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Integrators' global networks: A topology analysis with insights into the effect of the COVID-19 pandemic

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ABSTRACT

In this paper we propose, to the best of our knowledge, the first analysis of the global networks of integrators FedEx, UPS, and DHL using network science. While noticing that all three networks rely on a "hub-and-spoke" structure, the network configuration of DHL leans towards a multi-"hub-and-spoke" structure that reflects the different business strategy of the integrator. We also analyzed the robustness of the networks, identified the most critical airports per integrator, and assessed that the network of DHL is the most robust according to our definition of robustness. Finally, given the unprecedented historical time that the airline industry is facing at the moment of writing, we provided some insights into how the COVID-19 pandemic affected the global capacity of integrators and other cargo airlines. Our results suggest that full-cargo airlines and, much more dramatically, combination airlines were impacted by the pandemic. On the other hand, apart from fluctuations in offered capacity due to travel bans that were quickly recovered thanks to the resilience of their networks, integrators seem to have escaped the early months of the pandemic unscathed.

1. Introduction

Air cargo transportation plays a role of paramount importance in the global economy, especially when time and safety are crucial factors. In fact, while roughly 1% of the overall cargo volume worldwide is transported via air, the percentage spikes to 35% if value is used as a measure (IATA website, 2020). As example, transport of high-value, perishable, or emergency-related products is generally carried out via air, because it is the only mode that guarantees shipping times consistent with the user's requirements and needs. At the time of writing, this factor is even more crucial because of the COVID-19 pandemic. Transport of lifesaving medical devices (e.g., ventilators) and masks to help people worldwide contrast the disease has been possible only with air transport (Aviation Business website, 2020).

Air cargo transport can be carried out in two ways: (i) in the belly space of passenger aircraft, and (ii) using dedicated full freighter aircraft. The first option offers more flexibility in terms of frequencies and destinations, but a limited cargo capacity per aircraft. This cargo capacity can also suffer from unexpected variations, because it depends on how much luggage passengers check in for a specific flight (Morrell and Klein, 2018; Delgado et al., 2020). Given the aforementioned two transport strategies, three different air cargo service providers can be identified: (i) passenger airlines offering cargo services (also known as combination airlines), (ii) full-cargo airlines, and (iii) integrators. Differently from (i) and (ii), that only offer air transport services between airports and rely on freight forwarders and ground handlers for the landside logistics, integrators offer a door-to-door service to customers. The American FedEx and UPS, and the European DHL are the "three-headed" kings of the integrator business worldwide. TNT, another important integrator in the past, was acquired by FedEx in 2016. On the other hand, Amazon has recently invested into the creation of its own aircraft fleet, i.e., Amazon Air, hence paving the way to become de facto a fourth major integrator. While, until now, all its fleet was leased from other cargo airlines, by 2021 Amazon Air will own more than 70 full freighters (The Motley Fool website, 2020).

Similarly to other transportation modes, network science can be used to study characteristics, similarities and differences between the networks of the different players in the air cargo world, and specifically of integrators. This approach can provide useful insights into expansion opportunities or network re-structure strategies in such a competitive business. As example, the analysis of which airport connection, if added to the current network structure, might be more beneficial for the overall connectivity, can be of interest for stakeholders, as well as the effect of a temporary (or permanent) closure of an airport. While the literature is relatively rich of works addressing the network structure of airlines using a passenger perspective (Guimera et al., 2005; Malighetti et al., 2008; Paleari et al., 2010; Lordan et al., 2014), the cargo counterpart is still a fairly unexplored territory, especially when it comes to integrators. To the best of our knowledge, academic papers only focused on basic properties of integrators' networks (Bowen, 2012; Bombelli et al., 2020), or were spatially and temporally limited to subsets of the global networks (Malighetti et al., 2019a; Malighetti et al., 2019b). This factor is consistent with the difficulty to find reliable and complete data on air cargo operations, where confidentiality and

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competition are crucial factors. This applies both to passenger airlines offering cargo services and, even more strongly, to integrators (Malighetti et al., 2019a; Lakew, 2014).

Our first contribution fills in this gap. Using publicly available data from global aviation data services over a period of eight months, we built global networks for integrators FedEx, UPS, and DHL, and provided a thorough analysis and comparison of such networks. The second contribution contextualizes the peculiar historical period that coincides with the preparation of this paper. While the COVID-19 pandemic inflicted an unprecedented blow on passenger airlines (City AM website, 2020), the effect on the cargo industry was evident (Accenture website, 2020), yet not so dramatic. As mentioned before, global transport of goods was needed ever more during the pandemic, and lockdown flight restrictions and bans on passengers did not apply with the same severity to cargo schedules. Given that the dataset we collected refers to a time-span that covers a pre- and a pandemic period, we analyzed how network characteristics and connectivity evolved with time for the three integrators and, to have a more thorough analysis, for three other airlines relevant from a cargo perspective.

The rest of the paper is organized as follows. In Section 2, a literature review on network science applied to the cargo industry, and specifically to integrators is provided. Section 3 describes the characteristics, assumptions, and limitations of the collected dataset. In Section 4, a network analysis in terms of topology and robustness is shown for integrators FedEx, UPS, and DHL. Section 5 describes the effect of the COVID-19 pandemic on the network characteristics of different cargo carriers, while Section 6 states conclusions and recommendations for future work.

2. Literature review

The existing literature pertaining integrators mainly addresses two aspects: (i) their business and cost models, and (ii) their network configuration and characteristics. Although our work belongs to the second category, we argue that the two categories are strongly intertwined, and hence provide a comprehensive literature review addressing both.

As it concerns business and cost models, in (Kiesling and Hansen, 1993) the cost structure of FedEx between the late 80s and early 90s was analyzed, and considerable economies of densities were highlighted. It should also be noted that each of the integrators considered in this work has undergone massive changes, acquisitions, and network re-designs in the last thirty years, due to the soaring of the Internet and the e-commerce, as highlighted in (Morrell and Klein, 2018) and (Lakew, 2014). In addition, in (Lakew, 2014) the cost structure of FedEx and UPS was assessed using quarterly data on domestic operations and costs for the years 2003–2011. It was shown that (i) accounting for carrier-specific differences in cost structure and network size, FedEx is more cost efficient than UPS, and (ii) both integrators display economies of size. The latter result was also confirmed by (Onghena et al., 2014).

Before analyzing the relevant literature on the network configuration and characteristics of integrators, we provide a general framing of complex network theory. The term *complex network* refers to those networks whose topological characteristics are non-trivial, with patterns and relationships between nodes that would generally not occur in a randomly generated network (Barabási and Albert, 1999, Barabási, 2009, Strogatz, 2001). Many systems where hierarchical and community-like structures between elements are present can be modeled as complex networks. Systems of this kind are, as example, the Internet (Cohen et al., 2000), epidemic spreading models (Stegehuis et al., 2016), and transport networks such as air transport networks (Guimera et al., 2005). Our work belongs to this last category.

Focusing on papers addressing the network configuration of integrators from a quantitative perspective, (Kuby and Gray, 1993) analyzed the FedEx network. In contrast to the general research on hub-and-spoke systems, where it is assumed every node has a direct connection to the hub, it was shown that in the FedEx network most routes to the main hub make one or more stopovers. The paper explores the trade-offs and savings involved with stopovers and feeders, and evaluates the optimality of the FedEx network using a mixed integer linear programming formulation. More recently, (Bowen, 2012) provided a comparison of the network structures of FedEx and UPS with the network structure of American Airlines and Southwest using complex network theory indicators. Although this work is the first one, to the best of our knowledge, to provide such analysis, we believe the comparison between passenger airlines and integrators' networks might not be totally appropriate. In fact, while in the former demand is generally symmetric, in the latter there is a high imbalance in demand and many routes are unidirectional (and sometimes dubbed as "triangular"). As such, modeling integrators' networks with undirected edges and, as a consequence, using network indicators that do not consider directionality of connections (as the γ index in the paper) might lead to biased results. This issue was addressed in (Malighetti et al., 2019a; Malighetti et al., 2019b) and (Bombelli et al., 2020), where the analysis of integrators' networks was carried out considering the directionality of connections. In (Malighetti et al., 2019a) and (Malighetti et al., 2019b) the authors focused, respectively, on the European and Asian network structure of FedEx, UPS, DHL, and TNT (the analysis covers a time-period prior to the FedEx acquisition), which are based on a limited temporal dataset of one week. In both works, the different strategies of the main integrators were highlighted, with DHL focusing more on efficiency and exhibiting the highest centralization and the lowest density, and FedEx and UPS showing a higher density and transitivity and a lower centralization. In (Bombelli et al., 2020), the authors relied on a temporally larger dataset and focused on the global networks of FedEx, UPS, and DHL. After some preliminary considerations on the different networks, that confirmed the different characteristics of the networks at the global scale, most of the complex network analysis addressed the global air cargo transport network that also includes passenger airlines. Since all the different networks were merged, integrator-specific insights were not traceable any longer. Hence, in comparison to the existing literature on integrators, the contribution of this paper is twofold as already anticipated in Section 1. First, we provide a topological analysis of integrators' networks that is both spatially and temporally more complete. Second, we add a robustness analysis that, after addressing the general structure of the networks, focuses on time-dependent variations due to the COVID-19 pandemic.

3. Dataset

In this section, we provide a thorough description of the dataset used in the paper. As highlighted in other works (Malighetti et al., 2019a; Malighetti et al., 2019b), data on integrators' schedules is scarce and difficult to retrieve as a stand-alone product. To circumvent this issue, we have been collecting integrator-specific data from public sources for a time period of eight months. In particular, we retrieved data from global aviation data services *Flightaware*[1] and *Flightradar24,*[2] which report for all airports in their database departures of the previous 14 days and 7 days, respectively. We used Flightaware as the main data source, and used data from Flightradar24 to enrich our dataset by adding flights that might not have been included in the Flightaware database. Since the process was carried out either via the dedicated API, with a limited set of requests (Flightaware), or manually (both data services), we pre-selected a set of 336 airports deemed relevant from a cargo perspective (i.e., with an annual cargo throughput in 2014 greater or equal to 5000 t (Meijs, 2017)) to limit the data retrieval process effort. All the main and second-tier hubs of the three integrators were considered, as well as other airports with a non-negligible yearly

[1] www.flightaware.com
[2] www.flightradar24.com

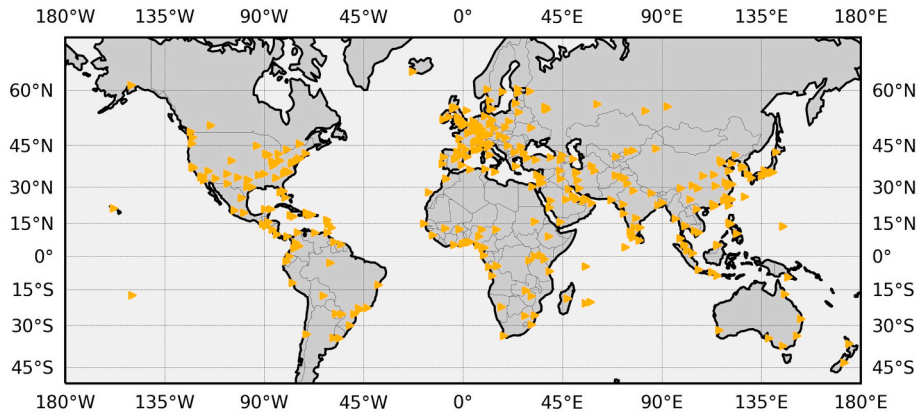


Fig. 1. Initial set of airports to build the FedEx, UPS, and DHL networks.

cargo throughput. As will be highlighted later in this work, this airport filtering step can have the undesired effect of ruling out some lower-tier airports used by the integrators. Notwithstanding, we believe our approach to provide a good trade-off between computational effort and faithful network representation. We also acknowledge that, while the dataset could be more extensive, cargo operations generally rely on a smaller set of involved airports when compared to the passenger counterpart. Because of the extensive freight ground transportation network, the catchment area for cargo transport can increase up to 10 times with respect to the catchment area for passengers (Boonekamp and Burghouwt, 2017). The list of the considered airports is available as part of our online dataset (https://data.4tu.nl/repository/uuid:2e9b04dd-70fe-4f16-abd4-873be4b2c4b1), while their geographical location is depicted in Fig. 1. In the rest of the paper, we will generally refer to specific airports using their IATA code unless, for sake of clarity, the full name is preferable.

We collected data on dates November 20th 2019, December 3rd 2019, December 16th 2019, December 30th 2019, January 13th 2020, January 27th 2020, February 14th 2020, March 2nd 2020, April 6th 2020, April 27th 2020, May 11th 2020, May 26th 2020, June 18th 2020 and will name each of these thirteen data retrieval blocks an *observation* for the rest of the paper. We additionally retrieved data from Flightradar24 seven days prior to each observation, so that two consecutive data retrieval processes from this data source would match the time-span of each observation from Flightaware. Given our notation, each observation's retrieval date refers to the end of the time-period that observation covers. As example, an observation with date April 27th, 2020 refers to the time-period April 13th-April 27th, 2020. The first six observations cover consecutive 14-day periods. Apart from negligible temporal holes, due to the fact we did not always start the data retrieval process at the same time, this means that roughly half of our dataset covers 84 consecutive days. This is important to ensure that triangular routes that were flown infrequently are considered. Since the process was carried out manually and each data retrieval is generally lengthy, the other seven observations were retrieved with time-intervals ranging from 17 to 25 days. Nothwithstanding the presence of more pronounced temporal holes in this case, the addition of these observations is important to account, at least partially, for seasonality effects. In fact, our dataset contains the peak season (November and December) and another above average month (March), below average months (January, February, and April), and average months (May and June). While we acknowledge that seasonality effects can only be fully accounted for with a complete year of data, we believe our dataset to be sufficient, especially when compared to the existing literature, to provide useful insights into integrators' global networks. All thirteen observations were used both to build the networks described in Section 4, and to create time-series in Section 5 to analyze the effect of COVID-19 on cargo capacity and network indices. Overall, our dataset covers 182 days between the second half of 2019 and the first half of 2020. For each observation, we created 336 distinct (airport,date) tuples, each containing departures from a specific airport in the 14-day period culminating in the date specified in the tuple. An extract from the data associated with the (Hong Kong International airport (HKG), April 27th, 2020) tuple is reported in Table 1. Each entry is characterized by a flight code, an aircraft code, a destination airport, a departure time, and an Estimated Time of Arrival (ETA).

Each observation was then split into specific Origin-Destination (OD) airport pairs. Having 336 airports and thirteen observations, a maximum number of $13 \cdot 336 \cdot 335 = 1{,}463{,}280$ distinct tuples characterized by a unique (OD airport pair,date) was generated. For each tuple, flights specific to FedEx, UPS, and DHL were searched using a list of integrator-specific airlines and aircraft types. We focused on the *flight code* column of each tuple to identify integrator-specific flights, and looked for airline codes as follows:

- FedEx: - FDX (FedEx Airlines)
- UPS: - UPS (UPS Airlines), − SRR (Star Air, if the origin or the destination of the associated flight corresponded to a UPS hub)
- DHL: - AHK (Air Hong Kong), − ABR (ASL Airlines Ireland, for Airbus A300-600F, Airbus A330-200F, and Airbus A330-300F aircraft types), − BCS (European Air Transport), − BDA (Blue Dart Aviation), − BOX (AeroLogic, for weekday flights), − DAE (DHL

Table 1
Extract from (HKG, April 27th 2020) tuple data.

