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# Contrasts in Sustainability between Hub-Based and Point-to-Point Airline Networks

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**Abstract:** Airline hubs are often defined as nodes with a high degree of connectivity. Connectivity is measured by the "degree" of the node. The degree distribution of hub networks tends to have a convex shape (curved towards the origin), while point-to-point networks have a higher number of high-degree nodes and a concave shape. This study aims to classify airline networks based on their hub orientation, expanding our understanding of network differences. The analysis in this paper involves fitting a power-law distribution, determining the range of degree distribution, and calculating the distribution of betweenness. These analyses provide insight into the classification of each airline. Each measurement helps to clarify the ambiguity in other scores. The goal is to establish a small set of rules that can clearly distinguish between the main types of networks. The classification includes four types of networks: One-hub, P2P (point-to-point), Multi-hub, and Complex networks. There is a well-recognized empirical distinction between hub networks, which have a few places with large betweenness, and point-to-point cases, which have a larger number of places with moderate betweenness. The significance of these results in terms of geographic importance is demonstrated by sorting 284 different airline networks based on these dimensions. These findings are expected to provide valuable information about the resilience and recovery of a network, as networks with many long-range connections are particularly vulnerable to a decrease in traffic. Additionally, these results have implications for the ability of networks to recover from a downturn.

**Keywords:** airline network; network classification; hub-and-spoke system; point-to-point system; fleet operation



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## 1. Introduction

Hubs are crucial components of airline networks as they handle significant traffic to and from other nodes through their extensive connections. Hubs are often considered special and essential for the network's operation. In practical terms, these nodes are sometimes classified based on traffic levels, such as the classification used by the Federal Aviation Administration (FAA) for American hubs [1]. In analytical transport research, hubs are defined based on the throughput and connectivity they provide [2,3]. Hubs serve as facilities through which flows are channelled, while spokes are arcs connecting origins or destinations to one or more hubs. Hubs are designed to ensure efficiency within the operational constraints faced by airlines [4,5].

The main aim of this paper is to explore the specific characteristics that can be used to identify network structures. For example, a hub should have strong connections to other hubs and many regular nodes, while each regular node should be connected to only a few hubs. Additionally, we would expect minimal direct connections between non-hub nodes, and each non-hub node to be connected to an average of two or three hubs. By examining the degree distribution of nodes, we can identify the characteristic shape of hub networks. This contrasts with point-to-point (P2P) networks, which tend to have numerous short-range connections between a small number of city pairs. P2P networks also have relatively few nodes with low degrees, and many places are connected to multiple partners. But it also should be noted that the network structures of airlines are not completely aligned to one of these network types. Rather, many airlines are likely to show nuanced structures in which the contrasting characteristics of the types are blended in a complex way.

This paper applies an objective quantitative classification scheme to explore the geography of a large number of airline networks. This application has current relevance as an airline's network structure greatly influences the fuel costs and pollutant emissions for the amount of movement accomplished. Networks with longer range connections have particular aircraft needs [6] and their resilience and ability to rebound from disruption (such as COVID-19) depend on the extent to which the carrier is committed to a hub structure [7,8]. Alternatively, it might be anticipated that point-to-point networks may be capable of rapid rebound due to their operational simplicity. Airlines adapt their aircraft fleets to the varying operational conditions induced by their network structures, which results in differential economic/environmental effects.

The foundation of our approach lies in using measurements not only for the levels of the direct and indirect connections of airports, but also their respective distributions. This provides a framework for comparing networks based on their distinctive topological characteristics. It is also useful to perform such a comparison because there is a strong possibility that airlines with a similar network structure might have similar cost structures and environmental impacts. This approach will provide a framework for airlines to address issues such as cost allocation for their shared infrastructure. This refers to the problem of sharing costs over multiple users of their links, and to impute costs and to understand the effects of congestion and bottlenecks. The paper also adds to our understanding of network organization as it identifies opportunities to add more links and may justify decisions to acquire aircraft with new range characteristics, such as single-aisle high-efficiency medium-haul jets (e.g., Boeing 737 Max).

## 2. The Literature

Air transport networks display complex topological characteristics, attributable to the airlines operating various networking strategies and aircraft fleets. For example, *Low Cost Carriers* (LCCs) tend to organize their route networks in the form of point-to-point networks with single aircraft-type fleets usually consisting of narrow-body aircraft. Major network carriers on the other hand, prefer the hub-and-spoke system, concentrating their flows on a few main airports, and operating through a combination of small and large aircraft [9]. Also, through cooperating with major airlines, some regional airlines in the US and Europe maintain routes that are usually feeder ones into the hub-and-spoke networks of major airlines [10,11]. Recently, LHLCCs (Long-Haul LCCs) such as Norwegian have entered the inter-continental-route markets through utilizing relatively new aircraft types with a long range and of medium size [12]. Worldwide or regional air transport networks are shaped by subnetworks of airlines reflecting their complex aircraft operations across routes. Therefore, decomposing the subnetworks and comparing the topological characteristics between them can be an effective way to understand useful details in the complex topology of the aggregated network.

We are not the first to explore network structure. Indeed, there has been a fascinating variety of prior works exploring many facets of the organization of air networks (Further reading material is in the following: [13–15]). Network analysis has been widely applied to complex air transport networks at varying geographical scales to characterize their topologies, as well as to recognize the relevant network properties in the transport systems [16–20]. This methodology is often applied to understand the topological features of the worldwide air transport network (WAN). For example, Guimera et al. [17] examine the large-scale structure of the WAN, and confirm the disparity between the centrality and betweenness of core airports in particular, due to the reality of geopolitical constraints. Woolley-Meza et al. [21] find unusual discontinuity in the node and link betweenness distributions of the WAN such that the nodes and links of the network naturally segregate into two distinctive functional groups. Wandelt and Sun [22] find stability in the scale-free and small-world properties of the international air transport networks from 2002 to 2013. Recent similar analyses focus on the emerging aviation markets including China, India, and South East Asia, and also confirm the existence of those two properties in these regional markets with rapidly growing network connectivity [23–27]. Identifying core hubs and assessing their competitiveness, in terms of connectivity, is another topic addressed [20]. Also, the vulnerability/resilience of air transport networks to random or targeted events are often examined based on topological properties derived through network analysis [28–30]. These studies focus on exploring the accumulated structures of global/regional air transport networks through employing network- or node (and link)-level measurements. And they regard hub airports as core observation targets that affect the overall structure of the networks [26].

Finally, network analysis is often utilized to detect temporal changes in air transport networks. For example, Azzam et al. [31] find non-stationarity in degree distributions of the WAN for 1979~2007 because the rapid growth of the number of links leads to the continuous densification of the network. (As a result, the average degree increases while the average shortest path length decreases.) Recently, many studies have analyzed the abrupt shrinkages in the worldwide or regional aviation markets during COVID-19 using network analysis [32–36]. These studies identify the differential changes (shrinkages and recoveries) of network connectivity (and structure) affected by the geographical and functional conditions of airports and routes. The structural changes in the networks during COVID-19 reflect the various reactions of airlines to the market crisis, but few look at them based on the subnetworks of airlines.

