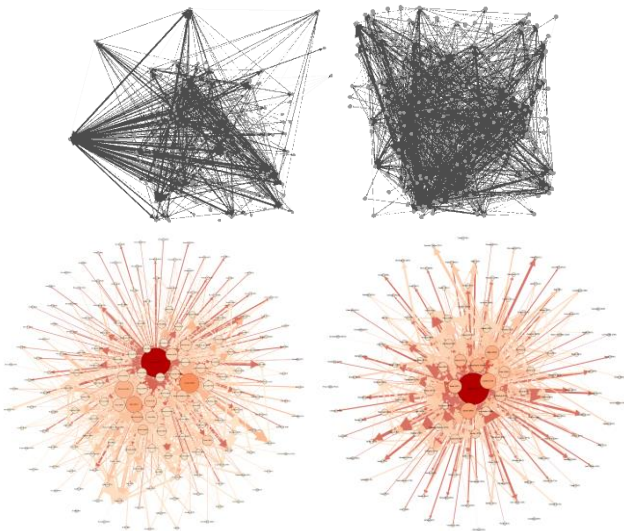

Figure 5: Network visualisation of routes
Airline A (left), Airline B (right).

V. DISCUSSION

A. Fleet Overview

In a straightforward comparison, we can see from Table 1 that Airline B has approximately 3,550 (40%) more flights than Airline A during the seven-day period. We can also see that Airline B flew over twice as many unique journey legs (one direction of a route) as Airline A. Of all flights, Airline B used 105 more aircraft (approximately 50% more) than Airline A to service their routes. In addition, Airline B flew from/to 55 more airports than Airline A during the period. This comparison shows the relative sizes of the two airlines, highlighting that Airline B is larger than Airline A in terms of their route network coverage, number of flights and aircraft used. However, the average number of flights per week per airport is comparable for both Airlines (*average weighted degree*).

The ratio of number of edges per node (degree) is an indication of the amount of flexibility in the network. Typical ratios are around two, but both Airlines seem to have a higher than average degree suggesting that they are both mature organisations, who have organically grown over time. Airline B has a higher degree on average compared to Airline A, indicating flexibility in the service it offers. However, Airline A will have a better redundancy in operations.

B. Key Airports

On observing the top ranking airports with most flights from/to them, we can see that both airlines have one main hub airport that is used significantly more than the others. This same ranking is also reflected in the PageRank measures of airport importance within their route network. This shows that the most important airports situated within the networks are also the ones with most flights. In the case of both airlines, it is evident that each single top airport are in the region of twice as important and frequently used as the second on the lists. Figure 1 and Figure 2 visually demonstrates this step difference, which is larger for Airline A than it is for Airline B. If we take the total flights for each airline, we can see that the top ranking airport alone represents approximately 28% and 18% of the total flights for the airlines respectively, highlighting the reliance on these top key airport hubs.

It can be seen that the total number of flights for each airport gradually tail-off after the top 15, showing that these two airlines rely heavily on their top 15 airports within their route networks. Given that each airline has flights associated with 130 and 185 different airports, these 15 key airports represent a relatively small proportion of the overall visited airports at approximately 12% and 8% respectively for Airline A and B. We can see that the top five airports for each airline represent approximately 62% and 49% of their total flights. This again highlights that a large proportion of all flights are from/to a relatively small number of airports. For Airline A, approximately two thirds of the total flights are from/to only five airports (4% of all airports visited). For Airline B, approximately half of the total flights are from/to only five airports (3% of all airports visited). These insights can be used when modeling the ATS to reflect these weightings.

On inspecting the list of most frequent 25 airports of both airlines, it reveals that there are only six airports that are common to both, suggesting that they tend to not occupy the same airports for their top airports. The differences in the type of airports they service also indicates that they have different business models, in that Airline A in general appears to favour

larger airports in major European cities, whereas Airline B tends to occupy more secondary airports for the cities. This understanding can be used when deciding upon reasonable assumptions within the ATS modeling.

C. Key Routes

Airline B flew more routes overall than Airline A, but less frequently (for the whole network). These less frequent routes for Airline B are shown as a stepped distribution in Figure 4. Airline A has a more distributed frequency of top 25 routes than Airline B. Airline B appear to operate regularly between hubs and secondary (reliever) airports, not reliant on conventional traffic flows, i.e. implementing new routes.

When comparing the most frequent 25 routes for each airline, we can see that there is not one single route that is common to both. However, whilst they are not in direct competition, it is clear that two routes (i.e. four journey legs) are comparable. The first is London-Milan, whereby there is a common connection between cities, but both are from different airports in UK and Italy. The second is London-Barcelona, whereby both airlines fly from BCN airport to London (and vice versa), but to two different London airports, i.e. LGW and STN. The analysis shows that the two airlines are not in direct competition on their most frequent routes in terms of their route networks.