Flight code	Aircraft type	Destination airport	Departure	ETA
FDX5391	B77L	Kansai Int'l (KIX / RJBB)	Mon 23:26 HKT	Tue 03:15 JST
CLX7211	B744	Luxembourg Int'l (LUX / ELLX)	Mon 23:05 HKT	Tue 06:05 CEST
CPA23	B748	Sydney (SYD / YSSY)	Mon 22:30 HKT	Tue 08:35 AEST
THY71	B77W	Istanbul Airport (IST / LTFM)	Mon 22:28 HKT	Tue 04:48 + 03
SOO276	B77L	Cincinnati/Northern Kentucky International Airport (KCVG)	Mon 22:25 HKT	Tue 00:53 EDT
CLX8591	B748	Anchorage Intl (PANC)	Mon 22:20 HKT	Mon 15:20 AKDT
CAL928	A333	Taiwan Taoyuan Int'l (TPE / RCTP)	Mon 22:16 HKT	Mon 23:28 CST
CPA41	B744	Chennai Int'l (MAA / VOMM)	Mon 22:10 HKT	Tue 00:30 IST

(a) Air Hong Kong. (b) Southern Air.

Fig. 2. Examples of airlines flying under the DHL livery. Source of images: http://www.airliners.net/photo/Air-Hong-Kong/Airbus-A300F4-605R/1931759/L/ (left) and https://www.flickr.com/photos/40563877@N00/8213198478 (right).

Aero Expreso), − DHK (DHL Air UK), − DHX (DHL International Aviation ME), − PAC (Polar Air Cargo), − SOO (Southern Air, for Boeing 737-400SF and Boeing 777F aircraft types).

The aforementioned list highlights a different business strategy between DHL and the other two integrators. In fact, while FedEx and UPS mainly rely on their own fleet, DHL relies on a vast set of partner airlines that are owned/co-owned and generally fly under the DHL livery, as shown in Fig. 2. While most of the listed airlines operate solely for DHL, other airlines might be offering part of their capacity to other freight forwarders. As example, while DHL severely relies on Polar Air Cargo services, especially for U.S.-Asian routes, this airline might offer part of its cargo capacity to other forwarding companies such as DB Schenker or Kuehne Nagel. As a consequence, we might overestimate the overall capacity for the DHL network. We tried to mitigate this effect as much as we could, for example choosing only aircraft type, tail number (when available), and OD airport pairs combinations we knew had a high chance to be uniquely flown for DHL. FedEx and UPS rely on other airlines as well, but to a much lesser extent or for contingency reasons that cannot be easily traced and recognized in our dataset. FedEx relies on a fleet of ASL Airlines Ireland ATR 42-300F and ATR 72-200F turboprobs for local cargo transport, as example within Canada. UPS has an agreement with Western Global Airlines to sub-contract five McDonnell Douglas MD-11F aircraft for up to 30 days a year for temporary volume spikes.

For each integrator, we focused on the aircraft types listed as either belonging to their own fleet, or to subsidiary airlines. We considered all narrow-body and wide-body full freighters, and did not consider turboprops, because they contribute less significantly to the overall capacity and generally only operate in a point-to-point manner between local airports. In Appendix A, the full list of aircraft is provided, with model, aircraft code, and maximum transportable payload (in tonnes). The maximum payload, as Section 4 will reveal, is a crucial measure in this work, because it is used to compute the theoretical maximum cargo capacity between OD airport pairs. We also want to highlight two characteristics of the air cargo network that are strongly related to our modeling choice:

1. full freighters seldom flight at full weight capacity. Lacking data on average load factors per OD airport pair, we believe that using the maximum theoretical weight capacity is a good indicator of the relevance of an OD airport pair connection
2. some flights might be volume-bounded (Malighetti et al., 2019b) rather than weight-bounded, which means that their maximum volume capacity is reached before their weight capacity (i.e., they are "low density" flights in jargon). This might be especially true for high-tech commodities such as TVs. Notwithstanding, we decided to focus on weight capacity because we believe it to be easier to quantify.

We conclude the dataset analysis by describing how the maximum transportable tonnage per OD airport pair connection and integrator was computed. Given, for each OD airport pair, the subset of (OD airport pair,date) tuples containing recorded flights for that connection and a specific integrator, we summed the transportable payloads of all aircraft involved to determine the maximum weight capacity. As example, if the analysis of the thirteen (A-B,date) tuples provided as cumulative outcome for a specific integrator 50 Boeing B747-400F and 75 Boeing B747-800F, then the weight capacity of the A-B connection for that integrator was computed as 50 times the payload of a B747-400F plus 75 times the payload of a B747-800F. For sake of clarity, we want to highlight that in the paper we will be using interchangeably the terms OD airport pair and route to represent the direct connection between two airports. As such, and not having data on preferred cargo itineraries between airport pairs, weight capacity represents the maximum estimated payload that can be transported along the direct route OD, where O might not be the initial origin and D might not be the final destination for some cargo.

4. Integrators' network analysis

We begin this section with an overview of the methods that will be used to model and compare integrators' networks in Section 4.1. Then, in Section 4.2 we provide a thorough overview of the topological properties of the FedEx, UPS, and DHL networks, and conclude with a robustness analysis in Section 4.3.

4.1. Methods

We modeled each integrator's network as a directed graph $\mathscr{G} = (\mathscr{N}, \mathscr{E})$, where $\mathscr{N}$ is the set of nodes (airports), and $\mathscr{E}$ is the set of directed edges (connections between OD airport pairs). In a graph, edges can be unweighted or weighted. In the first case, they are all assigned a unitary value. In the second case, the weight of each edge should be representative of the relevance of such edge within the graph. In this work the weight of each edge is the maximum transportable tonnage capacity, as underlined in Section 3. An unweighted directed graph can be represented in compact form with an adjacency matrix $\mathscr{A}_{|\mathscr{N}|\times|\mathscr{N}|}$, where $a_{ij} = 1$ if a directed edge connects nodes i and j. All the nodes j that are directly reachable from node i, i.e., $a_{ij} = 1$, are its neighbors. If the graph is weighted, $\mathscr{A}$ is replaced with the weight matrix $\mathscr{W}$, where w_{ij} represents the weight of the directed edge connecting i and j.

The *indegree* of node i is $k_i^{in} = \sum_{j=1}^{|\mathscr{N}|} a_{ji}$ and represents the number of nodes directly connected to node i (i.e., it is the inflow of node i). The *outdegree* of node i is $k_i^{out} = \sum_{j=1}^{|\mathscr{N}|} a_{ij}$ and represents the number of nodes reachable from node i (i.e., it is the outflow of node i). The summation of the two defines the degree of node i, i.e., k_i. For an airport, the degree represents the number of OD airport pairs for which the current airport

is either the destination (indegree) or the origin (outdegree). If we define $n(\hat{k})$ the number of nodes in the network with a degree equal to $\hat{k}$, the *cumulative degree distribution*

$$P(\geq \hat{k}) = \frac{\sum_{t=\hat{k}}^{\infty} n(t)}{|\mathscr{N}|} \tag{1}$$

expresses the ratio of nodes in the network with a degree greater or equal to $\hat{k}$. The *strength* s_i of node i is defined as $s_i = \sum_{k=1,k\neq i}^{|\mathscr{N}|} a_{ki}w_{ki} + \sum_{k=1,k\neq i}^{|\mathscr{N}|} a_{ik}w_{ik}$, i.e., it is the summation of the weights of all edges departing from/arriving to node i. Using available capacity as the weight, the strength of an airports provides an estimate of its potential cargo throughput. The normalized *local clustering coefficient* C_i (Fagiolo, 2007) of node i in a directed graph is defined as

$$C_i = \frac{(\mathscr{A} + \mathscr{A}^T)^3_{ii}}{2[k_i(k_i - 1) - 2k_i^{\leftrightarrow}]} \tag{2}$$

where $k_i^{\leftrightarrow} = \mathscr{A}^2_{ii}$ is the number of neighbors of node i for which i is a neighbor. In a fully-connected graph, $C_i = 1 \quad \forall \quad i \in \mathscr{N}$. The normalized *betweenness centrality* (Freeman, 1977) g_i of node i is defined as

$$g_i = \frac{1}{(|\mathscr{N}|-1)(|\mathscr{N}|-2)} \sum_{i\neq j\neq k} \frac{\sigma^i_{jk}}{\sigma_{jk}} \tag{3}$$

where σ_{jk} is the number of shortest paths between nodes j and k, and $\sigma_{jk}{}^i$ is the number of those paths passing through node i. The normalization term in Eq. (3) accounts for the fact that paths starting or ending in i are not considered. This index correlates the relevance of a node in a network with the frequency the node appears in shortest paths that neither start nor end in i. If an airport is characterized by a high betweenness centrality, it means it is an important transshipment hub for cargo.

Focusing on network-specific indices, some of them are averages of node-specific indices. As example, the *average degree* is $\langle k \rangle = \frac{1}{|\mathscr{N}|}\sum_{i=1}^{|\mathscr{N}|} k_i$, while the average clustering coefficient, also known as *global clustering coefficient* (Watts and Strogatz, 1998; Fagiolo, 2007; Opsahl and Panzarasa, 2009) is $\langle C \rangle = \frac{1}{|\mathscr{N}|}\sum_{i=1}^{|\mathscr{N}|} C_i$. Note that we use the notation $\langle \vec{a} \rangle$ to indicate the arithmetic mean of vector $\vec{a}$. We define the *characteristic path length* of a network as

$$\langle L \rangle = \frac{1}{|\mathscr{N}|(|\mathscr{N}|-1)} \sum_{i=1}^{|\mathscr{N}|} \sum_{\substack{j=1 \\ j\neq i}}^{|\mathscr{N}|} d_{ij} \tag{4}$$

where d_{ij} i the number of steps from node i to node j. Note that, given Eq. (4), we assume an unweighted formulation. We define the diameter $D = \max(d_{ij})$ as the longest shortest path in the graph. The component of a graph is a subset of the graph where does exist a path between each pair of nodes belonging to the component. The *giant component* $\mathscr{G}_c$ is the component with the highest number of nodes. If a path exists between every node pair in the graph, the graph itself is the giant component.

4.2. Topology of the FedEx, UPS, and DHL networks

We begin our topology analysis highlighting the basic characteristics of the three networks, as summarized in Table 2. For each integrator, the number of nodes is equivalent to the cardinality of the subset of the 336 airports that appeared in at least one (OD airport pair,date) tuple. The same concept was applied to determine the number of edges. Similarly to (Malighetti et al., 2019a), we defined the maximum transportable tonnage per edge Available Freight Tonnes (AFT), and the product of each AFT and the geodesic distance of the associated OD airport pair Available Freight Tonnes Kilometer (AFTK). The three networks are graphically visualized in Fig. 3. Note that, for sake of visual clarity, we plotted edges as undirected. As such, the thickness of each edge is proportional to the cumulative AFT characterizing the OD airport pair connection in both directions.

The DHL network is the most developed in terms of number of nodes and edges, probably due to the set of auxiliary airlines that operate under its livery. This more extensive network does not translate into a higher cargo capacity, as the overall AFT and AFTK testify. In terms of overall capacity, FedEx outperforms both UPS and DHL. DHL performs better than UPS in terms of AFTK because of the considerable higher number of connections. Analyzing the density, i.e., the ratio between the edges and the potential number of edges of a network (that is, $|\mathscr{N}|\cdot|\mathscr{N}-1|$ for a directed graph), FedEx and UPS are characterized by a comparable value, with DHL being a sparser and more concentrated network. All three values of reciprocity, i.e., the ratio between the number of node pairs connected in both directions and the number of node pairs connected in at least one direction, are low. This justifies the modeling assumption of relying on a directed graph to model demand and flow imbalances in the cargo network.

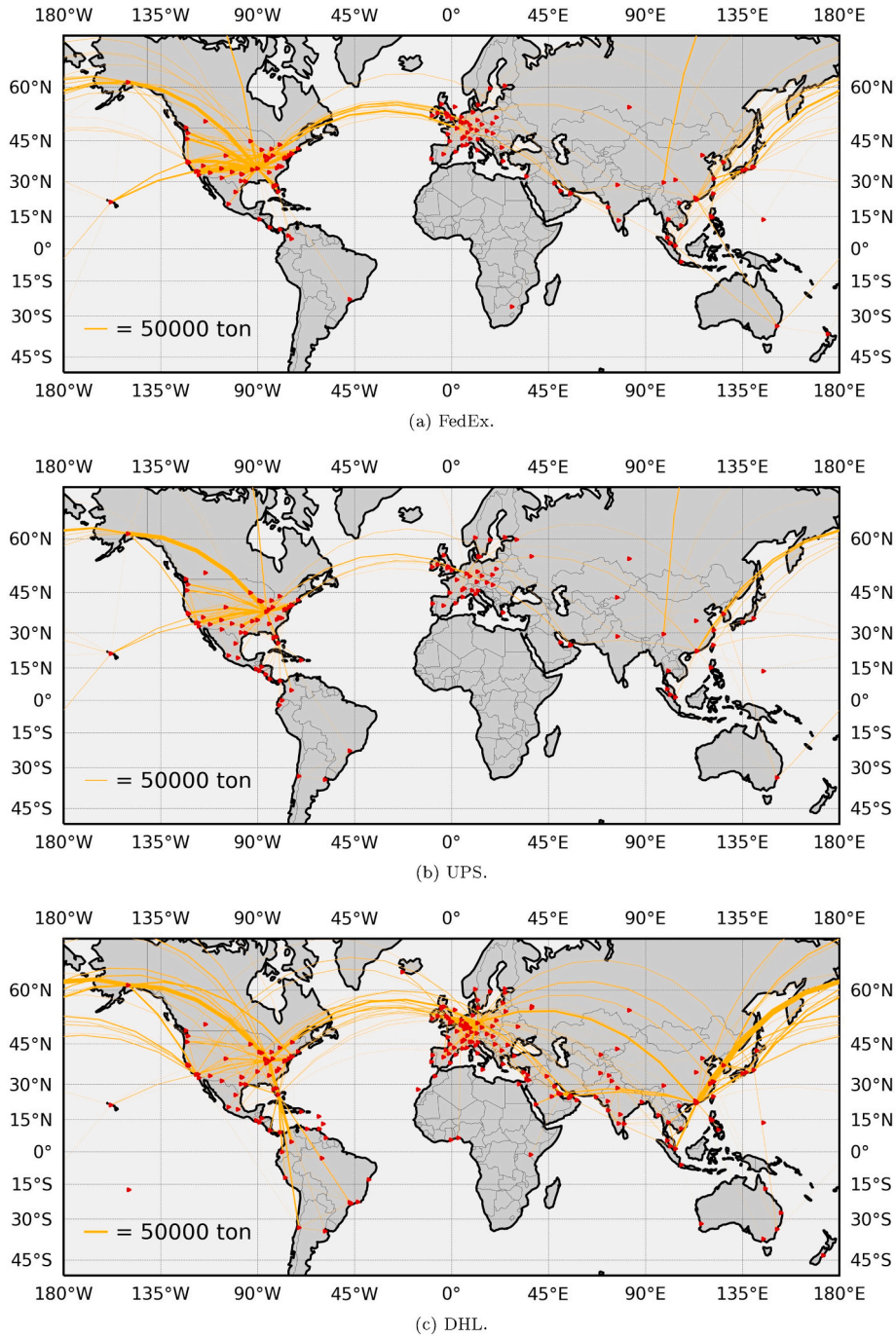
Table 2
Comparison of the FedEx, UPS, and DHL networks.

	FedEx	UPS	DHL
Nodes	129	115	204
Edges	903	700	1,326
Density	0.055	0.053	0.032
Reciprocity	0.56	0.53	0.46
$\langle k \rangle$	13.8	12.2	13.0
$\langle C \rangle$	0.55	0.48	0.47
$\lvert\mathscr{G}_c\rvert$	113	105	188
$\langle L \rangle$	2.55	2.77	2.84
D	5	8	7
Overall AFT	4,746,117	4,024,924	3,998,264
Overall AFTK	13,143,808,955	11,242,319,058	12,757,305,598

The global clustering coefficient of FedEx is higher than the ones characterizing UPS and DHL, meaning that airports in the FedEx network are clustered more closely. The three global clustering coefficients, paired with the small values of $\langle L \rangle$, ensure that the three networks are *small world* networks. This means that most airports are not neighbors of one another, but at least a subset of the neighbors of any given airports are likely to be neighbors of each other. In addition, most airports can be reached from every other airport by a small number of hops, generally using hubs as pivot nodes. In terms of diameter, FedEx still emerges as a more compact network.