This research paper builds upon previous studies by focusing on subnetworks, i.e., networks of airlines within the WAN. Previous studies in network analysis have primarily examined the overall shape and topological characteristics of airlines' networks, which are heavily influenced by the concentration of connectivity at hubs. Hub-and-spoke (HS) and point-to-point (P2P) networks are well-known representative types in airline networks, reflecting their operational strategies. However, in reality, airline networks often deviate from these two types in terms of network structure. Many airlines fall somewhere on a continuum between HS and P2P.

Based on network analysis, therefore, we propose a methodology for categorizing airline networks into four types, as One-hub, Multi-hub, Complex, and P2P networks. Recognizing gaps between the empirical networks of airlines and typical network types, our methodology aims to classify airlines into meaningful types along the continuum between HS and P2P by detecting variations in the presence and organization of hub-and-spoke arrangements using node-connectivity and distribution measurements. We then establish connections between the classified airlines and their distinctive network structures and operational characteristics, such as aircraft size and route distance, to show the usefulness of our classification method. This methodology not only enhances our understanding of the variation in network structures among the airlines but also enables us to track their short- and long-term changes resulting from various factors, such as the impact of the COVID-19 pandemic. It serves as a foundation for comprehending the dynamics of airlines' network structures and their evolution over time.

The remainder of this paper is organized as follows. Section 3 provides a method for classifying the networks of airlines into four types. Then, the results section examines the topological and operational differences among 284 air carriers in the world, based on their network types classified using our scheme. We conclude the paper with comments on contributions, limitations, and next research steps.

## 3. Methods

This research develops a classification that selects single-hub systems (using the betweenness distribution), point-to-point systems (using a power-law cut-off), and then multi-hub and complex systems (differentiated using the power-law slope). To operationalize this approach, we need some decision rules on these three dimensions. The rules are applied to 284 airlines and are illustrated in greater detail for the top 30 (in terms of the number of seats supplied) because the validity of the classification can be seen clearly in these well-known airlines. The analysis considers direct links for passenger transport between nodes as defined in the OAG flight schedules data in Q2 of 2012~Q1 of 2013.

### *3.1. Betweenness and Connectivity*

Imagine a trip from an origin (O) to a destination (D). The route could be direct or might pass through intermediate stops at hub locations. Each transition through a hub generates an additional betweenness count. The sum of *hops minus one* is the same as the sum of all the betweenness scores impinging on the hubs. In other words, every OD pair contributes *hops minus one* to the betweenness at some intermediate nodes. For example, consider nodes (A) and (D), connected by a 3-hop path A -> B -> C -> D. The path clearly passes through 2 intermediate nodes (B and C) and therefore adds 2 to the overall betweenness. Summing up over all the OD pairs, we get the total impact at all intermediate places. Such scores would be low for point-to-point cases. We can also compute the maximum betweenness over all nodes and the place where this occurs is almost certainly a main hub. If a network has only one hub (allowing for a few incidental added links), then all interactions must pass through that hub, and betweenness will approach its theoretical peak value.

Counting betweenness and assigning the score to places in the network is a quick tool for distinguishing hubs. A network with a peak level of betweenness (i.e., low dispersion, or *entropy*) contrasts with a network with many nodes sharing moderate levels of betweenness (and having a higher entropy score). For example, Emirates (EK) represents the former case as the betweenness score percentage of their main hub (DXB) is more than 90%. As an example of the latter, the percentages of Southwest (WN) betweenness scores are distributed over a wider node set (see Figure 1). On the other hand, there are other carriers that show somewhat moderate concentration patterns of betweenness scores on multiple nodes such as Delta (DL) and China Southern (CZ), which indicates the necessity of employing other complementary measurements. In our classification scheme, any node that accounts for more than 5% of the total level of betweenness is classified as a hub. This score is used to identify single-hub networks where one node dominates the betweenness.

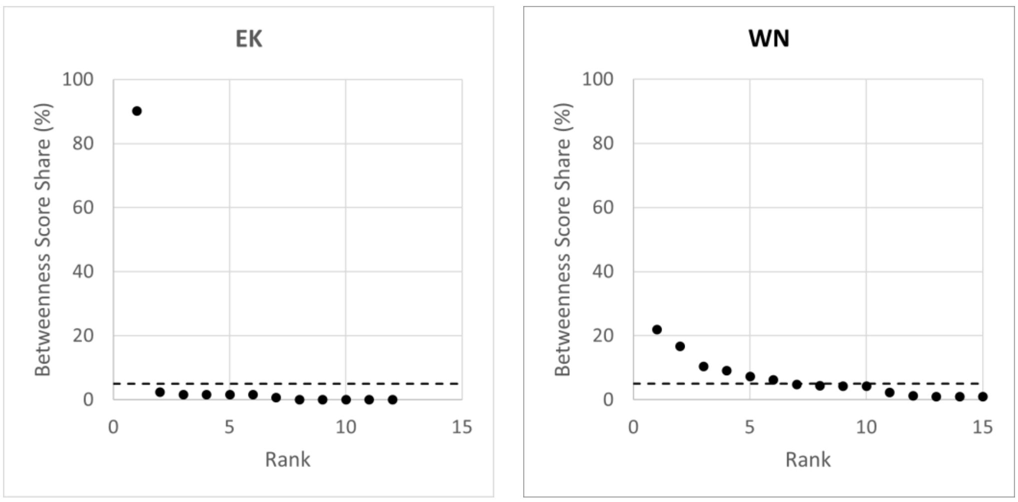


**Figure 1.** *Cont.*

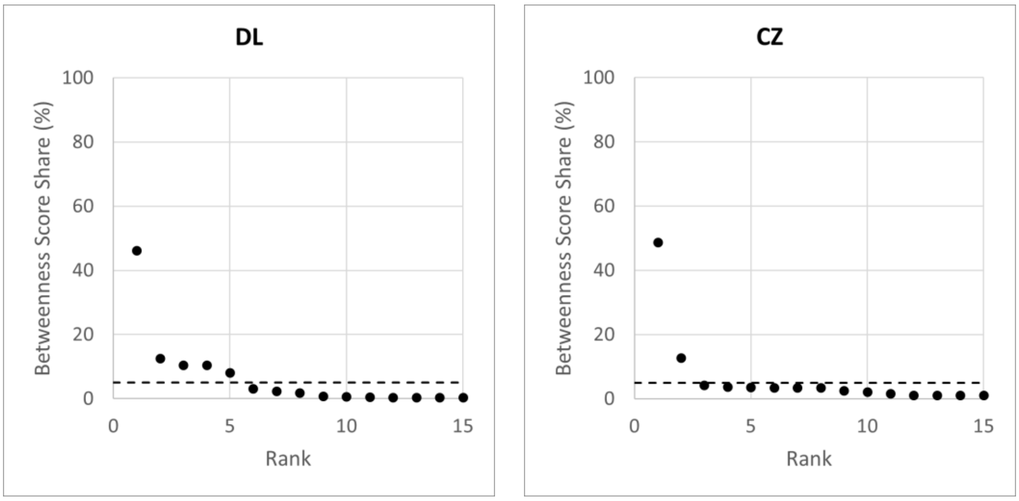


**Figure 1.** Distributions of betweenness score percentages of four air carriers (EK: Emirates, WN: Southwest, DL: Delta, CZ: China Southern, dotted-line indicates 5% of betweenness score).