D. Network Statistics

The data suggests that both European low-cost airlines have similar route network characteristics which are discussed below.

Average degree – this shows the average number of *journey legs* associated with an airport (node) for each airline. We can see that the comparative values for each airline differ by a value of approximately 4.7. This shows that Airline B has more journey routes, on average, associated with each airport.

Average weighted degree – this is a similar measure to the average degree, but factors in the weighting based on the number of flights for a given journey leg. So this measure shows the average number of *flights* associated with an airport (node) for each airline. These values are comparatively similar for both airlines at 69.131 and 67.622 respectively, suggesting that although the airlines fly different routes, they have similar network characteristics.

Network diameter – this shows the longest path between the airports (nodes) within the network. Both airlines have the same value of four hops, showing that they are comparable in terms of their network connectivity.

Graph density – this is a ratio of the number of journey legs (edges) that exist to the total number of journey legs (edges) possible. The density of an empty graph would be zero, conversely the density of a complete graph would be one, i.e. the graph density increases by the increasing number of journey routes (edges). The values of 0.070 and 0.074 show that the two airlines have a similar density. Low values also mean that the airports they service are not well connected with other airports.

Modularity – this is a measure of the structure of the network and shows how well the network decomposes into modular communities. This structure, describes how the network is compartmentalised into sub-networks, whereby the higher the value, the more defined the communities are within the network. Networks with high modularity have dense connections between the nodes within modules, but sparse connections between nodes in different modules. In the case of each airline, they have values of 0.216 and 0.259 respectively. This shows that airline A has somewhat less well-defined communities within it's route network, but this is not significant.

Connected components – this shows the number of unconnected sub-networks within the overall network. As one would expect, the value for both airlines is one, showing that there are no routes operating in isoltaion to the rest of the network. However, the analysis did reveal a test flight that took-off and landed at the same airport in a remote location separated from the rest of the network. This flight was not taken into account for this measure, but if it were to be considered then it would raise the connected component value from one to two for Airline B.

Average clustering coefficient – this shows how well the airports (nodes) are embedded within their neighbourhood. The two airlines have similar network characteristics in terms of the clustering coefficent at 0.393 and 0.373 respectively, showing that the airports (nodes) used are both similarly clustered within their overall route network.

Average path length – this shows the number of flights on average one can reach any airport (node) from any other airport in the network. The analysis implies that on avearge it is possible to get from one airport to another in the network within around two hops. These values are comparable to the study undertaken on four European airlines in 2009 [6]. The airlines A and B have similar values of 2.140 and 2.185 respectively, which show that both airlines have comparable connectivity of their airports within their respective networks.

VI. CONCLUSION

We have described the method and results by which a case study was undertaken to analyse two European low-cost airlines in terms of their route networks. Flight data was used to derive insights from the airline's operations aimed toward improving current operational understanding.

The two airlines are different in terms of total number of flights, number of routes and number of airports visited. We observe that:

- The two airlines are not in direct competition on their most frequent routes.

- Airline B has approximately 40% more flights than Airline A during the seven day period.

- Airline B flew more routes overall than Airline A, but less frequently (for the whole network)

- Airline B flew over twice as many unique journey legs (one direction of a route) as Airline A.

- Airline B flew from/to 55 more airports than Airline A during the same period

However, we can identify many similarities between the two airlines in terms of their route networks. The analysis revealed that both airlines:

- use a similar approach of relying on one main hub airport that is used significantly more than others.

- have a large proportion of flights from/to a relatively small number of their total airports.

- have a similar average number of flights associated with an airport.

- have a comparable network connectivity in terms of topological structure.

- have a similar network density, in terms of the ratio of the number of journey legs (edges) that exist to the total number of journey legs (edges) possible.

- have comparable network structures in terms of how well the network decomposes into modular communities.

Analysis of network topology statistics of the two Airlines operating in the same regional market has revealed similarities in spite of operating out of different geographical locations, and potentially having different business models. This indicates that network topology characteristics could be a major driver for assumptions modeling for agent based modeling of the ATS.

In order to simulate airline operations within the ATS it is possible to utilise the empirical flight data from source. However, an alternative approach is to artificially generate representative route networks for the purposes of simulation. The benefit of this latter approach is to be able to scale the network for a simplified or more complex use-case scenario. Such synthetic networks can be generated based on the characteristics and measures identified within this study [20].

In conclusion, the analysis shows that there are clearly some differences between the two low-cost airlines operating within Europe. However, the analysis also highlights that both airlines have similar route network characteristics. Further work could involve a comparative analysis, following the same approach, incorporating several types of representative airlines operating across different regions. Furthermore, a temporal analysis would show how airline route networks have evolved, which would be beneficial to understand how the ATS has developed over time. This comparison would be aimed at classifying airline types based on their route networks, which could be used to improve understanding and inform future ATS models.

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