Note that both $\langle L \rangle$ and D were computed with respect to the giant component of each network, to avoid numerical errors. As Table 2 shows, for all three networks the giant component $\mathscr{G}_c$ does not coincide with the full network. We investigated this behavior, and found for each integrator a small number of airports with a unitary degree. Being the graph directed, this means that those airports behave only as sinks (unitary indegree) or sources (unitary outdegree). Having collected enough data, temporally-wise, to cover possible seasonal or infrequent routes, we attributed this fact to our initial set of airports. Most likely, some lower-tier airports that appear in the same circular routes as the unitary degree airports were omitted. A refinement of the initial set of airports is one of the first directions to pursue as part of our future work.

To provide more tangible insights into the role of airports and OD airport pair connections, for each integrator we list the top-five airports according to degree, strength, and betweenness centrality. We computed betweenness using two approaches, unweighted betweenness g and weighted betweenness g_w. In the unweighted formulation, every edge is treated equally and assigned a unitary cost. For the weighted formulation, we used a heuristic approach to translate each AFT into a proper cost. For each integrator, we identified the minimum and maximum AFT (resp. a_m and a_M) over the whole network, and associated with the two values a maximum and minimum cost (resp. c_m and c_M). We wanted costs to decrease for increasing values of AFT to represent the easiness of use of high-capacity routes over low-capacity routes. We used a linear function in the form $c_i = c_m + \frac{c_M - c_m}{a_M - a_m}(a_i - a_m)$, where c_i is the cost of an edge whose AFT is a_i. Note that given our



(a) FedEx.

(b) UPS.

(c) DHL.

Fig. 3. FedEx, UPS, and DHL networks.

definition of costs, the slope of the aforementioned formula is negative, correctly modeling a decrease in cost for increasing values of AFT. For all three networks, we set $c_m = 5$ and $c_M = 1$. Consistently with previous considerations, the two betweenness centrality measures were computed using the giant component of each network. The top-five airports for FedEx, UPS, and DHL are reported in Table 3.

The analysis of Table 3 reveals, not surprisingly, that the main hubs of each integrator are generally at the top of the table regardless of the index chosen. For FedEx, their global hub Memphis International airport (MEM), for UPS, their Worldport worldwide hub Louisville International airport (SDF), for DHL, their European hub Leipzig/Halle airport (LEJ) and American hub Cincinnati/Northern Kentucky International airport (CVG). For each integrator other major hubs appear at different positions, depending on the index, in the table. As example, Charles de Gaulle airport (CDG), Cologne Bonn airport (CGN), Kansai International airport (KIX) for FedEx, CGN, Hong Kong International airport (HKG), Miami International airport (MIA), Ontario International airport (ONT), Philadelphia International airport (PHL) for UPS, Bahrain International airport (BAH) for DHL. Intuitively, American integrators FedEx and UPS pair their main domestic hub (MEM and SDF, respectively) with a European hub (CDG and CGN, respectively) to cover their second biggest market. European integrator DHL relies on a similar strategy, with the main hub LEJ paired with the American hub CVG. Note that all European hubs are located inside or in close proximity to the so called “blue banana” industrialized region, that offers a catchment area rich of industries and retailers. On the other hand, all American hubs belong to the Midwest, which offers a strategic geographical position especially for domestic connections.

Table 3
Top-five airports according to degree k, strength s, unweighted betweenness centrality g, and weighted betweenness centrality g_w for FedEx, UPS, and DHL networks.

rank	k		s [tonnes·1e6]		g		g_w	
	airport	value	airport	value	airport	value	airport	value
				FedEx				
1	MEM	120	MEM	2.47	MEM	0.36	MEM	0.57
2	CDG	82	IND	0.65	CDG	0.30	CDG	0.37
3	IND	77	OAK	0.39	CGN	0.10	KIX	0.06
4	LAX	51	ANC	0.34	IND	0.10	CGN	0.06
5	EWR	47	CDG	0.32	KIX	0.08	DXB	0.04
				UPS				
1	SDF	102	SDF	1.98	CGN	0.42	SDF	0.63
2	CGN	71	ANC	0.51	SDF	0.39	CGN	0.41
3	DFW	58	ONT	0.44	MIA	0.20	MIA	0.19
4	PHL	56	CGN	0.40	PHL	0.10	ANC	0.14
5	ONT	55	DFW	0.33	ANC	0.09	HKG	0.05
				DHL				
1	LEJ	133	LEJ	0.76	LEJ	0.28	LEJ	0.40
2	CVG	90	CVG	0.65	CVG	0.17	CVG	0.28
3	MIA	87	HKG	0.55	HKG	0.16	HKG	0.22
4	HKG	77	ANC	0.50	MIA	0.16	MIA	0.16
5	ANC	56	MIA	0.35	BAH	0.12	ANC	0.12

A tangible difference between integrators FedEx, UPS and integrator DHL can be appreciated if strength and betweenness are analyzed. For FedEx and UPS, the gap between their main hub (resp. MEM and SDF) and the next airports is quite significant both in terms of strength and betweenness (g_w in particular). The strength of their top airport is more than one order of magnitude greater than the strength of the next airport, while roughly 60% of all shortest paths pass through their main hubs, with the percentage dropping to 40% for the second airport. This behavior is consistent with a network characterized by a single "top-hub". On the other hand, DHL seems to be a hybrid version of a hub-and-spoke network, as already highlighted in (Malighetti et al., 2019a; Bombelli et al., 2020), where LEJ, CVG, and to a slightly lesser extent HKG share the control of the network. Both strength and weighted betweenness confirm this hybrid system for the DHL network, where no top airport clearly outperforms the others, resulting in more balanced cargo capacities between geographical regions. Fig. 3 provides hints in this sense as well, with very imbalanced flows for FedEx and UPS (towards/from MEM and SDF), and more balanced flows in the DHL network. A similar conclusion can be inferred analyzing Table 4, where the five OD airport pairs characterized by the highest AFT are listed per integrator. Both for FedEx and UPS, all five connections either start or end in the main hub, while for DHL hubs LEJ, CVG, and HKG all appear. Focusing on FedEx and UPS, every connection is domestic. As (Bowen, 2012) pointed out, despite the integrators' internationalization, the routes with the highest capacity in both networks remain overwhelmingly domestic. This consideration also fosters a more methodologically-oriented question. FedEx, UPS, and DHL are obviously international in nature, yet characterized by a different market share depending on the region of interest. Hence, are we comparing companies serving the same markets, but with a different network structure, or are discrepancies in the network structure caused by the different market shares? To answer this (very relevant) question, we would need to dive more into business models and economic factors that go beyond the scope of this paper. In addition, given the door-to-door nature of integrators, we might need to combine the air transport network with the ground transport one to get a better picture. This is another research direction this paper does not aim to address.

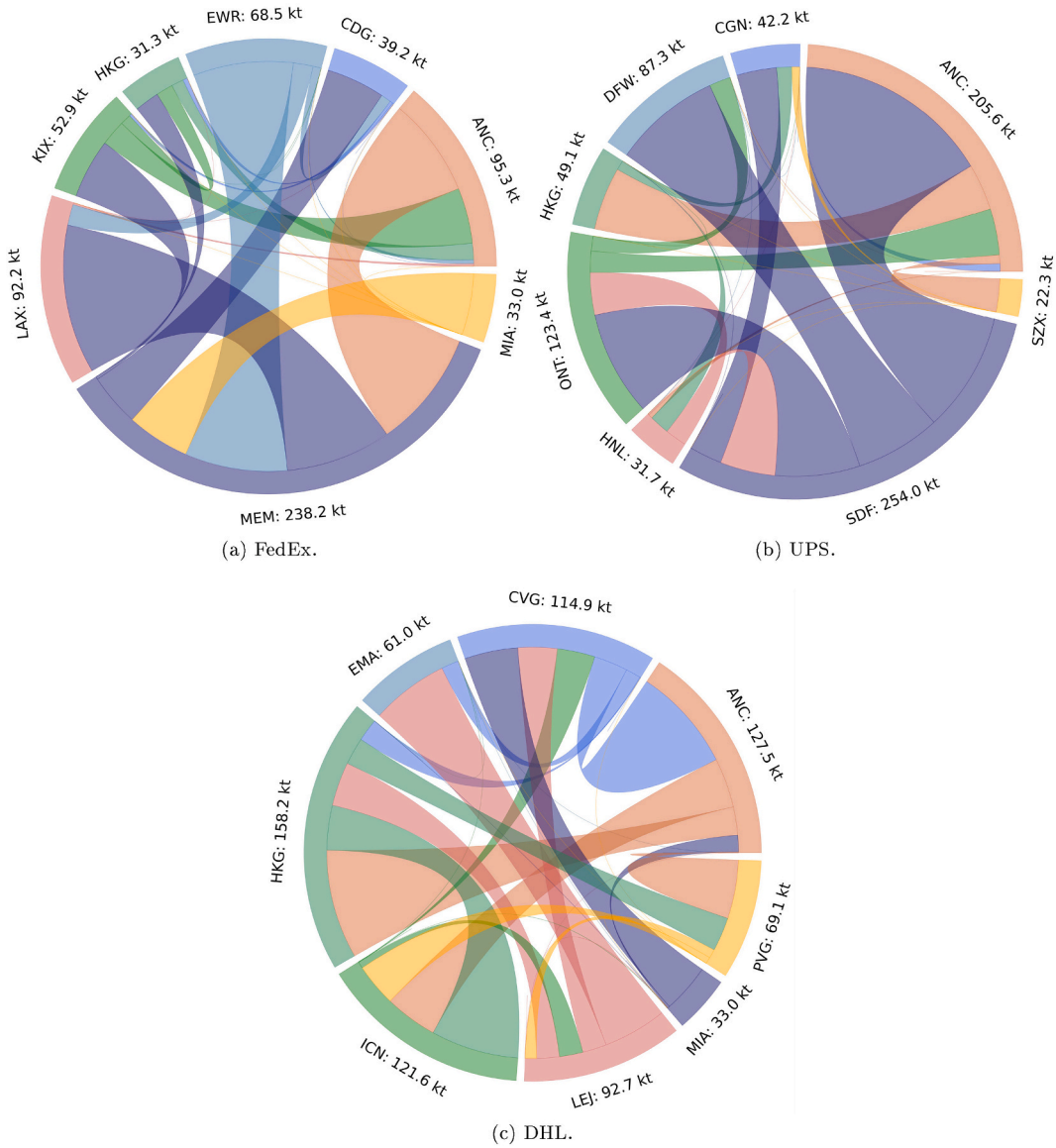
We conclude the discussion on hubs and cargo flows with Fig. 4. Here, we reported the AFT between the first eight airports to appear in the sorted list of busiest OD airport pair connections of each integrator. We represented such AFT using chord diagrams. Outgoing capacities of each airport are plotted radially, and occupy a portion of the circumference that is proportional to their value. Every capacity flow between airports is represented by an arc, whose thickness is also proportional to its value. Since each airport is mapped with a different color, the color of each arc is the color of the airport characterized by the positive imbalance of the flow. As example, in Fig. 4(a), the arc between MEM and LAX is purple because the LAX-MEM route has a higher AFT than the MEM-LAX connection. To corroborate our previous findings, in Fig. 4(a) and Fig. 4(b) the flows are dominated by a single airport, which in both cases accounts for roughly one third of the overall AFT exchanged between the airports. In the DHL case (Fig. 4(c)), there is a stronger balance between airports.

Before providing some insights into robustness, we analyzed more into details the degree distribution of the three networks using histograms and plotted the resulting cumulative degree distribution of each network in Fig. 5. In the histograms (Fig. 5(a), (b), and (c)), we also highlight the IATA code of the three airports characterized by the three highest values of degree. All three histograms are strongly right-skewed, with the frequency of nodes with a degree equal to $\hat{k}$ steeply decreasing as $\hat{k}$ increases. This behavior is consistent with a hub-and-spoke system that all three integrators rely on, even with different nuances. We want to highlight the fact that the three histograms, without additional information, are extremely similar and might lead to the (wrong) conclusion that the networks of FedEx, UPS, and DHL are extremely similar as well. Together with the number and distribution of connections, their strength and the likeliness of a node to appear in shortest paths (betweenness centrality) need to be investigated to fully reveal the features of a network. Without these additional indices, as example, the multi-hub nature of the DHL network might have been harder to spot.

In Fig. 5(d), the cumulative degree distribution $P(\geq\hat{k})$ of the FedEx, UPS, and DHL networks is reported. Notwithstanding the aforementioned differences between the three networks, the trend of $P(\geq\hat{k})$ is very similar, and follows a truncated power law consistently with other air transportation networks (Guimera et al., 2005; Lordan et al., 2014) that confirms *scale free* properties. In a scale free network, the cumulative degree distribution follows a (truncated) power law. This means that the number of nodes with an extremely high degree is generally higher than what would be expected from a normal distribution. On the other hand, well-connected (i.e., where $k \simeq \langle k \rangle$) nodes are much more common in networks whose degree distribution follows a normal distribution rather than a power law. The presence of nodes with an

Table 4
Top-five OD airport pair connections according to AFT for FedEx, UPS, and DHL networks.

rank	FedEx		UPS		DHL	
	OD	capacity [tonnes·1e3]	OD	capacity [tonnes·1e3]	OD	capacity [tonnes·1e3]
1	LAX-MEM	80.0	ANC-SDF	132.1	HKG-ANC	69.7
2	MEM-ANC	63.2	SDF-ANC	80.4	ANC-CVG	66.6
3	MEM-LAX	56.5	DFW-SDF	72.8	ICN-HKG	56.1
4	MEM-OAK	55.5	ONT-SDF	70.7	EMA-LEJ	49.7
5	MEM-EWR	55.0	SDF-DFW	57.5	LEJ-EMA	40.6



(a) FedEx. (b) UPS.

(c) DHL.