*3.2. Power-Law Curve Fitting*

When we organize the nodes by degree, we obtain a rank order distribution from the rank 1 node (with the highest degree) to the lower order nodes that have a degree of one or two. An analytical distribution for this, relating degree (D) to rank (R) is

$$D = k\,R^{-y}$$

where k and y are empirical parameters chosen to fit particular data. The maximum value of R is the number of ranked entities. A sketch of this relationship, in log form, is shown in Figure 2 for Southwest Airlines (WN).

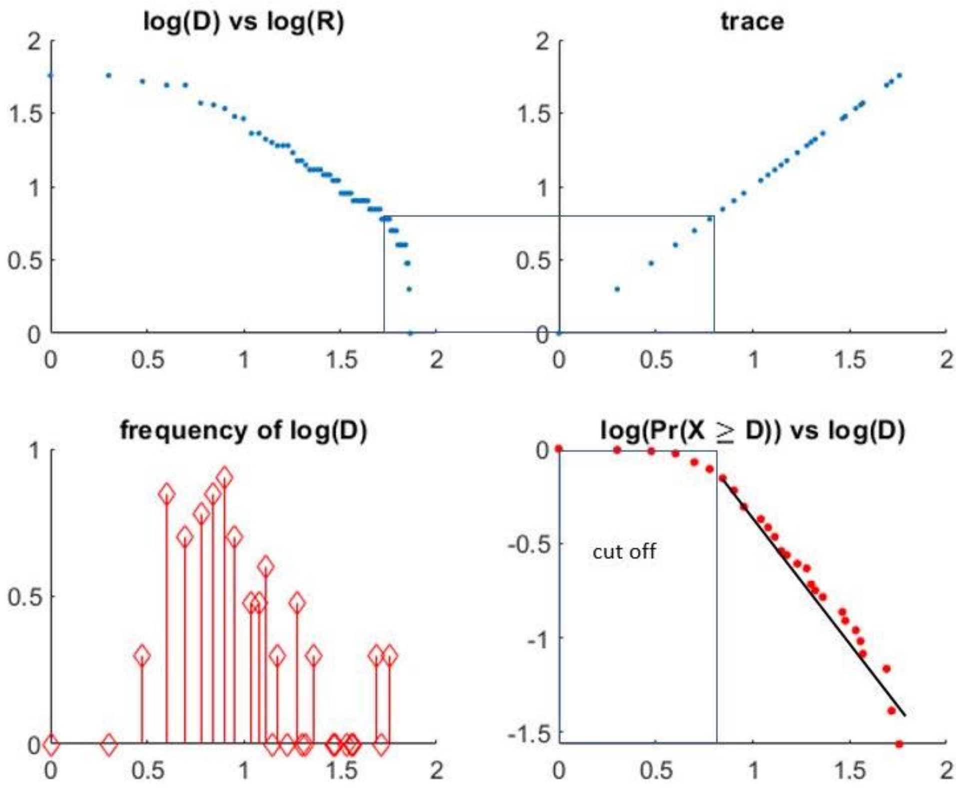


**Figure 2.** Detail for Southwest (log–log plots), see text for discussion.

In Figure 2, Panel (top left) shows the degree vs. the rank, in logarithm form. Panel (top right) shows the gaps between degrees—computed as the step between degrees at each rank—and computes the biggest such gap as 12 in this particular network. Generally, this gap will be large for very bi-modal distributions and will be smaller when there is greater continuity in rank sizes. In fact, the gap averages about 80% for one-hub systems and 18.2% for point-to-point cases. The significance here is that the greatest difference between node degrees is large for one-hub (bi-modal) networks, and much smaller for point-to-point systems. Panel (lower left) shows the occurrence of each degree value. Few nodes in this network have a degree of one, shown as the intercept on the $y$-axis. Panel (lower right) shows the complementary cumulative probability for each degree level. This curve measures the probability that a node has a degree greater than or equal to D (shown on the $x$-axis). Of course, the probability that a node has a degree *at least equal to one*, is one; recall that these values are plotted on logarithmic axes and log (1) = 0. The log of probabilities (numbers less than or equal to 1) are less than 0. As we obtain higher degree values, the probability of that degree or higher decreases. Fitting to this empirical distribution provides the power-law parameter.

Interpreting Panel (lower right) helps us to understand the methodology we should use: The first six points are in an area labelled as the cut-off. This means that the share of the cumulative distribution accounted for in lower degree nodes (1–6) is not important to the fitted distribution. To the right, the fitted complementary cumulative distribution function (CCDF) is shown with a slope of $-1.28$. This corresponds to a power-law parameter of $-2.28$ and is often reported without the sign, as it is added to the equation with a negative sign.

To fit an empirical function to data of this kind, we use the robust fitting techniques provided by Clauset et al. [37]. Their paper endogenously estimates the cut-off and power-law parameter according to a goodness-of-fit-based method. They describe the fitting procedure as follows: (1) for each possible choice of the cut-off, estimate the power-law parameter (slope) via the method of maximum likelihood, and (2) calculate the Kolmogorov–Smirnov goodness-of-fit statistic Z. The selected cut-off is the value that gives the minimum value of Z. In some cases, the power-law relationship fits only the upper portion of the data. This occurs when the distribution has a large number of nodes with fairly high degrees. This happens for point-to-point systems, so identifying the cut-off can help facilitate their detection.

There are expectations regarding the size of the power-law parameter depending on the type of network. Barabasi and Oltvai [38] show that values of this resultant parameter in specific numerical ranges are "hub"-oriented: for $b = 2$ a hub-and-spoke network emerges, and for $2 < b < 3$ multi-hubs do. However, it is not enough to judge complex network topology with that single parameter, since there are variations in empirical connectivity patterns even between airlines that have similar power-law parameters. Also, there exist some ambiguous networks, perhaps located on a continuum between hub-and-spoke and point-to-point ones. Therefore, we suggest a classification scheme with multiple steps in order to divide the various forms of airlines' networks into four types.

A classification tree, allowing the cases to be broken into systematic categories, is shown in Figure 3. There are four classification types, determined by exploring the networks and defining their characteristic features. There are three elements to the classification rules: (1) how many nodes have a large proportion of betweenness; (2) what the cut-off is; and (3) what the power-law parameter is. A power-law analysis is useful here—especially with the endogenous selection of a cut-off (i.e., an indication of the range of values where the power law holds). Curve fitting software that endogenously determines the cut-off allows us to find the range of values over which a power law fits—it is shown that cases with a large cutoff value tend to be point-to-point networks.