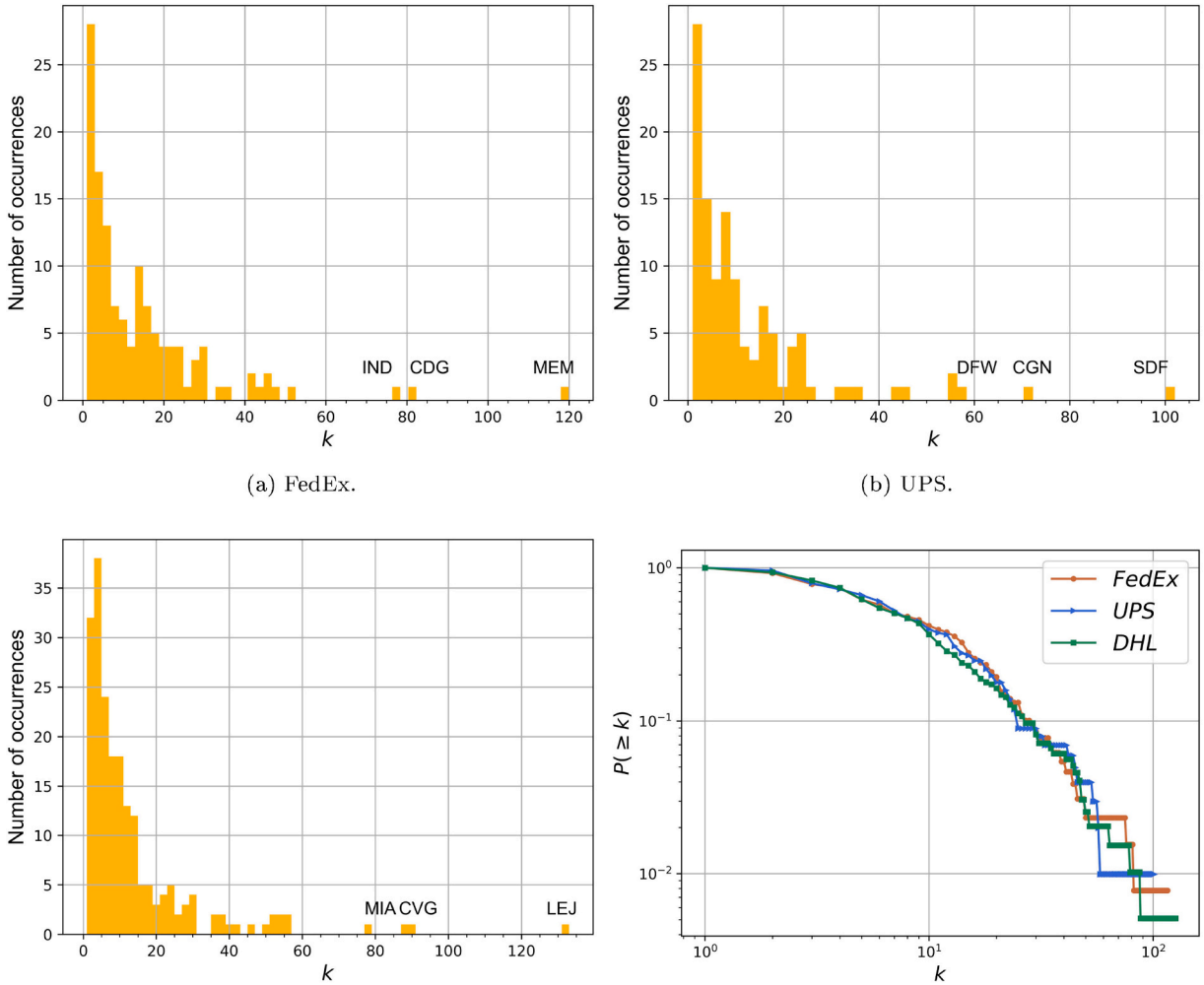
Fig. 4. Chord diagrams representing cargo capacities between top airports.

extremely high degree, i.e., the hubs, is a distinctive feature of air cargo networks. As such, Fig. 5(d) confirms, using a network science perspective, one of the underlying operational rules of integrators.

4.3. Robustness of the FedEx, UPS, and DHL networks

In this section, we took a step further and performed a robustness analysis of the three integrators' networks. In fact, all the analyses of Section 4.2 rely on a static network, where all nodes and edges are fixed. Here, although the definition of network robustness is not univocal, we adopted the same strategy as in (Guimera et al., 2005) and (Lordan et al., 2014), and simulated an ad-hoc disruption by an intruder with knowledge of the characteristics of the network. In particular, the intruder focuses on a specific index, and sequentially attacks (which, from a network perspective, reads as "removes") the airport whose selected index is the maximum, i.e., the airport whose removal should be, in principle, most catastrophic. Note that this is a dynamic approach, since the removal of each airport, together with all the incoming and outgoing edges, modifies the topology of the reduced network. Referring back to Table 3, an intruder attacking the FedEx network and focusing on degree, would choose MEM as the first airport to eliminate. Given the reduced network that does not contain MEM, CDG might not be the new airport with the highest degree because of the modified topology. In this context, we first eliminate a node (i.e., an airport), and as a consequence all the edges entering or exiting such node. In real applications, the two steps might be reversed and still lead to the same outcome. As example, during the COVID-19 pandemic some airports were entirely closed by governments in order to better control air transport (direct elimination of a node). For other airports, the set of connections might have been dramatically reduced, or even completely eliminated, as an indirect consequence of the closure of the aforementioned airports (indirect elimination of a node). This approach will be shown more into details in Section 5 when analyzing time-dependent network characteristics for the different airlines.

To compute the disruption severity after each airport removal, we monitored the normalized size of the giant component, defined as $S(q) = |\mathscr{G}_c(q)|/|\mathscr{G}_c|$, where q is the ratio between removed airports and initially available airports, and $\mathscr{G}_c$ is the initial giant component of the network. Consistently with Section 4.2, we focused on the following four node-specific indices as removal strategies: - degree k, - strength s, - betweenness centrality g, and - weighted betweenness centrality g_w. For each of the three networks, we used as starting network the giant



(a) FedEx. (b) UPS.

(c) DHL. (d) $P(\geq k)$.

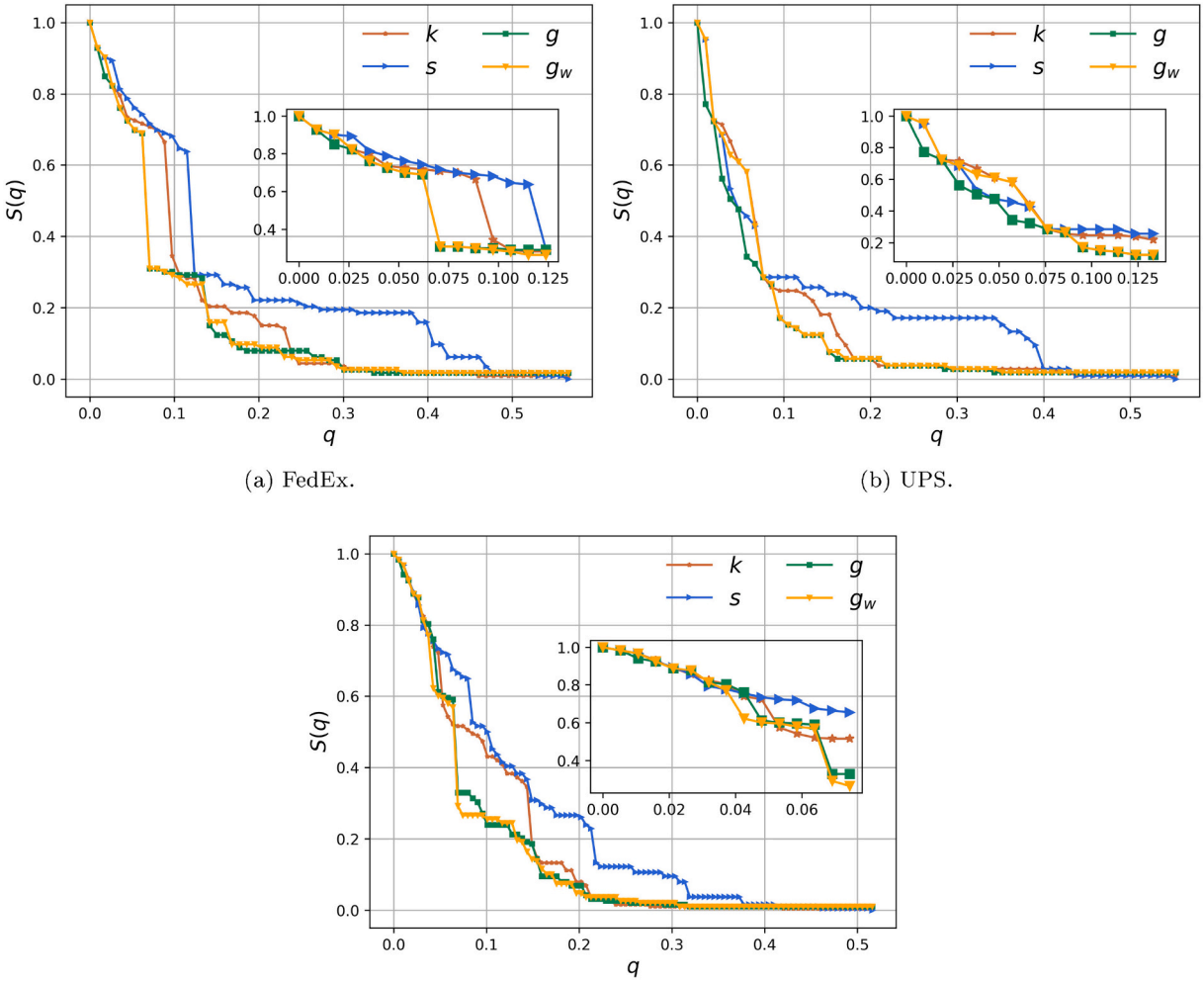
Fig. 5. Histograms depicting the degree distribution and cumulative probability distribution $P(\geq\hat{k})$ for the FedEx, UPS, and DHL networks (log-log scale).

component of the associated integrator (that did not coincide with the overall network) in order to have an initial $S(q)$ equal to 1. In Fig. 6 we report results in a vertical manner, i.e., per integrator, while in Fig. 7 we report results in a horizontal manner, i.e., per removal strategy. In all figures, we also provide an inset plot that highlights the $S(q)$ curve for the first fifteen airports removed, to better highlight how the different networks react when the first (most important) airports are attacked.

Results in Fig. 6 display a high level of consistency across integrators. Attacks targeting betweenness centrality and, in particular, weighted betweenness centrality disintegrate the network more abruptly than attacks focusing on other indices. This is due to the transshipment nature of airports characterized by a high betweenness centrality. Although they might not be connected to many other airports, they play the crucial role of connecting bridges between airport communities. The best example in this sense is Ted Stevens Anchorage International airport (ANC), which plays a key connecting role for cargo flows between Asia and North America. Focusing on Fig. 7, the effectiveness of attack strategies based on g and g_w is confirmed. In fact, these are the two strategies that cause $S(q)$ to drop more steeply. On the other hand, s seems to be the least effective index to target, as the less concave shape of all three curves in Fig. 7(b) suggests. Note that this is also a natural consequence of the indicator we chose to assess the severity of the disruption. We are basing our results on a connectivity measure (i.e., the size of the giant component), rather than an estimate of the overall cargo capacity capabilities of the remaining network. In the latter case, attacks based on degree or strength would be much more effective because the system would be deprived of the main processing centers.

Analyzing the different integrators, UPS has the least robust network for low values of q across all indices. In particular, when s is considered and $q\simeq 0.07$, the size of the giant component for UPS is only the 30% of the original size, while the value increases to at least 60% for the other two integrators. We believe the reason lies in the fact that, for UPS, high-capacity airports are also crucial transshipment nodes, and hence disruptions focusing on strength implicitly disintegrate the network as well. On the other hand, at least for small values of q, DHL seems to have most robust network.

To summarize the outcome of Fig. 6 and Fig. 7, in Table 5 the first six removed airports per removal strategy and per integrator are listed, together with the normalized size of the giant component after their removal. We highlighted in bold the airports whose removal produced a percentile reduction of the giant component greater than 10%. Only for UPS such drops occurred, for CGN (main European hub), ANC, and MIA (north American hub). Both for FedEx and DHL, no such cases occurred. Analyzing the inset plots, the degradation of $S(q)$ is more regular, which might be a desirable effect against network attacks. DHL is confirmed to be the most robust network, if the size of the giant component is used as measure. In fact, after the removal of the first six airports, DHL constantly ranks best, with the size of the giant component 10% and 30%



(a) FedEx.

(b) UPS.

(c) DHL.

Fig. 6. Normalized size of the giant component S as a function of the ratio of removed airports q per integrator.

larger, respectively, than FedEx and UPS.

5. Analysis of the COVID-19 pandemic effect on cargo networks

At the time of writing, the COVID-19 pandemic has caused more than 14.3 million confirmed cases, with about 602,800 deaths (Johns Hopkins Coronavirus Resource Center website, 2020). More than one third of the global population has been, or still is under a partial or total form of lockdown. The ensuing economic crisis is believed to become the most severe crisis in the last decades.

Among the most affected industries, transportation is one of the businesses that took the hardest blow. While the COVID-19 pandemic brought many passenger airlines to the brink of failure, the cargo industry suffered a blow that, although indisputable (Accenture website, 2020), is more difficult to quantify. Combination airlines lost most of their belly cargo capacity and are experiencing a slow recovery process. Full-cargo airlines and integrators should have been affected to a much lesser extent, if not for the unclarity of travel bans. As example, when United States President Donald Trump announced the travel ban from Europe on March 11th, 2020, he initially stated that prohibitions would also affect trade and cargo, only to tweet shortly later that the "restriction stops people not goods" (Forbes website, 2020).

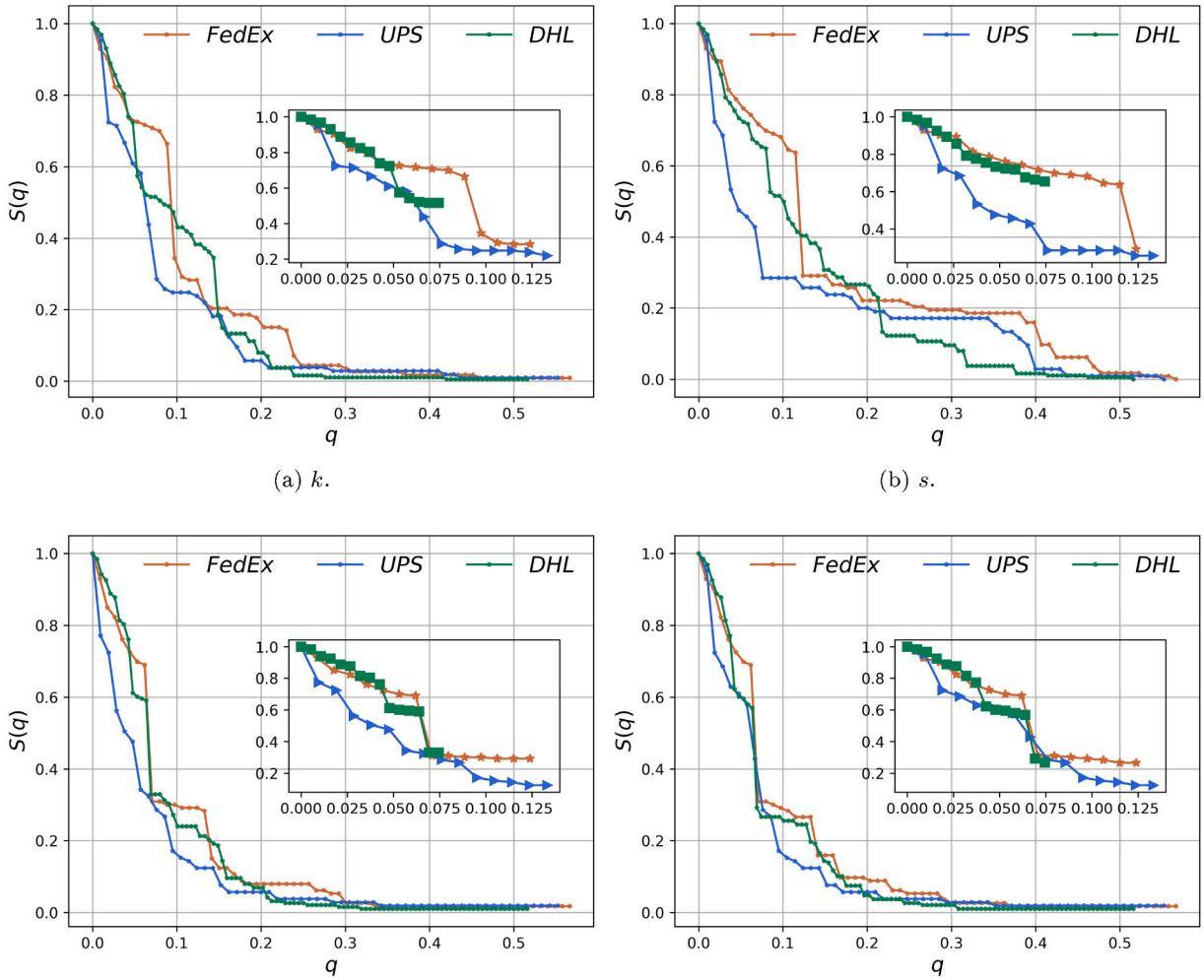
Relying on a dataset that covers both a pre- and a pandemic phase, in this section we shed some light upon the effect of the COVID-19 pandemic and the ensuing bans on integrators' capacity. In particular, in Section 5.1 we analyzed AFT time-series for the three integrators and three other major airlines. We used this analysis to detect temporal variations in air cargo capacity due, most likely, to disruptions caused by COVID-19 and as a first assessment of how the pandemic re-shaped cargo flows. Then, in Section 5.2 we used a complex network theory approach, and computed for the same set of airlines time-varying network characteristics to assess how the connectivity of cargo networks was affected.