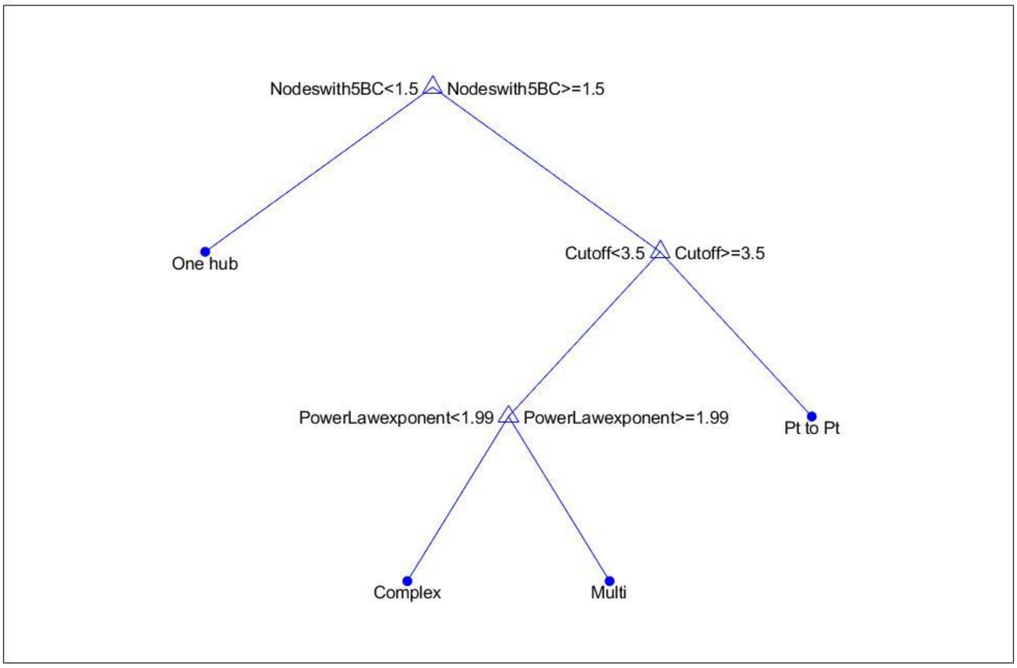


**Figure 3.** Classification tree moves from top to bottom, selecting single hub-systems (using betweenness) as One-hub, point-to-point systems (using power-law cut-off) as P2P, and then Multi-hub and Complex systems (differentiating them using the power-law slope).

Step 1: Detect the obvious one-hub systems called the One-hub type. For them, there is typically an order of magnitude drop between the degree of the first- and second-rank nodes. A simple way to confirm this pattern is that the single hub will have a dominant proportion of all the betweenness scores. These systems also have one node with a significant betweenness score. A pure one-hub system, without side connections, has $2(n-1)$ edges, and a betweenness score of $(n-1)(n-2)$.

Step 2: Determine cases with a large power-law cut-off, meaning that the power law is fitted only to larger degree values. Typically, a cut-off of $c \geq 3.5$ corresponds to a point-to-point network called the P2P type, and the resultant degree distribution will have a concave shape.

Step 3: Moving now to networks without a high cut-off, there are several systems with very typical power-law parameters (a power law greater than 2), consistent with Barabasi, these are classed as multi-hub systems and called the Multi-hub type.

Step 4: Detect systems that have such an unusual degree pattern that they are very unlikely to be purely hub-based, for example systems where the average number of links is multiple times the expectation for most other systems, which are called the Complex type. (As a corroborating observation, there are many nodes with a high proportion of betweenness).

## 4. Results

### *4.1. The Classification Results*

Applying the classification routine to our 284 carriers' networks yields a network typology. Table 1 shows the descriptive statistics of the carrier networks sorted by the four network types resulting from our classification scheme. For each type of network, we see the number of associated carriers, the average size of the network in terms of nodes and edges, the average number of nodes with at least a 5% share of the total betweenness, and finally two measures from the fitted power law: averages of power-law exponents and cut-off values, respectively. Each of the network types has distinctive descriptive statistics compared to the other types; One-hub networks have the smallest number (on average) of nodes with a significant proportion of betweenness (exactly equal to 1). P2P networks have the largest cut-off value (on average) with strong variability, which is in turn related to the largest number of nodes with a significant proportion of betweenness. Multi-hub networks have power-law exponents between 2 and 3 (as expected) while Complex networks have ones less than 2. Even though they have a similar number of nodes with a significant proportion of betweenness, these two network types show quite distinctive characteristics in terms of their cut-off values on average; in our classification routine, the cut-off value is not the criterion used to divide networks into Complex and Multi-hub types. The average cut-off of Complex network carriers is close to the One-hub type (rather than the Multi-hub type), while their average number of significant BC share nodes is the second highest after P2P. This implies that the Complex type is close to a hybrid of the One-hub and P2P network types; their networks are largely based on a few hubs but their connections are more distributed over hub and non-hub nodes in a complex manner. Several possible explanations for this observation are as follows: the Complex case might represent networks that are still evolving towards the creation of a hub; another possibility is that the network has emerged as an assemblage of other earlier networks, and the points of contact between the two or more joined systems take on a special joining or gateway function. Finally, some complex cases cover very far-flung regions (e.g., Qantas) so it is possible that their complexity arises from arms stretching far beyond their core neighbourhood. The results indicate the importance of the complementary use of the three measures because of their distinctive scope in characterizing network structure.

**Table 1.** Descriptive statistics of 284 carriers using four network types.

| Network Type | Number of Carriers | Average (std.) Number of Nodes | Average (std.) Number of Edges | Average (std.) Number of Nodes with BC (>5%) | Average (std.) of Power-Law Exponents | Average (std.) of Cut-off Values |
|---|---|---|---|---|---|---|
| One-hub | 45 | 65.47 (35.92) | 164.53 (96.16) | 1.00 (0.00) | 2.58 (0.45) | 1.13 (0.40) |
| P2P | 33 | 55.03 (37.91) | 392.09 (462.13) | 4.82 (1.70) | 2.96 (0.45) | 6.85 (4.19) |
| Multi-hub | 187 | 44.95 (52.05) | 152.89 (251.51) | 3.93 (1.51) | 2.55 (0.43) | 1.85 (0.66) |
| Complex | 19 | 50.90 (35.46) | 230.21 (258.02) | 4.05 (1.43) | 1.87 (0.11) | 1.05 (0.22) |
| Total | 284 | 49.77 (47.93) | 187.70 (279.72) | 3.58 (1.82) | 2.55 (0.48) | 2.26 (2.28) |

The results of applying this analysis to the top 30 airlines are shown in Table 2. The networks are organized in groups by type, One-hub, P2P, Multi-hub, and Complex, based on the tabulated values of their scores. The top 30 carriers are among the most recognized airlines with very large passenger flows. We used these because they are thought to be easily characterized, visualized, and understood examples of the types of carriers, and so our classification results will in some sense be unsurprising for them. For example, the contrast between Delta and Southwest is clear in their operations and in the statistics we present. We also present selected organized graphics from these main cases. We then use that same method for many hundreds of other carriers. The top 30 cases provide a manageable set of networks where the known characteristics of the cases are widely appreciated.

**Table 2.** Summary of 30 air carrier networks with measurements related to the network classification scheme.

| Airline | Carrier Code | Nodes | Edges | Nodes with >5% BC | Cut-Off | Power-Law Exponent | *p* | Goodness of Fit | Type |
|---|---|---|---|---|---|---|---|---|---|
| Emirates | EK | 114 | 246 | 1 | 1 | 2.97 | 0.27 | 0.02 | One-hub |
| Turkish Airlines | TK | 186 | 499 | 1 | 1 | 2.46 | 0.90 | 0.01 | One-hub |
| Iberia Airlines | IB | 127 | 408 | 1 | 1 | 2.06 | 0.66 | 0.03 | One-hub |
| KLM Royal Dutch | KL | 135 | 268 | 1 | 1 | 3.50 | 0.19 | 0.03 | One-hub |
| Alitalia | AZ | 87 | 289 | 1 | 1 | 2.01 | 0.75 | 0.03 | One-hub |
| Southwest Airlines | WN | 73 | 1012 | 6 | 7 | 2.28 | 0.43 | 0.07 | P2P |

**Table 2.** *Cont.*

| Airline | Carrier Code | Nodes | Edges | Nodes with >5% BC | Cut-Off | Power-Law Exponent | *p* | Goodness of Fit | Type |
|---|---|---|---|---|---|---|---|---|---|
| Ryanair | FR | 161 | 2278 | 5 | 24 | 3.35 | 0.39 | 0.09 | P2P |
| easyJet | U2 | 132 | 1272 | 6 | 19 | 3.07 | 0.26 | 0.11 | P2P |
| TAM Brazilian Airlines | JJ | 65 | 345 | 6 | 7 | 2.67 | 0.58 | 0.09 | P2P |
| Air Berlin | AB | 142 | 1123 | 6 | 4 | 2.01 | 0.45 | 0.06 | P2P |
| Delta Air Lines | DL | 353 | 1925 | 5 | 2 | 2.05 | 0.30 | 0.04 | Multi-hub |
| United Airlines | UA | 404 | 2164 | 8 | 3 | 2.28 | 0.00 | 0.07 | Multi-hub |
| American Airlines | AA | 273 | 1088 | 4 | 2 | 2.36 | 0.01 | 0.08 | Multi-hub |
| US Airways | US | 209 | 888 | 3 | 2 | 2.37 | 0.00 | 0.14 | Multi-hub |
| Lufthansa | LH | 219 | 924 | 3 | 2 | 2.43 | 0.00 | 0.08 | Multi-hub |
| Air France | AF | 193 | 708 | 3 | 1 | 2.00 | 0.15 | 0.04 | Multi-hub |
| All Nippon Airways | NH | 81 | 351 | 4 | 2 | 2.06 | 0.40 | 0.07 | Multi-hub |
| Air China | CA | 121 | 528 | 2 | 2 | 2.07 | 0.53 | 0.05 | Multi-hub |
| British Airways | BA | 171 | 411 | 4 | 1 | 2.49 | 0.07 | 0.04 | Multi-hub |
| Gol Transportes Aéreos | G3 | 62 | 336 | 5 | 3 | 2.05 | 0.15 | 0.10 | Multi-hub |
| Japan Airlines | JL | 72 | 231 | 6 | 1 | 2.00 | 0.07 | 0.07 | Multi-hub |
| Air Canada | AC | 176 | 716 | 3 | 2 | 2.27 | 0.04 | 0.07 | Multi-hub |
| Lion Mentari Airlines | JT | 42 | 139 | 5 | 2 | 2.11 | 0.30 | 0.09 | Multi-hub |
| Scandinavian Airlines | SK | 95 | 383 | 3 | 2 | 2.14 | 0.10 | 0.08 | Multi-hub |
| Korean Air | KE | 110 | 284 | 2 | 1 | 2.40 | 0.31 | 0.03 | Multi-hub |
| Alaska Airlines | AS | 96 | 372 | 4 | 2 | 2.29 | 0.86 | 0.03 | Multi-hub |
| Saudi Arabian Airlines | SV | 102 | 408 | 4 | 2 | 2.59 | 0.00 | 0.11 | Multi-hub |
| China Southern Airlines | CZ | 134 | 988 | 2 | 1 | 1.61 | 0.00 | 0.10 | Complex |
| China Eastern Airlines | MU | 126 | 806 | 4 | 1 | 1.63 | 0.01 | 0.08 | Complex |
| Qantas | QF | 73 | 272 | 6 | 1 | 1.87 | 0.45 | 0.05 | Complex |

From these results, Figure 4 represents three exemplary networks for each of the four groups, respectively (see Figure 4a–d). There is a stark organizational contrast between those at the top of the table (e.g., Emirates) and those at the bottom (e.g., Ryanair).

- The first type of network is a One-hub network, with some added links in a few cases. The networks included here have degree distributions with a convex shape of distribution and power-law parameters that are generally greater than two. Overall, there are 45 airlines in this group. Five clear examples are Emirates, Alitalia, Turkish Airlines, KLM Royal Dutch Airlines, and Iberia Airlines.
- P2P networks have a very different configuration from Figure 4a. In these cases, the distribution of nodes cuts off those with small degrees. In other words, the fitted curve begins to the right of the origin. Their rank-size distributions tend to be concave. These cases have a plausible power-law parameter applied to the relevant range. Many more nodal pairs are directly connected. Overall, 33 airlines have these type of networks; typical cases are Southwest, Ryanair, and easyJet
- The third type of network is best thought of as a Multi-hub connection pattern, represented by a convex-shaped distribution and a power-law parameter consistently between two and three. This group includes the bulk of the networks including Delta, American Airlines, Lufthansa, and others.
- Finally, in the Complex networks the power-law-fitted parameter is below the usual range (two to three) and the diagram of the network shows that there is a large number of interconnected nodes without having either a completely connected system or a hub system. Three example cases are China Southern Airlines, China Eastern Airlines, and Qantas.