5.1. AFT time-series analysis for major OD airport pairs

Although the focus of this paper is on integrators, we decided to consider cargo airlines of different kinds for the analyses presented in this section, to offer readers a more comprehensive study. In particular, we selected the three additional cargo operators:

- Cargolux, a full-cargo airline from Luxembourg
- Cathay Pacific Cargo, the cargo subsidiary of Cathay Pacific, the flag carrier of Hong Kong
- Koninklijke Luchtvaart Maatschappij N.V. (KLM), the flag carrier of the Netherlands.

We motivate the choice as follows. Cargolux constantly ranks in the top-ten of cargo airlines for freight tonne-kilometres, as well as Cathay Pacific Cargo. Although Cathay Pacific, being a passenger airline, can rely on belly space as well, we decided to focus only on its cargo subsidiary. On the other hand, KLM is a top-European combination airline



(a) k. (b) s.

(c) g. (d) g_w.

Fig. 7. Normalized size of the giant component S as a function of the ratio of removed airports q per removal strategy.

in terms of cargo throughput and heavily relies on its belly space. Hence, for KLM we considered both passenger aircraft and full freighters. For full freighters, we considered both its own fleet, and those operated by Martinair Holland N.V. (MP). It should be noted that, as far as cargo transport is concerned, KLM has a partnership with Air France (AF) and MP, and cargo operations are carried out in synergy as testified by the name of the joint cargo department AFKLMP, that is a portmanteau of the three acronyms. While we considered the contribution of MP due to its full freighter-oriented nature, we omitted AF to have a more unbiased focus on a single combination airline. As such, we will be using the acronym KLMP to represent the combined network of KLM and MP. For the three additional airlines, we initially computed their network structure as shown in Section 4. Details regarding the networks structures are given in Appendix B. Note that, since our initial choice of airports focused on airports deemed relevant from a cargo perspective, the generated KLMP network is missing several airports that are only relevant from a passenger perspective (i.e., airports serving vacation-oriented regions, remote islands, etc). Given the nature of this work, this shortcoming was considered negligible.

To better characterize the time-series, we also selected five dates that we considered relevant. They are in chronological order: 1) December 31st, 2019 - Chinese Health officials inform the World Health Organization about a cluster of 41 patients with a mysterious pneumonia. Most are connected to Huanan Seafood Wholesale Market, 2) January 11th, 2020 - The first death caused by COVID-19 is recorded in China, 3) January 31st, 2020 - United States President Donald Trump bans foreign nationals from entering the United States if they were in China within the prior two weeks, 4) March 11th, 2020 - United States President Donald Trump bans all travel from 26 European countries, and 5) May 11th, 2020 - Several countries (such as Spain, Iran, and Italy) begin to ease their lockdown restrictions.

For the three integrator, we focused on cargo capacities along major connections and generated time-series using the AFT associated to each observation. In Fig. 8, 9, and 10 AFT time-series for FedEx, UPS, and DHL are respectively reported.

All three integrators display a spike between mid and late December that is consistent with the well-known peak season. If we analyze the trend in February, a substantial difference exists between FedEx and the other two integrators. In fact, while AFT of FedEx remained roughly leveled for all OD airport pairs, consistent drops occurred for UPS and DHL. For UPS, the ANC-SDF line experienced a 30% decrease in AFT. For DHL, the HKG-ANC and ANC-CVG lines, i.e., the two major legs of the Asian export line to their American hub, experienced a strikingly similar 80% decrease. These drops in capacity correspond to the observation that was retrieved on February 14th, 2020, right after the travel ban to the United States for foreign nationals who were in China in the previous two weeks.

We believe that the initial uncertainty regarding the ban (e.g., whether a pilot of a full freighter scheduled to fly from China to the United States would be exempted or not), caused the aforementioned drop. Interestingly, after mid February AFT for all OD airport pairs, on average, either stabilized around the pre-pandemic level or grew to

Table 5
First six removed airports according to degree k, strength s, unweighted betweenness centrality g, and weighted betweenness centrality g_w for FedEx, UPS, and DHL networks.

rank	k		s		g		g_w	
	airport	$S(q)$	airport	$S(q)$	airport	$S(q)$	airport	$S(q)$
				FedEx				
1	MEM	0.93	MEM	0.93	MEM	0.93	MEM	0.93
2	IND	0.90	IND	0.90	CDG	0.85	IND	0.90
3	CDG	0.82	OAK	0.89	IND	0.82	CDG	0.82
4	LAX	0.80	CDG	0.81	CGN	0.76	CGN	0.76
5	CGN	0.73	KIX	0.79	LGG	0.73	LGG	0.73
6	OAK	0.72	ANC	0.76	ANC	0.70	ANC	0.70
				UPS				
1	SDF	0.95	SDF	0.95	**CGN**	**0.77**	SDF	0.95
2	**CGN**	**0.72**	**CGN**	**0.72**	SDF	0.72	**CGN**	**0.72**
3	DFW	0.71	ONT	0.69	**ANC**	**0.56**	ONT	0.69
4	ONT	0.67	**ANC**	**0.53**	PHL	0.50	PHL	0.63
5	PHL	0.61	PHL	0.48	ONT	0.48	DFW	0.61
6	RFD	0.58	DFW	0.46	**MIA**	**0.34**	RFD	0.58
				DHL				
1	LEJ	0.98	LEJ	0.98	LEJ	0.98	LEJ	0.98
2	CVG	0.97	CVG	0.97	HKG	0.94	CVG	0.97
3	MIA	0.93	HKG	0.93	CVG	0.93	HKG	0.93
4	HKG	0.89	ANC	0.89	MIA	0.89	MIA	0.89
5	CDG	0.86	MIA	0.86	FRA	0.88	FRA	0.88
6	ANC	0.82	BAH	0.79	BAH	0.82	BAH	0.81

even surpass the December's peaks. A striking example is the steady growth of the ANC-SDF line for UPS.

We also performed a network-wide analysis of the three integrators. For each of them, we constructed three networks, each network being generated following the same routine describe in Section 3, but using only a single observation as input. In particular, the three observations we used were January 27th 2020, February 14th 2020, March 2nd 2020, i.e., the three observations associated with the drop in AFT. Although we previously claimed that a 14-day time-span might not be sufficient to characterize an integrator network, our focus here was mainly on major connections (e.g., flows from Asia to the United States) that are flown regularly. Hence, comparing networks built using a 14-day time-span was deemed reasonable.

For each integrator, we plotted the percentile difference between the AFT of an observation and the previous one for all OD airport pairs characterized by a cargo flow in both observations. The color of each connection is proportional to the percentile difference, with blue colors identifying a strong increase and red colors a strong decrease in ATF, respectively. For OD airport pairs served in both directions, for plotting purposes we used the average between the two percentile differences as the value representative of the connection. In each colorbar, we limited the upper bound to an increase of 320% and the lower bound to a decrease of −100% to have a clear transition between shades. In Fig. 11 and 12 we report the changes in AFT between early February and late January 2020, and between late and early February 2020, respectively, for FedEx. The same output is shown for UPS in Fig. 13 and 14, and DHL in Fig. 15 and 16. Tables 6 and 7 report, respectively, the five OD airport pairs characterized by the highest decrease and increase in AFT between observations; only OD airport pairs with a maximum value of 800 t or more (between the two observations) are reported in the tables.

Consistently with Figs. 8, 9, and 10, the comparison between early February and late January highlights a strong decrease in AFT from North East Asia (NEA) airports towards the United States, which seem too abrupt to be only a seasonal effect. The effect seems to be most severe for UPS and DHL rather than for FedEx. In most of the top entries of Table 6, NEA airports appear as the origin or destination of the affected cargo flow. The transshipment role of ANC for flows from NEA to mainland United States (and vice versa) is also highlighted by its presence in eight out of fifteen OD airport pairs. The majority of connections with increased AFT is represented by intra-continental and intra-national routes, mostly between hubs of the associated integrator. Examples in this sense are PVG-KIX (FedEx) and MIA-SDF (UPS).

Moving to the comparison between late and early February, the MIA-BOG connection appeared for all three integrators as one of the connections with the highest percentile decrease. We believe this decrease to be due to Valentine's Day flower export from Colombia (Air Cargo News website, 2020) rather than an effect of COVID-19. More in

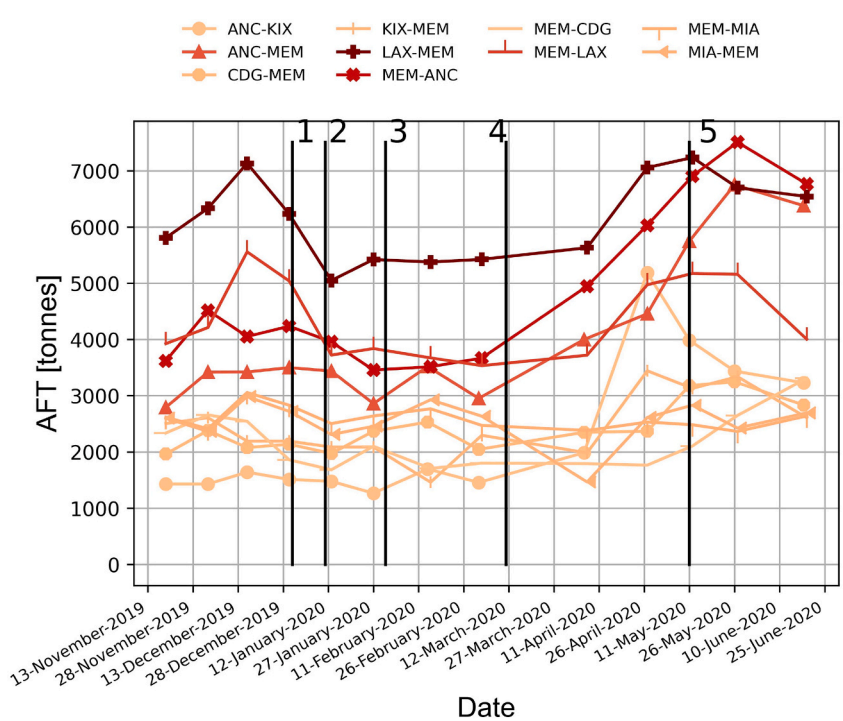


Fig. 8. Time-series depicting AFT along major routes for FedEx.

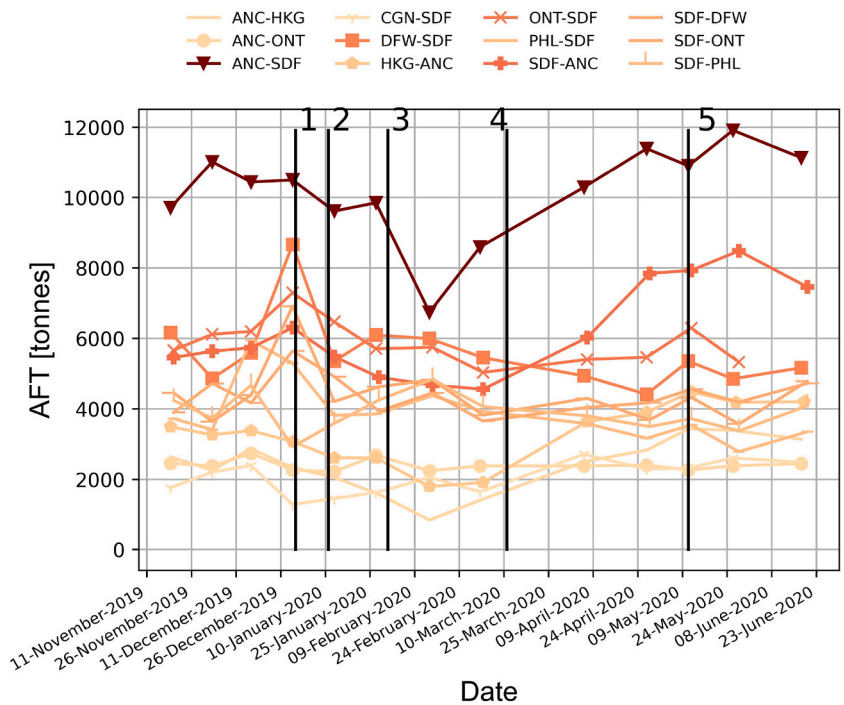


Fig. 9. Time-series depicting AFT along major routes for UPS.

general, the situation depicted in Table 7 is specular with respect to what is shown in Table 6. AFT between NEA and United States increased by several orders of magnitude, such as TPE-ANC for FedEx (+133%), SZX-ANC for UPS (+1000%), and ORD-ANC for DHL (+978%).The crucial role of ANC is highlighted by its inclusion in twelve out of fifteen OD airport pairs. Temporal differences in AFT of OD airport pairs relying on ANC can also be appreciated comparing Figs. 11–12 (FedEx), Figs. 13–14 (UPS), and Figs. 15–16 (DHL), with the color of such connections transitioning from a dark red shade (strong decrease) to a dark blue shade (strong increase).

We then focused on the three other airlines. We provide results, limited to the time-series format, in Fig. 17, Fig. 18, and Fig. 19 respectively. Notwithstanding differences in average AFT and number of OD airport pairs served, the similarity with the trends noticed for UPS and DHL is striking. For Cathay Pacific Cargo, the connection between ANC and HKG suffered a decrease of 30% in both directions. For Cargolux, the HKG-ANC connection suffered an even more substantial drop of 85%, while the connection between Novosibirsk Tolmachevo airport

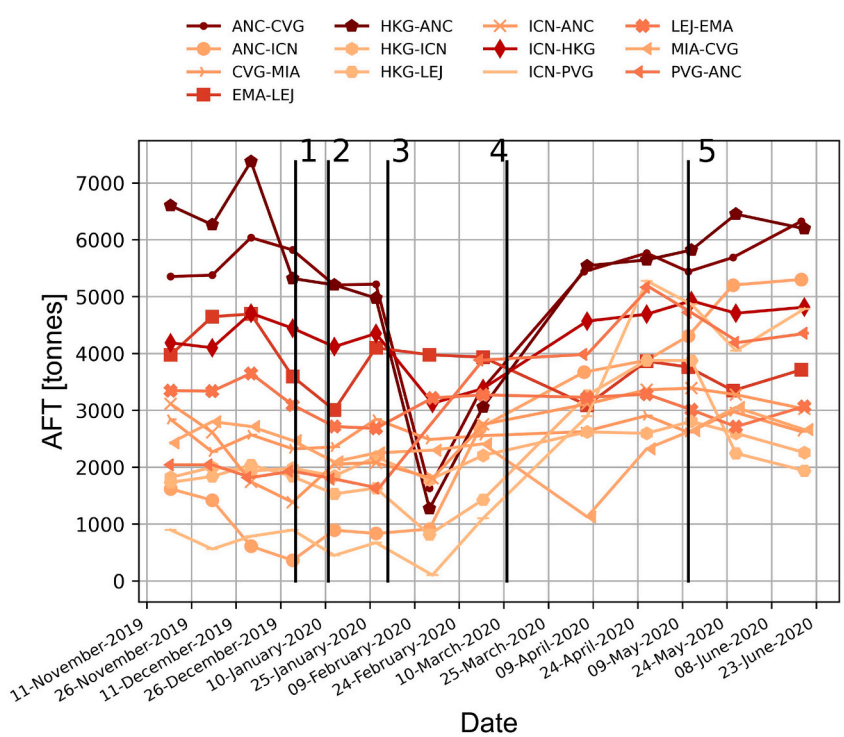


Fig. 10. Time-series depicting AFT along major routes for DHL.