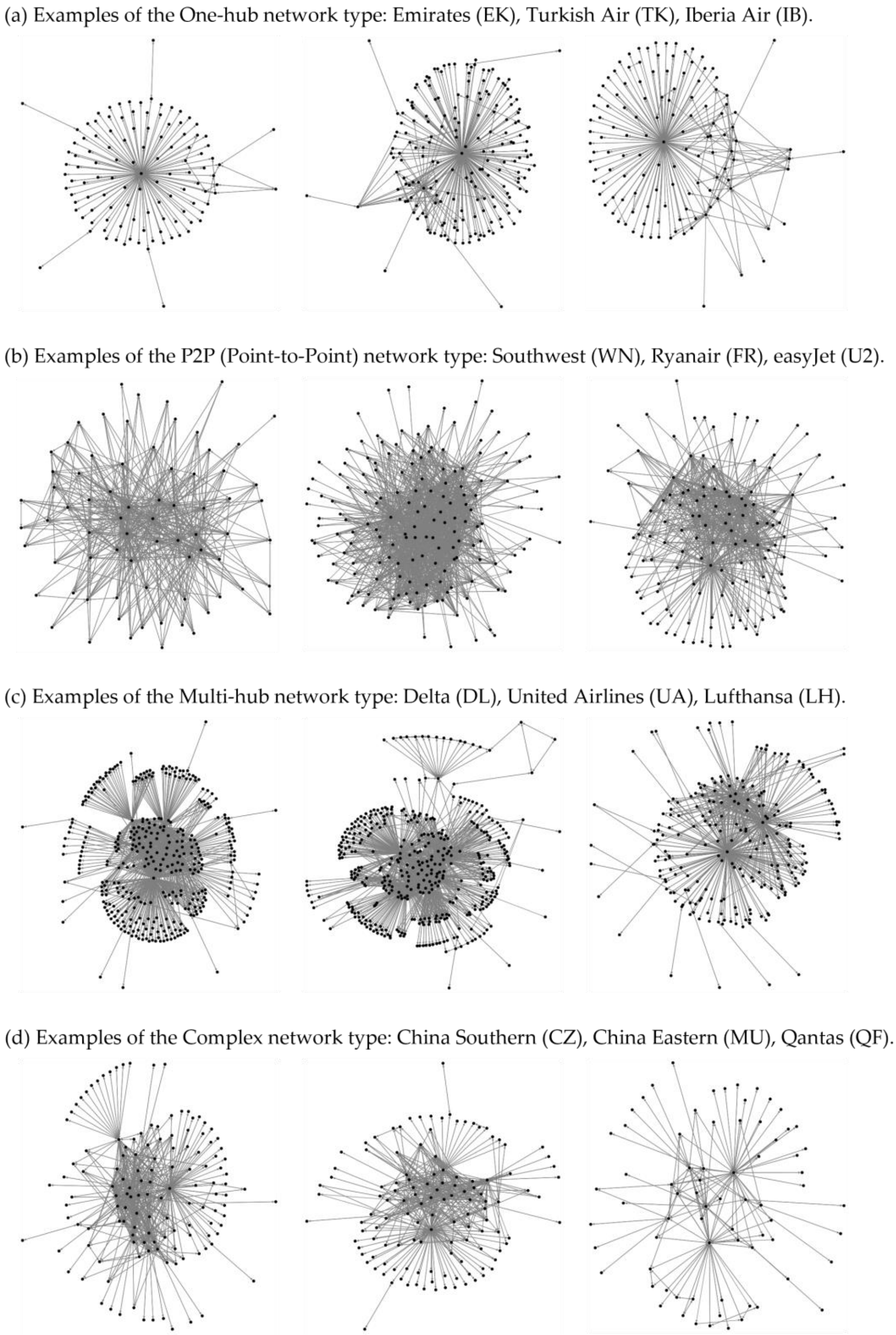


**Figure 4.** Examples of the four network types (One-hub, P2P, Multi-hub, Complex), created with NodeXL.

### 4.2. Structural and Operational Contrasts between the Four Network Types

Figure 5 represents the distinctive distributions of network density among the 284 carriers classified using the four network types. The network density is a ratio of the number of actual direct connections to the potential maximum; computed from the number of nodes as $[n(n-1)]$. Overall, One-hub carriers show the lowest density trend with the smallest variation, as their average density (std. of densities) is 0.06 (0.04). This indicates the strong dependence of these carriers on a single hub to run their networks, using only 6% of the potential connections. This is compared to other network types. Particularly, P2P carriers show the highest density (on average) with the largest variation, which reflects the varying connection levels among carriers of this type caused by their operational simplicity in connecting cities. (This corresponds to the differential descriptive statistics of nodes and edges between the One-hub and P2P carriers shown in Table 1). Multi-hub- and Complex-type carriers show intermediate distributions between the distributions of the One-hub and P2P carriers.

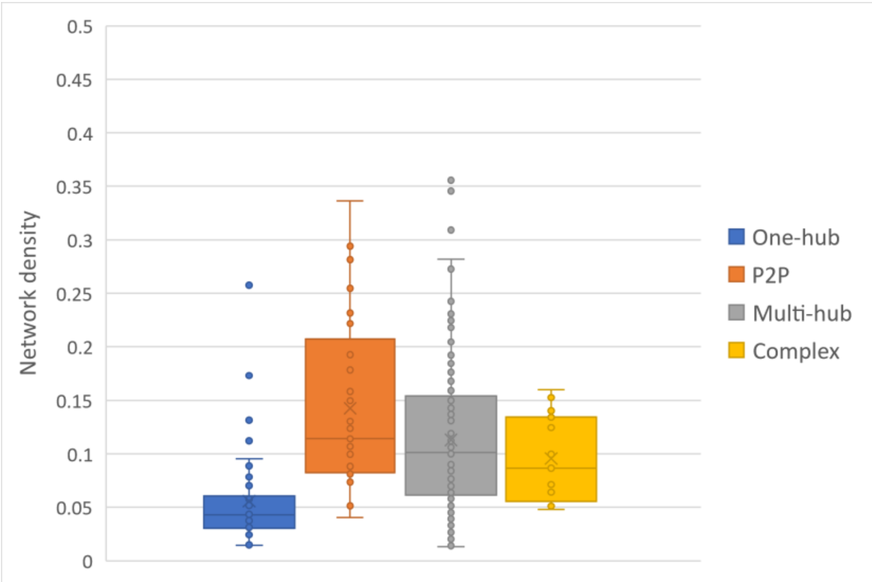


**Figure 5.** Network density distributions of 284 air carriers using four network classes.

Figure 6 shows the operational contrast between the four types of carrier networks through the shares of their fleet operations (upper) and of output generated by these operations, i.e., seat-nautical miles (lower) of air carriers in each network type and each range of aircraft size (0–100, 100–200, 200–300, 300–400, greater than 400 seats) (The operational statistics of the airlines, including flight counts and seat-nautical miles, are compiled based on passenger flight schedules of categories G and J in the OAG data). The operations of P2P carriers are highly concentrated on 100–200-seat aircraft such as the Airbus A320 and Boeing B737 series; their share is 89.6%, while wide-body aircraft operations are about 3% (200–300-seat a/c, 2.63%; 300–400-seat a/c, 0.5%, and greater than 400-seat a/c, 0%, respectively). This contrasts with the other types of carrier networks. Even though the operational concentration on the 100–200-seat aircraft is similar to the P2P case, aircraft utilization on the other network types are relatively distributed over the five aircraft size ranges. Their shares of the 0–100-seat aircraft operations are obviously higher than the P2P share; the shares of One-hub, Multi-hub, and Complex carrier networks are 26.1%, 41.0%, and 25.4%, respectively. Particularly, the Multi-hub type's share is higher than others, showing a similar level with its 100–200-seat aircraft operations. Generally, network carriers utilize regional aircraft (less than 100 seats) to maintain their regional markets, as well as to deliver transfer passengers to their hubs. Multi-hub carriers are likely to cover broader regional markets based on their multiple hubs, so the utilization of small aircraft is more frequent than other network types. Complex network carriers show a similar pattern to the One-hub type in terms of the distribution of their fleet operations according to aircraft sizes. But their operational share of mid-size aircraft (100–200-seat) is larger than the One-hub case, which is connected to the smaller proportions of large aircraft (greater than 200-seat) in their operations. As mentioned earlier, Complex type carriers have a hybrid topology largely shaped by a single-hub-based network with denser connections than the One-hub case, so that mid-size aircraft are likely to be utilized for extensive route markets.