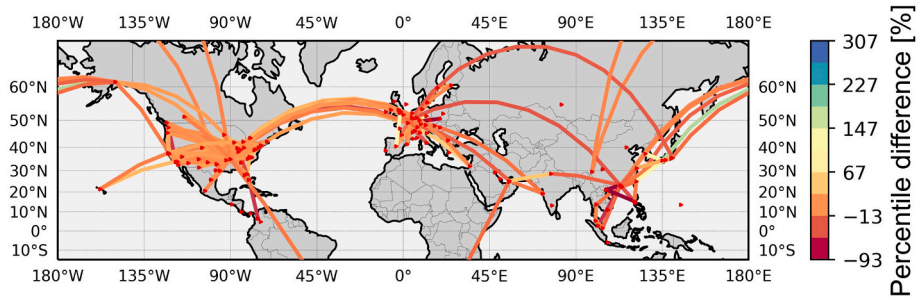


Fig. 11. AFT percentile difference between early February and late January 2020 for FedEx.

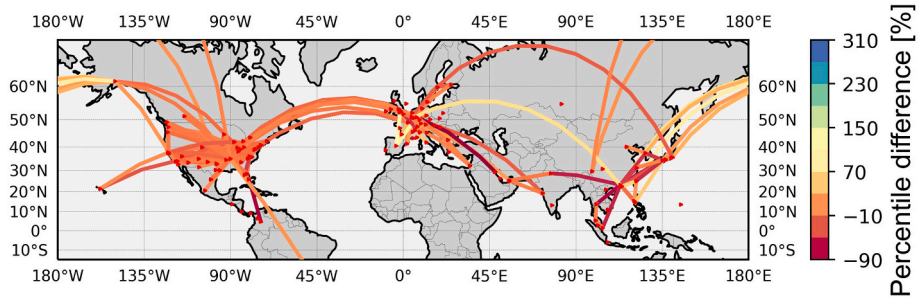


Fig. 12. AFT percentile difference between late and early February 2020 for FedEx.

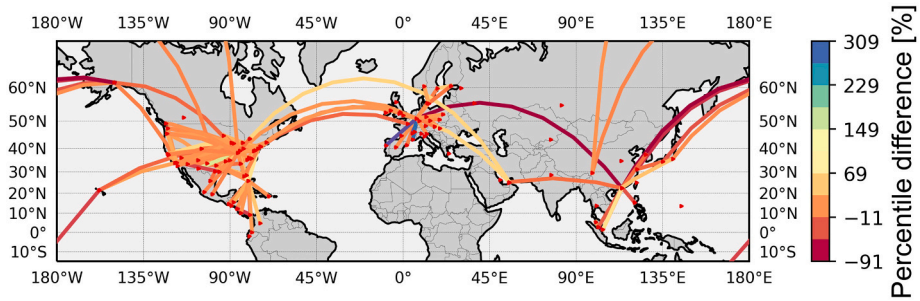


Fig. 13. AFT percentile difference between early February and late January 2020 for UPS.

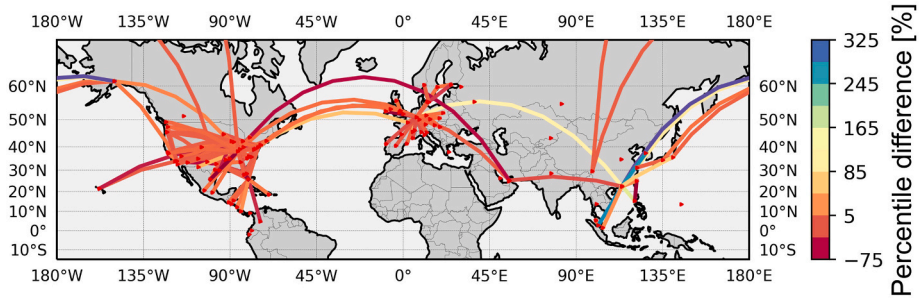


Fig. 14. AFT percentile difference between late and early February 2020 for UPS.

(OVB) and their main hub Luxembourg airport (LUX) experienced an AFT decrease of 50%. Interestingly, two new routes appeared from mid February onwards. The first route is LUX-OVB, that in the last observations is the one with the highest AFT. An explanation for the new prominence of OVB is likely related to cargo carriers preferring resting stops for trans-Eurasian route in Russia rather than China, to avoid the risk of being stranded for unexpected travel bans (The Loadstar website, 2020). The second route connects the second European hub Milano Malpensa airport (MXP) with their main hub. For KLMP, we noticed how AFT decrease relatively later, i.e., between late March and early April (see as example the MIA-AMS and AMS-VCP route in Fig. 19). Differently from the other airlines, the passenger (and more European) oriented nature of KLMP resulted in reduced capacities once European airports closed most of their intra- and inter-European passenger connections. On a similar note, the same capacities regained values comparable (yet still considerably lower) to the pre-pandemic phases once lockdown restrictions were relaxed (line 5 in Fig. 19).

5.2. Networks' connectivity time-series analysis

The analyses carried out in Section 5.1 highlighted geographically-specific variations in network capacity and the resilience of cargo networks to recover from drops in available capacity. On the other hand, information on how the pandemic affected the connectivity of the

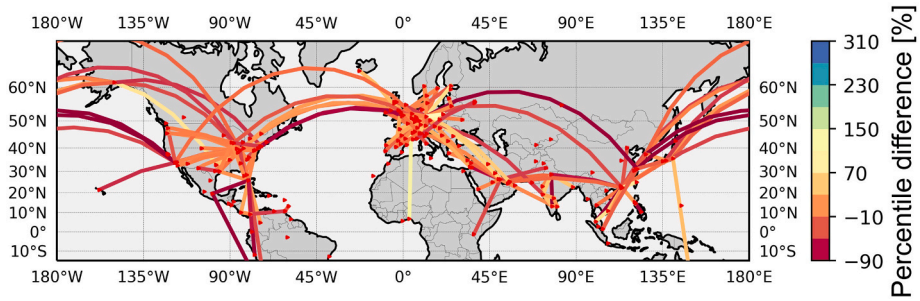


Fig. 15. AFT percentile difference between early February and late January 2020 for DHL.

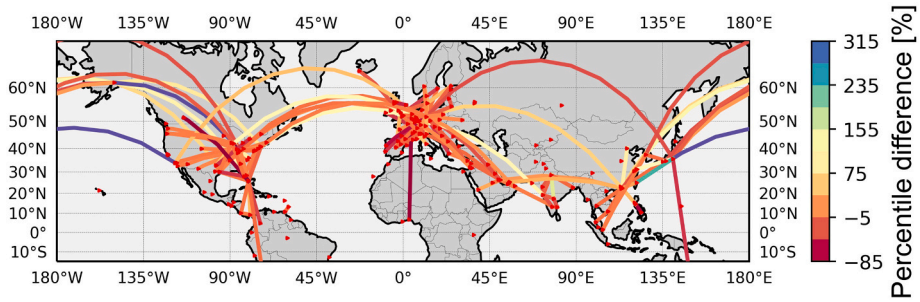


Fig. 16. AFT percentile difference between late and early February 2020 for DHL.

Table 6
OD connections with the highest percentile decrease/increase for FedEx, UPS, and DHL between the first half of February 2020 and the second half of January.

FedEx				UPS				DHL			
OD	[%]	Late Jan. [AFT]	Early Feb. [AFT]	OD	[%]	Late Jan. [AFT]	Early Feb. [AFT]	OD	[%]	Late Jan. [AFT]	Early Feb. [AFT]
ANC-PVG	−55.6	938.9	417.3	SZX-ANC	−91.2	1586.4	139.6	LAX-NRT	−90.9	1232.0	112.0
TPE-ANC	−47.9	870.8	453.5	TPE-ANC	−65.4	1212.0	418.8	ANC-LAX	−80.2	2079.0	411.0
CDG-DXB	−32.7	957.0	644.7	ICN-CGN	−57.1	821.8	352.2	ANC-JFK	−78.8	1488.0	316.0
KIX-MEM	−30.0	2086.5	1460.6	ANC-HKG	−47.9	1607.5	837.6	HKG-PVG	−76.2	1156.5	275.5
CGN-CDG	−24.2	1292.0	979.0	PVG-ANC	−39.8	1167.6	703.3	HKG-ANC	−74.5	4972.0	1269.0
ELP-MEM	35.2	1229.0	1661.9	CDG-CGN	70.0	600.3	1020.5	DXB-LEJ	85.7	714.0	1326.0
MSP-IND	46.0	571.5	834.6	MIA-SDF	73.1	1356.7	2348.3	BSL-LEJ	91.5	523.0	1001.6
PVG-KIX	50.2	665.3	999.4	CGN-CDG	100.0	600.3	1200.6	MXP-LEJ	98.6	516.0	1024.6
TPE-KIX	65.8	870.7	1443.9	DXB-CGN	116.5	900.8	1949.9	LEJ-ICN	116.7	612.0	1326.0
MIA-BOG	91.7	653.2	1251.9	CGN-EMA	122.4	660.3	1468.5	LEJ-NRT	350.0	204	918.0

Table 7
OD connections with the highest percentile decrease/increase for FedEx, UPS, and DHL between the second and first half of February 2020.

FedEx				UPS				DHL			
OD	[%]	Early Feb. [AFT]	Late Feb. [AFT]	OD	[%]	Early Feb. [AFT]	Late Feb. [AFT]	OD	[%]	Early Feb. [AFT]	Late Feb. [AFT]
MIA-BOG	−56.5	1251.9	544.3	MIA-BOG	−49.2	1655.1	840.4	BAH-LEJ	−47.0	1256.0	666.0
CAN-SIN	−56.4	926.1	403.6	BOG-MIA	−40.4	2214.3	1320.7	MIA-BOG	−41.7	3102.0	1808.0
CAN-KIX	−50.5	2014.8	997.9	DXB-CGN	−34.4	1949.9	1279.5	BOG-MIA	−39.8	3102.0	1866.0
TPE-KIX	−45.3	1443.9	789.1	MIA-SDF	−32.3	2348.3	1590.3	ICN-NGO	−22.2	1008.0	784.0
CAN-NRT	−41.9	1351.5	784.7	HNL-ONT	−26.1	1272.1	940.6	MAD-LEJ	−21.0	807.8	638.4
ICN-ANC	43.0	675.5	965.8	EMA-CGN	30.8	1019.5	1333.8	ANC-ORD	160.0	1120.0	2912.0
ANC-NRT	54.6	997.8	1542.2	PVG-ANC	39.9	703.3	983.6	ANC-ICN	195.4	911.0	2691.0
KIX-MEM	57.1	1460.6	2295.2	ANC-HKG	66.7	837.6	1396.0	ANC-LAX	202.9	411.0	1245.0
ANC-PVG	100.0	417.3	834.6	TPE-ANC	190.0	418.8	1212.0	ORD-ANC	800.0	112.0	1008.0
TPE-ANC	133.0	453.5	1056.7	SZX-ANC	1000.0	139.6	1535.6	ICN-PVG	978.4	102.0	1100.0

different networks could be guessed, but not explicitly quantified. To this avail, in this section we provide a complex network theory analysis mapping the temporal evolution of connectivity indices for the three integrators and the three other airlines.

In particular, in Section 4 we generated the cargo networks considering the entire set of thirteen observations to mitigate seasonal effects. Following a different approach, in this section we will generate a cargo network for each observation, using the same procedure shown in Section 4, in order to highlight *unusual* seasonal effects. We want to stress the relevance of the word unusual, since we expect to highlight some seasonal effects, such as a spike in available capacity and served connections during the holiday season. What we are looking for are unforeseen outliers that are most likely imputable to the pandemic.

For the three integrators and the three other airlines, the temporal

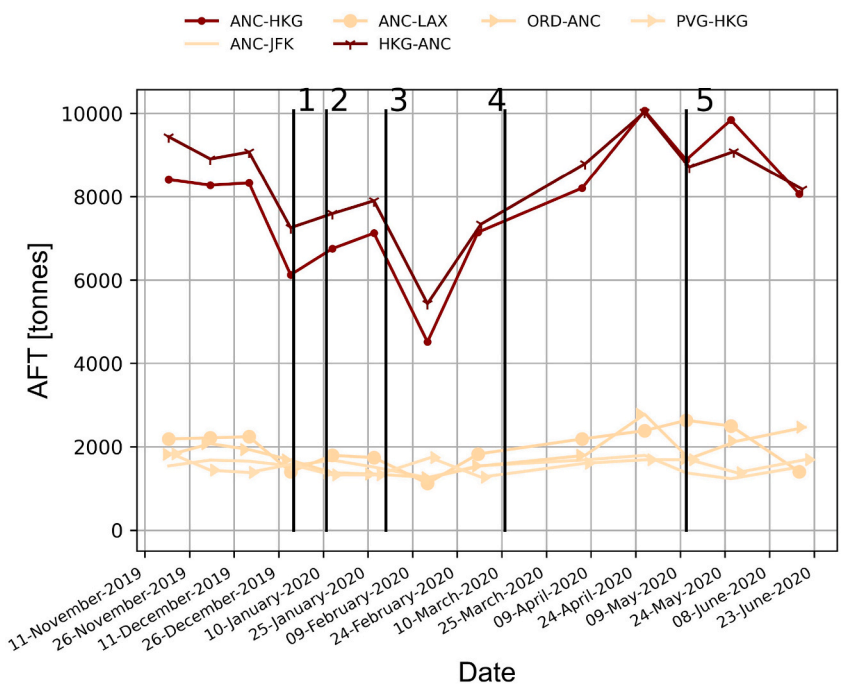


Fig. 17. Time-series depicting AFT along major routes for Cathay Pacific Cargo.

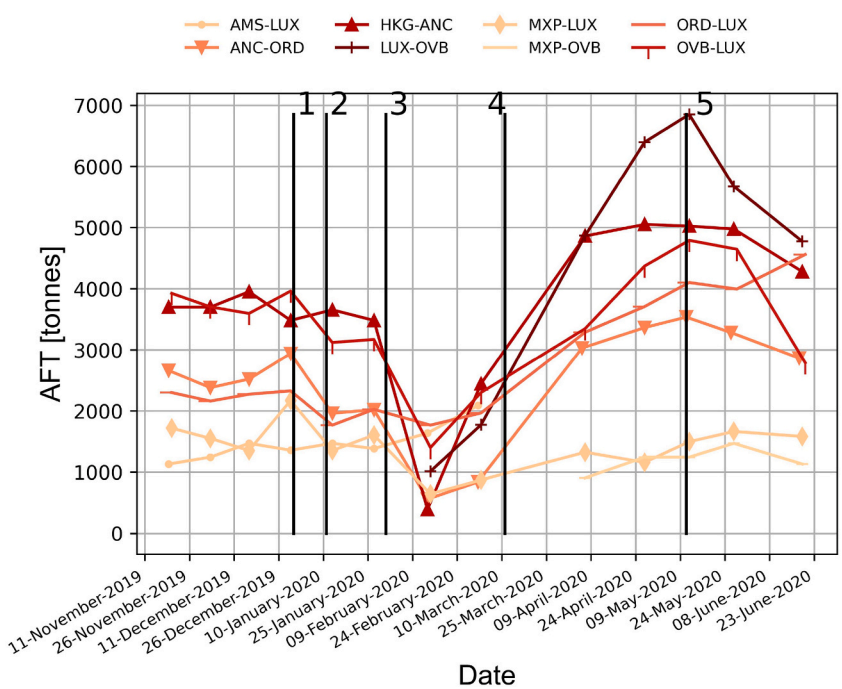


Fig. 18. Time-series depicting AFT along major routes for Cargolux.

evolution of five indices is presented: network-wide AFT, - number of edges $|\mathscr{E}|$, - size of the giant component $\mathscr{G}_c$, - average degree $\langle k \rangle$, and characteristic path length $\langle L \rangle$.

In Fig. 20 the network-wide AFT for FedEx, UPS, DHL, Cathay Pacific Cargo, Cargolux, and KLMP are presented. For this specific plot, we report the time-series of both KLM and MP, together with their cumulative time-series representing KLMP, to better understand how the two sub-networks performed during the pandemic in terms of available capacity. For the three integrators, an expected spike in available capacity is detected between mid and late December. The spike is particularly pronounced for FedEx and UPS. On the other hand, the strong decrease in available capacity from/to NEA in early February that was shown in Section 5.1, seems to have caused a tangible effect at the network-wide level only to DHL and, with a more pronounced note, to Cathay Pacific Cargo and Cargolux. For KLMP, a considerable drop in available capacity occurs in mid March, where lockdown restrictions in many European countries severely affected airports' operations. Note that the drop is caused by the sudden unavailability of passenger aircraft, and hence is caused by the KLM network, while operations for the MP network remain roughly constant throughout the time-horizon.

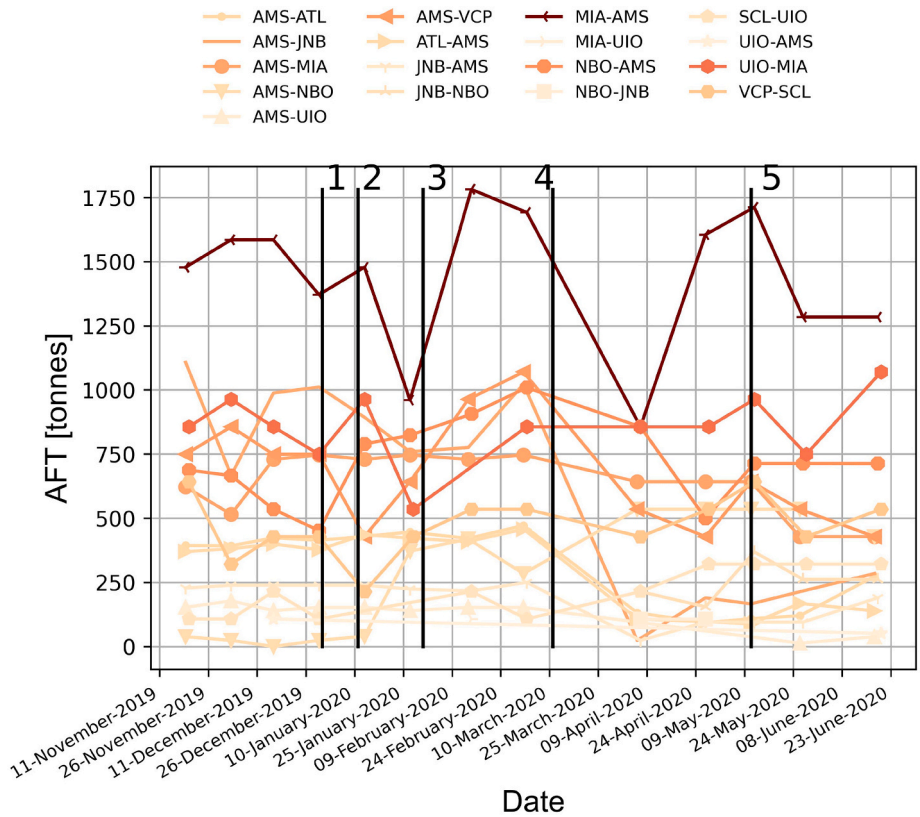


Fig. 19. Time-series depicting AFT along major routes for KLMP.

Given the different order of magnitude in AFT between integrators and KLMP, an inset plot focused solely on KLMP is also provided in Fig. 20. Analyzing the inset plot, a reduction greater than 50% in available AFT for the KLM network is evident.

A similar trend can be observed in Fig. 21, where the number of edges $|\mathscr{E}|$ is reported. All integrators are characterized by an increase in available connections during the peak season, with little to none decrease effect in February. On the contrary, both Cathay Pacific Cargo and Cargolux experienced a 10–15% decrease in available connections in the same time-frame. As it concerns KLMP, a 50% decrease was experienced in March, similarly to what shown for AFT. This is clearly due to the partial or total closure of airports worldwide for passenger traffic.

Fig. 22 shows the temporal evolution of the giant component for each network. Instead of the actual size of the giant component per observation $|\mathscr{G}_c|$, we report the percentile normalized value $\frac{|\mathscr{G}_c|}{\max(|\mathscr{G}_c|)}$, where with $\max(|\mathscr{G}_c|)$ we define the size of the giant component of each

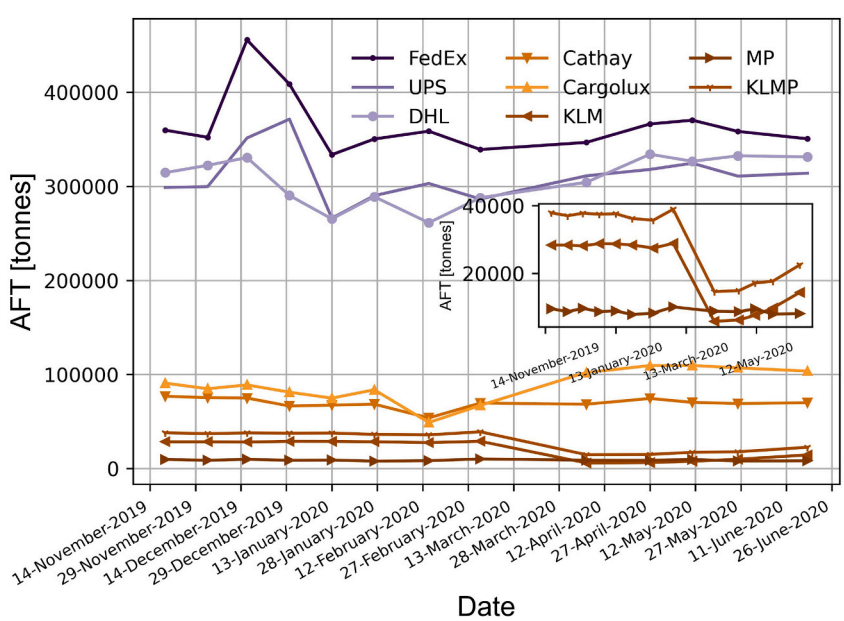


Fig. 20. AFT temporal evolution for the six airlines.

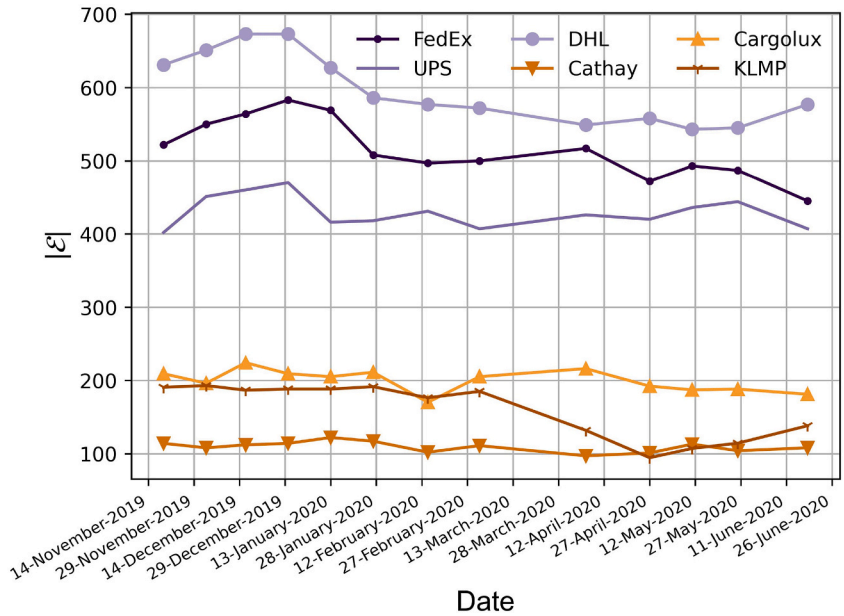


Fig. 21. $|\mathscr{E}|$ temporal evolution for the six airlines.

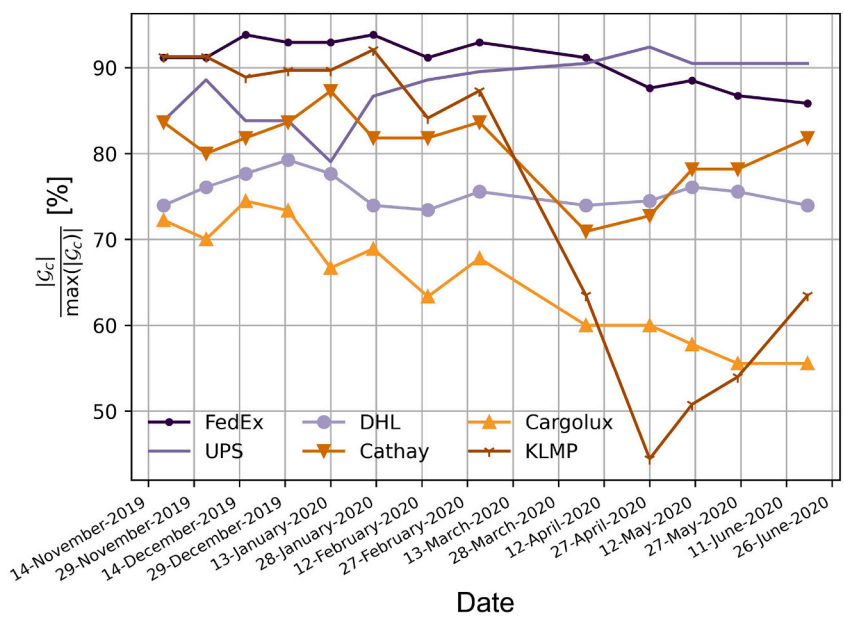


Fig. 22. $\frac{|\mathscr{G}_c|}{\max(|\mathscr{G}_c|)}$ temporal evolution for the six airlines.

full network (generated using all thirteen observations) as described in Section 4. As such, for all networks the reported values will range between 0% and 100% to provide a result that is easier to compare and interpret. Analyzing Fig. 22, it can be appreciated how the three integrators' networks proved to be more robust in tackling the pandemic, with $\frac{|\mathscr{G}_c|}{\max(|\mathscr{G}_c|)}$ remaining constant or increasing. Both Cathay Pacific Cargo and Cargolux experienced a drop in the size of the giant component, with the former being quicker in recovering. The most interesting trend is the one of KLMP, with a sudden drop from 90% to 45% due to the unavailability of belly space. An upward trend is also visible due to countries easing their lockdown restrictions and slowly reopening airports. It should also be noted that we did not set a minimum capacity threshold and artificially removed airports whose strength (i.e., AFT level) was lower than the threshold. The dramatic reduction in the size of the giant component is solely due to the lack of passenger connections airports were subject to during the lockdown.

We conclude our discussion with the analysis of Fig. 23 and Fig. 24, where the average degree $\langle k \rangle$ and the characteristic path length $\langle L \rangle$ are respectively reported. Consistently with the previous plots, integrators are characterized by a higher connectivity during the peak period, while $\langle k \rangle$ fluctuates around a constant value otherwise. The average degree is roughly constant for Cathay Pacific Cargo and Cargolux as well, apart from a decrease in mid February that might have been caused by the reduction in capacity from/to NEA airports. For KLMP, a decrease of roughly 50%, consistently with the other indices, was experienced. The decrease in average connections per airport resulted in a spike in $\langle L \rangle$ for KLMP (Fig. 24): some direct connections were lost and more transshipment stops were needed as a consequence. For the other

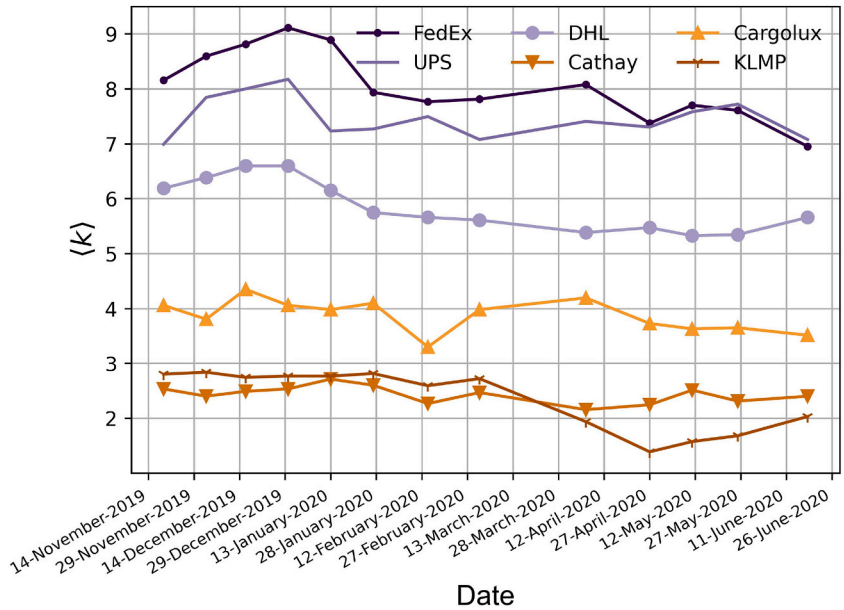


Fig. 23. ⟨k⟩ temporal evolution for the six airlines.

carriers, a decrease in ⟨L⟩ for Cargolux is evident, that is consistent with the increase of ⟨k⟩ due to the adoption of pandemic-induced new routes as shown in Section 5.1. For FedEx, UPS, DHL, and Cathay Pacific Cargo, the effects of the pandemic on ⟨L⟩ seem negligible.

Although the network analysis presented in this section focused on the short-term effects of the COVID-19 pandemic on cargo networks, some general conclusions can be drawn. Given the different trends we highlighted for network indices such as global strength (network-wide AFT), number and quality of connections, and connectivity (size of the giant component), we argue that:

1. integrators might be the great winners in this unforeseen set of circumstances (Suau-Sanchez et al., 2020). COVID-19 is potentially re-orienting some airports towards cargo as part of the growing importance of e-commerce, that during the pandemic saw a surge in usage rate. The forced quarantine led to unprecedented increases in purchases of the following categories: medical (+500%), baby products (+390%), food & beverage (+150%) (Big Commerce website, 2020), just to cite a few examples. Integrators were the only cargo airlines that, apart from capacity fluctuations during the most uncertain period of the pandemic, maintained a capacity level comparable, if not even higher, than the pre-pandemic level. Integrators' networks proved to be both robust and resilient. The robustness is confirmed by the fact that network indices such as network-wide AFT, number of connections $|\mathscr{E}|$, and size of the giant component $|\mathscr{G}_c|$ were marginally affected (Section 5.2). Their resilience is evident given their capability, thanks to flexible schedules for full freighters, to quickly rebound from momentarily losses in available capacity among major OD airport pairs (Section 5.1)
2. on the other hand, passenger airlines heavily relying on belly space

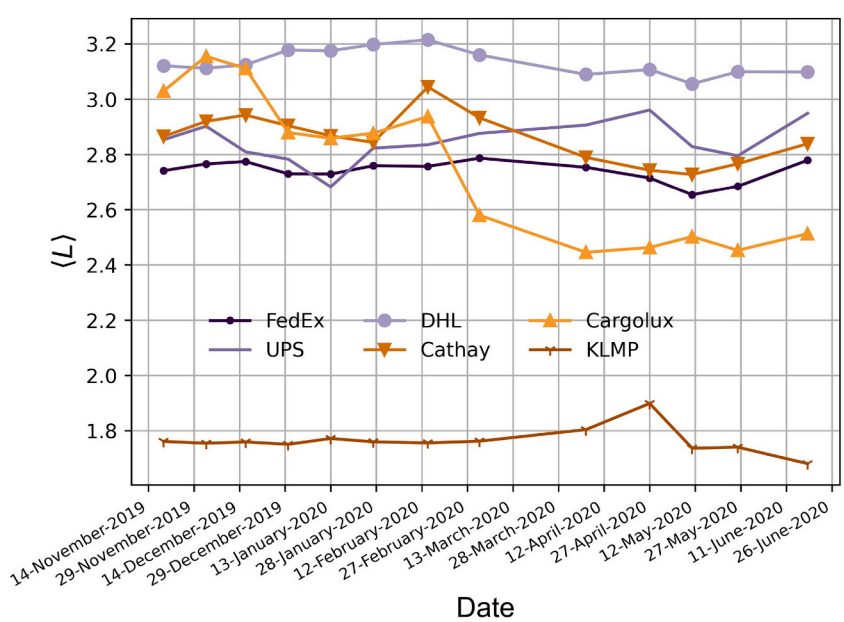


Fig. 24. ⟨L⟩ temporal evolution for the six airlines.

for cargo services might be the great losers. While we focused on a single combination airline in the paper, and hence our results might not be universally valid, the KLMP network proved to be somehow resilient (see recovery trend for all network indices), but not robust. The drop in network-wide AFT and $|\mathscr{G}_c|$ as a result of lockdown measures was extremely dramatic. Notwithstanding the fact that the air cargo business is generally of secondary relevance for combination airlines, they might be reconsidering the recent shift towards belly space utilization (potentially phasing-out full freighter aircraft). The trend, motivated by the extensive passenger network, proved to be a double-edged sword. While some airlines, including KLM, temporarily reconverted some of their passenger aircraft to "cargo-in-cabin" aircraft (KLM website, 2020), this is clearly not a long-term solution. As the passenger air network is much less robust to pandemic-induced disruptions than the cargo counterpart, combination airlines might have second thoughts before phasing-out full freighters (given their crucial role in case of a new pandemic wave, or of other unforeseen disruptions affecting the passenger network), if they plan to remain competitive in the air cargo business.