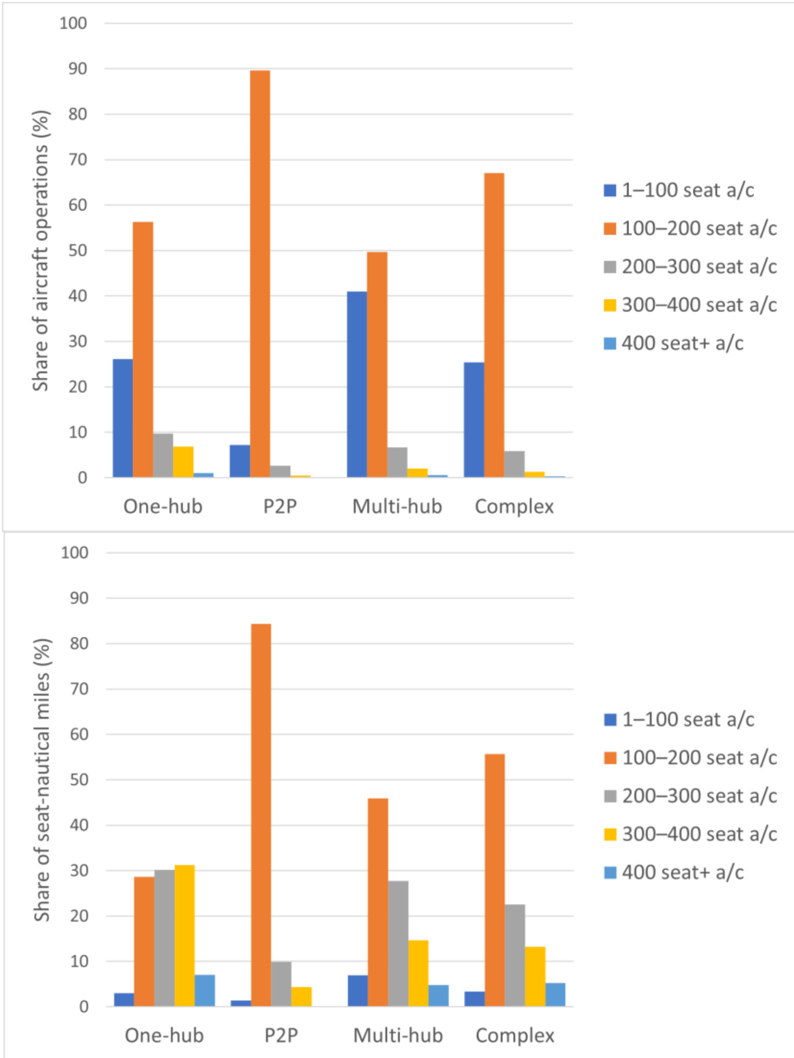


**Figure 6.** Proportions of aircraft operations (**upper**) and seat-nautical miles (**lower**) by aircraft sizes (0–100, 100–200, 200–300, 300–400, greater than 400 seats) and network types (One-hub, P2P, Multi-hub, Complex).

The share patterns of seat-nautical miles (the lower figure in Figure 6) are quite different from those of fleet operations. The concentration of P2P networks on 100–200-seat a/c slightly decreases, while its share of the larger aircraft increases a little (200–300-seat a/c, 9.9%; 300–400-seat, a/c 4.4%). On the other hand, the One-hub type shows remarkable changes from its operation share patterns as its shares of 100–200-, 200–300-, and 300–400-seat a/c are almost evenly distributed at around 30%. Overall, the proportions of less than 200-seat a/c operations across the four network types tend to be smaller while large aircraft sizes (greater than 200-seat) show larger shares than their flight frequency shares. Such a distributed trend is related to the airlines' practice of aircraft utilization; wide-body aircraft are usually employed in medium- and long-haul markets, so that the supplied seats and flight distances in their operations weigh more for seat-nautical miles than small aircraft operations. The share patterns of the One-hub and P2P networks are clearly distinguished, and those of Multi-hub and Complex types are located among them.

Along with the comparison above, another useful way to contrast the types of networks, with significance for their resilience and exposure to downturns, is to plot the proportions of their aircraft operations (the upper figure in Figure 7) and seat-nautical miles (the lower figure in Figure 7) in each distance band (0–500, 500–1000, etc.). Clearly there is a large active level in short ranges for the P2P type networks, and large proportions in longer ranges for the One-hub systems. It also makes sense that the Multi-hub systems have more short links (to their available hubs) and less extreme use of long distances than a single-hub system. In terms of resilience and sustainability, COVID-19 essentially grounded large parts of KLM and Lufthansa. This is consistent with our view that the major contrast between airlines is between the One-hub systems with high reliance on a central hub (and long connections to that hub—e.g., Lufthansa and Emirates) and P2P carriers such as Ryanair and Southwest Airlines. Ryanair was especially flexible in rebounding after COVID-19 and picking up portions of other failed operations (including Lufthansa's low-cost affiliate). While in normal circumstances we might simply say that these are two different ways to organize the system, under extreme pressure from a loss of demand, the hub system is particularly vulnerable as there is an almost complete collapse of the inter-regional traffic needed to sustain the major central hub. P2P carriers, in contrast, have shorter routes, and an apparent ability to rebound quickly as some of these routes come back online. In other words, the P2P network's solution does not rely on the recovery of the entire system to make some parts workable.