6. Conclusions

In this paper, we provided a thorough analysis of the network structure of integrators FedEx, UPS, and DHL, using historical data from public sources and estimated cargo weight capacity between airports to model each network. We considered networks as directed to model the strong flow imbalances and triangular routes that characterize cargo networks.

Our results show that FedEx owns the most developed network in terms of overall capacity, but DHL is more developed in terms of airports and connections. This factor can also be attributed to the different business strategy of DHL, which heavily relies on a set of airlines operating under its livery, differently from FedEx and UPS. In addition, while FedEx and UPS, although they do rely on a vast set of secondary hubs, seem to be based on networks designed following the classic "hub-and-spoke" paradigma, the structure of the network of DHL is more hybrid and steers towards a "multi-hub" system. Related to the previous point, we analyzed the robustness of the three networks under different node attack strategies, and used the size of the giant component (i.e., the cardinality of the set of nodes of the network that are all connected to each other) as a measure of robustness. We found out that the DHL network is more robust, with no node removal (among the first six removals) that reduces the size of the giant component more than 10% and a resulting final percentile size of the giant component greater than FedEx or UPS. We also want to highlight that our definition of robustness is based on a specific quality measure that focuses more on connectivity properties rather than the strength, measured as remaining overall capacity, of the network. Hence, it cannot be claimed that the DHL network is the most robust from a universal perspective.

Given that, at the time of writing, the COVID-19 pandemic is still affecting supply chains worldwide, we also performed a time-series analysis to assess how capacity along some major OD connections was affected, and how network-specific indices changed at different stages of the pandemic. In order to have a more comprehensive perspective, we also included three other relevant airlines: two full-cargo airlines and a major combination airline. We noticed a steep decrease in available capacity for integrators and full-cargo airlines between North East Asia and the United States and Europe in early February, i.e., right after the United States issued their travel ban from China. In early March the situation reversed and capacities recovered and even surpassed their nominal values especially for integrators. This factor testifies how integrators' networks are resilient and capable of quickly adapting to disruptions. We also proved that integrators' networks are robust, since network-wide indices did not show major changes during the pandemic. The same cannot be argued for the combination airline we considered. Although signs of a slower-paced resilience are irrefutable, its network is not robust and connectivity properties were severely affected during the pandemic. We used this result to argue that the inclination of some combination airlines towards belly space, rather than full freighters, might be re-evaluated considering the likelihood of a new pandemic wave and the relevance of cargo services for those airlines.

Although we believe this work to be a solid first step towards a better understanding of (i) the global network structure of integrators, and (ii) the effect of COVID-19 on cargo flows, we are also aware that it can be improved and extended in several ways by exploring some additional research directions.

As example, provided the availability of a broader dataset in terms of airports (or a way to quickly gather data), the lower-tier airports that were omitted in this work could be included to better model low-capacity routes.

Another interesting addition is the analysis of the network structure of Amazon Air. At the time of writing, the fleet of Amazon Air is still under development, and hence we deemed its inclusion in this work to be premature, but in one year from now time should be ripe. Although the business model of Amazon Air is slightly different than the other integrators (in the sense that, on top of being an integrator, it also directly sells the goods that are being transported and delivered), airport slot capacity and competition issues might influence the network strategy and configuration of the other integrators as well. As example, the main hub of Amazon Air will be Cincinnati/Northern Kentucky International airport that, coincidentally, is the main American hub for DHL. We do believe the introduction in the cargo game of such a huge player is worth a more extensive analysis.

The last research direction is related to the COVID-19 pandemic. In this paper, our analysis focused on short-term changes in network capacity and connectivity indices due to the pandemic. Similarly to the aforementioned point made for Amazon Air, it would be interesting to follow the evolution of airline networks over time and assess whether COVID-19 caused more permanent changes (e.g., creation of new routes, re-structuring of the connections to/from hubs) in their network.

Acknowledgments

I would like to thank Dr. Bruno F. Santos and Prof. Lori Tavasszy, both from Delft University of Technology, for our discussions on the cargo business that partially shaped this research. I also would like to thank the three anonymous reviewers for their comments and extremely careful reviews, that greatly improved the quality of this paper.

Appendix A. Aircraft fleet of FedEx, UPS, and DHL

For FedEx, UPS, and DHL we report in Table 8 the list of aircraft we considered, with full name, code, and maximum payload. Maximum payload values were obtained either from the integrator's webpage, or from the manufacturer's webpage. Since different cargo airlines generally have different Unit Load Device (ULD) configurations, maximum payload values for the same aircraft used by different integrators might differ.

Table 8
List of aircraft used for the FedEx, UPS, and DHL networks.

Aircraft model	Aircraft code	Payload [tonnes]
	FedEx	
Airbus A300-600F	A306	47.6
Airbus A310-300F	A310	39.0
Boeing B737-400F	B734	20.5
Boeing B747-400F	B744	113.0
Boeing B757-200F	B752	27.2
Boeing B767-300F	B763	54.4
Boeing 777F	B77L	104.3
Boeing MD-10-30F	DC10	77.1
Boeing MD-11F	MD11	81.6
	UPS	
Airbus A300-600F	A306	55.3
Boeing B747-400F	B744	117.4
Boeing B747-800F	B748	139.6
Boeing B757-200F	B752	39.5
Boeing B767-200F	B762	44.9
Boeing B767-300F	B763	60.0
Boeing MD-11F	MD11	94.1
	DHL	
Airbus A330-300F	33Y	65.0
Airbus A300-600F	A306	54.0
Airbus A300 B4-200F	A30B	45.0
Airbus A300-200F	A332	70.0
Boeing B737-300F	B733	14.8
Boeing B737-400F	B734	20.0
Boeing B737-800F	B738	23.0
Boeing B747-300F	B743	106.0
Boeing B747-400F	B744	112.0
Boeing B747-800F	B748	137.0
Boeing B757-200F	B752	30.7
Boeing B767-200F	B762	42.0
Boieng B767-300F	B763	58.0
Boieng B767-700F	B767	42.0
Boieng B777-200F	B772	103.0
Boeing 777F	B77L	102.0
Boeing 747-400LCF	BLCF	113.4

Appendix B. Network characteristics of Cathay Pacific Cargo, Cargolux, and KLMP

For Cathay Pacific Cargo, Cargolux, and KLMP we report the main characteristics of their networks in Table 9, their network visualization in Fig. 25, the five OD airport pair connections with the highest AFT in Table 10, and a chord diagram depicting major cargo flows between airports in Fig. 26.

Table 9
Cathay Pacific Cargo, Cargolux, and KLMP network characteristics.

	Cathay Pacific Cargo	Cargolux	KLMP
Nodes	90	103	136
Edges	190	480	323
Density	0.024	0.046	0.018
Reciprocity	0.41	0.29	0.65
$\langle k \rangle$	4.2	9.3	4.8
$\langle C \rangle$	0.36	0.50	0.36
$\lvert \mathscr{C} \rvert$	55	90	126
$\langle L \rangle$	2.56	2.50	2.20
D	5	6	4
Overall AFT	901,228	1,150,903	385,031
Overall AFTK	3,993,583,835	5,665,919,727	2,057,843,628

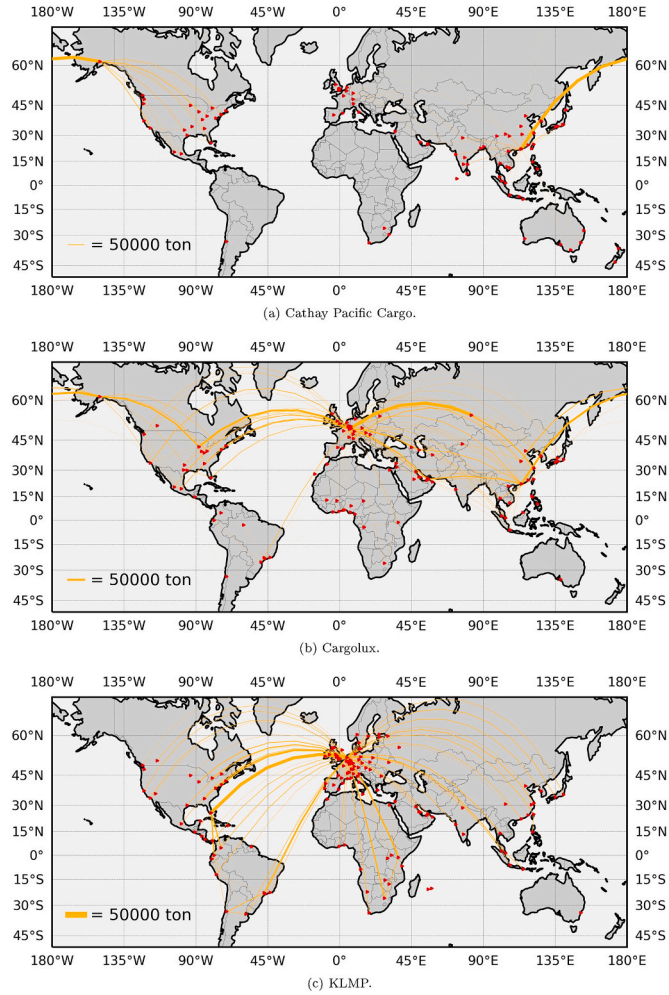
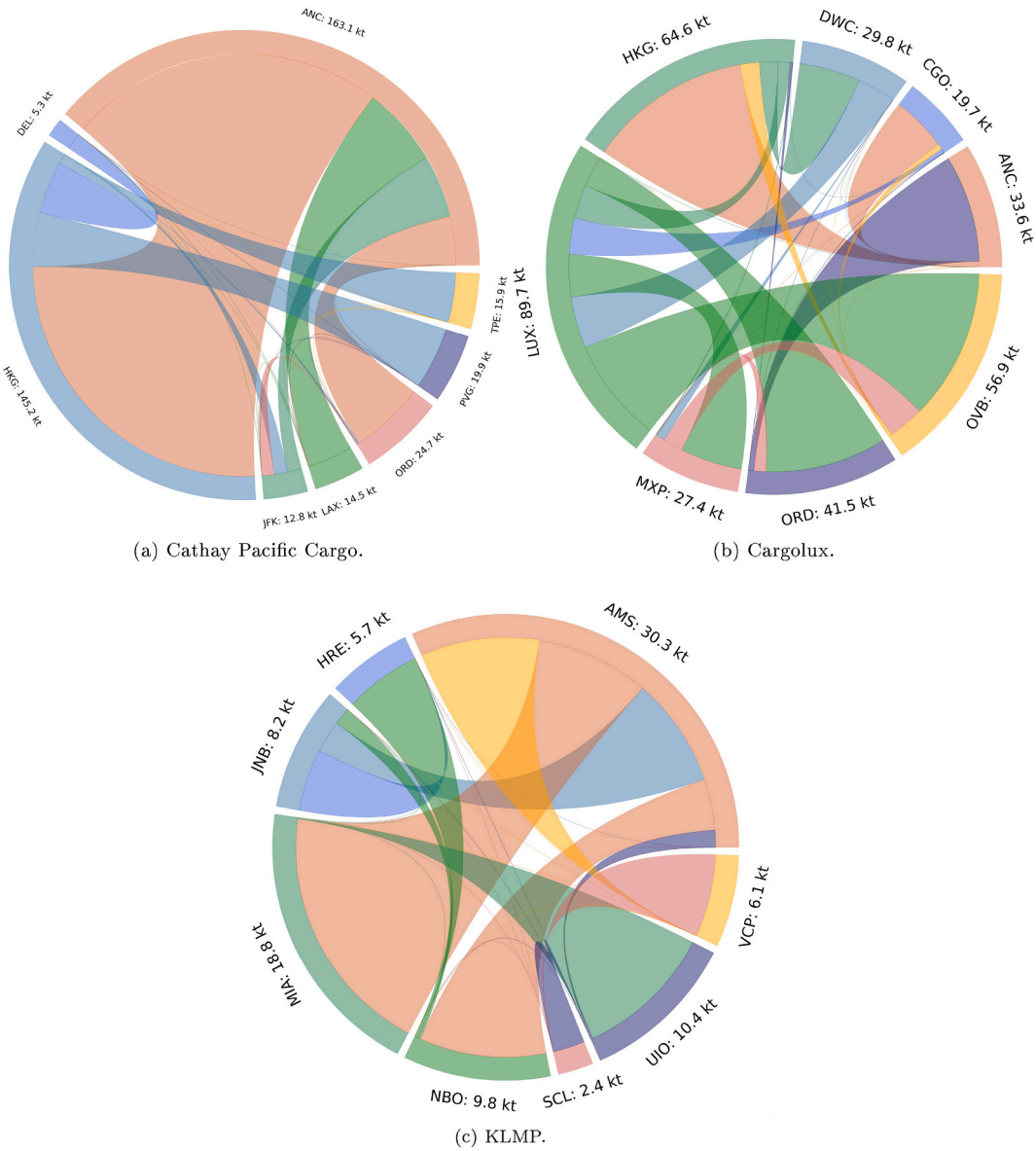


Fig. 25. Cathay Pacific Cargo, Cargolux, and KLMP networks.

Table 10
Top-five OD airport pair connections according to AFT.

rank	Cathay Pacific Cargo		Cargolux		KLMP	
	OD	capacity [tonnes·1e3]	OD	capacity [tonnes·1e3]	OD	capacity [tonnes·1e3]
1	HKG-ANC	107.7	HKG-ANC	49.0	MIA-AMS	18.7
2	ANC-HKG	101.7	OVB-LUX	45.1	UIO-MIA	10.3
3	ANC-LAX	25.6	ORD-LUX	36.2	NBO-AMS	9.4
4	ORD-ANC	23.9	ANC-ORD	32.0	AMS-VCP	8.8
5	ANC-JFK	20.0	LUX-OVB	31.3	AMS-MIA	8.3



(a) Cathay Pacific Cargo.

(b) Cargolux.

(c) KLMP.

Fig. 26. Chord diagrams representing cargo capacities between top airports.

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