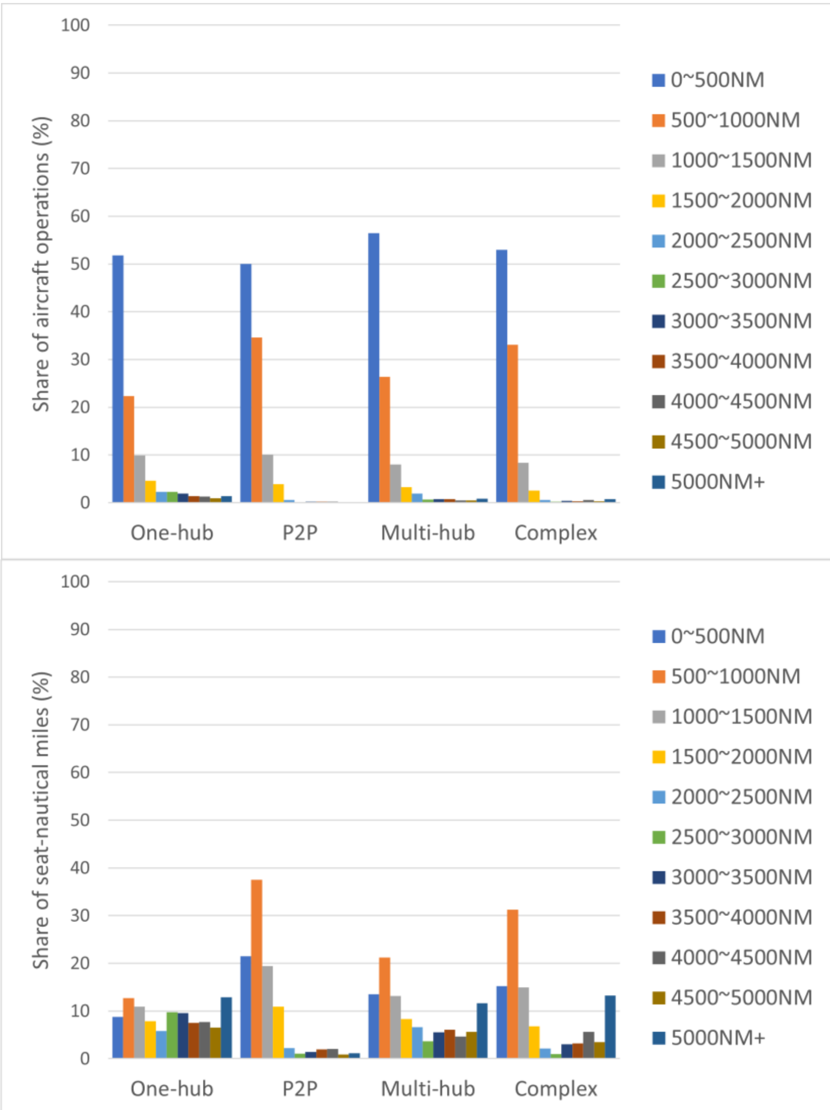


**Figure 7.** Proportions of aircraft operations (**upper**) and seat-nautical miles (**lower**) in terms of distance ranges and network types (One-hub, P2P, Multi-hub, Complex).

In sum, the four network types show distinctive characteristics in terms of operations, as well as network topology. The One-hub networks show the simplest topology in which connections are largely concentrated on a hub, but operations through the networks are quite distributed across varying aircraft sizes and route distances. Even the distributed patterns are strengthened in their seat-nautical mile proportions due to the large influence of large aircraft and long-haul routes on the operational output. In contrast, the P2P cases show disordered structures in which a dependency on a few core nodes is not clear, while operations through the networks are concentrated on particular aircraft types (and sizes) and distance ranges. The topological and operational features of the Multi-hub and Complex networks are positioned between those two typical types. But it should be noted that the Multi-hub networks have more feeder lines with low connectivity (as shown in their larger cut-off value on average) maintained by small aircraft operations than the Complex type.

## 5. Conclusions

There are many ways to detect hubs. Some recent research, for example, contrasts nodal flow-based measures with the size-based functional definition of hubs by the FAA (see [39]). Also, work has attempted to synthesize a merged network, which tends to have a concave shape for its degree distribution, due to the amalgamation of places from unique networks. Imagine airlines building their networks from existing cities. Each network is layered on top of others. Networks are likely to connect to at least some higher degree nodes that have a strong level of inter-hub connection. As the size of the number of data points grows, it becomes increasingly unlikely that a new previously undiscovered node can emerge with a high degree of connection [3]. These nodes have a consistent level of connection with other non-hub nodes and there are also relatively small levels of point-to-point contact between the non-hub nodes. There is a considerable drop in the number of nodes attached to each sequentially smaller hub. This is essentially the preferential argument used by Barabasi and Albert [40], and an added result is that an amalgamation of many underlying large networks results in a concave-shaped degree of distribution, having improved the point-to-point characteristics.

We can easily detect a single hub case, such as Emirates Airlines, because there is such a concentrated level of betweenness at the core hub (DXB). Intermediate cases occur where there is a clear level of break between the hubs and the non-hubs. Heterogeneous networks such as British Airways and United Airlines have a lot of direct connections, as well as long-haul connections between far-flung portions of their system. This creates the small-world phenomenon of a small number of hops needed to connect even the most distant pairs. And then there are clearly non-hub systems organized around more point-to-point organization such as Southwest Airlines, Ryanair, and others.

We might also recall the numerical values of the power-law parameter suggested above: values between two and three. Recognizing the need to include bimodal distributions, it is interesting to re-examine what part of that distribution has a power-law parameter. When a minimum cut-off is used, the upper degree nodes follow a linear power law. A feature of this work is that it helps with the detection of the number of hubs and it adds empirically based features to the discussion of power laws in terms of their relationship to hub networks.

This paper focuses on developing a network classification methodology for individual air carriers, based on utilizing measurements related to the levels of connectivity within their distributions. Applying the scheme results in sorting 284 air carriers into four network types, as One-hub, P2P (Point-to-Point), Multi-hub, and Complex networks. We confirm the clear contrast between the resulting One-hub and P2P networks with respect to network topology and carrier operation. Multi-hub and Complex networks are positioned between these types. Particularly, the Complex networks display hybrid characteristics, mixing the One-hub and P2P types. While no single network type is an obvious survivor under all circumstances, the system *gains resilience from the multiplicity of network types*. One strategy for airline partnerships would be to include components that have a strong regional presence in disparate areas, linked by robust and survivable inter-hub connections. In the event of a downturn, the most essential recovery would appear to be intense short- to medium-range interactions (intra-European, intra-US, intra-Asia) followed by the reconnection of global links (say, Singapore to NYC). Although we validate our classification scheme through exploring the distinctive characteristics of the four network types, the Complex type should be investigated in more detail in future, since it has mixed properties from the other networks. A time-series analysis could be a way to understand the type through tracing the topological network changes of individual air carriers. Furthermore, actual passenger or freight flow patterns can be utilized to further characterize the four network types. Flows between two cities are likely to be composed of direct, one- and multiple-stop trips via a few hubs. It is likely that a distinctive proportion of those pathway types will be shown among airlines; exploring the differential percentage patterns between the network types can be a base from which to understand the distinctive characteristics of the networks.

Finally, this paper has opened up an interesting puzzle in terms of sustainability. We have demonstrated a trade-off between an airline network configuration and its efficiency, and the resilience and sustainability of these cases co-vary as well. A very efficient hub system, with perhaps some added direct side-connections, with economies of scale and network effects, likely wins in terms of efficiency. But, as we saw in COVID-19, such systems can be subject to catastrophic collapse (due to the interdependence of all their flows). Thus, the hub system is vulnerable to failure in terms of resilience. In contrast, a point-to-point system has separable components that can individually survive some types of collapse, but as we know, this also requires many smaller (and possibly less efficient) aircraft. When the system is highly tuned and the aircraft are modern and fuel-efficient, the resilience coupled with the effective use of aircraft and minimization of passenger miles, can possibly give the system an edge. As for sustainability, more research is needed to reach definitive conclusions about the winners and losers.

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