Structure, Resilience and Evolution of the European Air Route Network From 2015 to 2018

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Abstract—**In spite of the dynamic nature of air transport, air route networks, i.e. the backbone used to organise aircraft flows, are expected to be mostly static, with small changes occasionally being introduced to improve the efficiency and resilience of the system. By leveraging a large data set of European flights comprising years 2015 to 2018, we analyse its structure and evolution from the perspective of complex networks, with the aim of firstly describing it, and secondly to confirm its static nature. Results depict a highly dynamic system, with major topological changes happening at the end of 2017. Peripheral links are usually more vulnerable, due to the lack of effective reroutings, as well as central regions; additionally, the overall resilience of the network is almost constant throughout time, in spite of an increase in traffic. We further test several hypotheses regarding the design considerations driving such evolution. Beyond specific operational insights, these results highlight the importance of taking into account the evolution of this network in the study of traffic flows.**

Index Terms—**Air transport, air route networks, network evolution, network resilience.**

I. Introduction

AMONG the many real-world systems that have been analysed using the tools provided by network science, of special interest is the air transportation system. This stems from two main aspects. On one hand, alongside other systems like the power grid [1] or Internet [2], air transport is one of the tenets of modern society, both for its economic impact and for enabling long-range mobility and hence the cohesion of scattered communities. To illustrate, 4.5 billion trips took place throughout the year 2019, for an economic impact estimated at 2.7 trillion US$(i.e. 3.6% of world GDP) and 65.5 million jobs supported [3]. On the other hand, air transport is a prototypical example of a complex system, composed of a large number of elements, acting and interacting at different scales - from individual passengers to large-scale transnational organisations. Making sense of the macro-scale dynamics of this system from the dynamics of its constituting elements is thus not always possible, and is in any case inefficient [4]. On the contrary, complex networks [5], [6] allow for a simplified representation of the structure created by the interactions between these elements, and can be used to support our understanding of emergent behaviours.

The most common representation of air transport through networks has been by far that of "airport networks," in which nodes represent airports that are pairwise connected whenever one or more direct flights operate between them [7], [8], [9]. These networks thus represent, and allow to model, the mobility in a given country or region, and more generally any process supported by such mobility [10], [11], [12]. Much less attention has nevertheless been devoted to air routes, i.e. fixed "highways" that aircraft have to follow to reach their destinations, and that are used to simplify the flows of aircraft and hence simplify the work of air traffic controllers.

In the last decade, a handful of research works have focused on these route networks, the first one being, to the best of our knowledge, [13] - see also Section II for a review of the available literature. Still, the attention that has been devoted to route networks has been substantially smaller than that devoted to, e.g., airport networks - for reviews of the latter ones, see [8], [9]. This apparent lack of interest from the complex network community can be attributed to two factors. Firstly, obtaining data about the organisation of the airspace and of its routes is generally not an easy task, as they are reserved for professional use by airlines and other organisations. Secondly, the route network is usually considered a static object, in which changes seldom happen; therefore, it may seem less interesting to analyse topological or resilience properties, as these are not expected to change, nor to be acted upon. To illustrate this lack of focus on the network evolution, only one of the papers reviewed in Section II uses data across multiple years [14], and even there the evolving network is only used to analyse the real movement of aircraft, and not the reconfiguration of the network itself; as taken for granted in that work, "[the network] does not change significantly in different AIRAC cycles" [14]. Also, most of them do not report which year and month the data correspond to, simply making reference to "the latest data provided by" some organisation - only [15], [16] report the exact date for which the data were in effect.

Contributions: In this contribution we leverage a large dataset describing the evolution of the air route structure in Europe from 2015 to 2018, to describe how its topology and resilience

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changed over time. This corresponds to a two-fold objective: to provide a description of the topology on spatial and temporal scales larger than other studies; and to evaluate the dynamics of the network, thus confirm its stationary nature. The detailed contributions include:

- We propose a detailed topological analysis of the structure of the European air route network and of its evolution across four years. We demonstrate that the structure is not static, as assumed in the literature; on the contrary, the number of nodes (i.e. waypoints) and links almost constantly grew in the studied time period, resulting in substantial topological differences between years 2015-2016 and 2017-2018.
- An analysis of the resilience of the system and its evolution through time is reported, where resilience is here understood as its capacity of providing alternative routes of similar length in case one link or portion of the airspace becomes unavailable. Similarly to the underlying route structure, the resilience of several regions presents an interesting phase change around the year 2017; this has nevertheless been a local effect, as the overall resilience of the network is not affected.
- A set of synthetic minimal models is further presented, based on adding and deleting links according to factors like link redundancy and the volume of traffic traversing them.
- We finally analyse how the evolution here described affects past and future analyses of the air transport system. Contrary to what is generally believed, the stationarity of the air route network cannot be given for granted when studying the dynamics of aircraft. Results thus sound a note of caution, that shall be taken into account by the research community.

The remainder of the contribution is organised as follows. Firstly, Section II presents a review of the state of the art, focusing on analyses of airport and air route networks. Secondly, Section III introduces the main methods of this study, including the description of the data sources (Section III-A), network topological metrics (Section III-B), and the analysis of the resilience (Section III-C). We then present the results of the study, in terms of topology (Section IV) and resilience (Section V). Next, the synthetic models used to probe the forces behind the observed evolution are presented in Section VI. Finally, Section VII discusses the impact that the evolution of the network has on air transport research, both in terms of lack of reproducibility of past works, and new lines that will open in the future.

II. Related Works

Research works related to the topic studied in this contribution can be organised into two groups: those focusing on the analysis of connections between airports and those studying the structure of air routes, in both cases from a complex network perspective [5], [6], [17]. Note that air routes represent the way aircraft can move between airports, and hence constitute the backbone of airport networks.

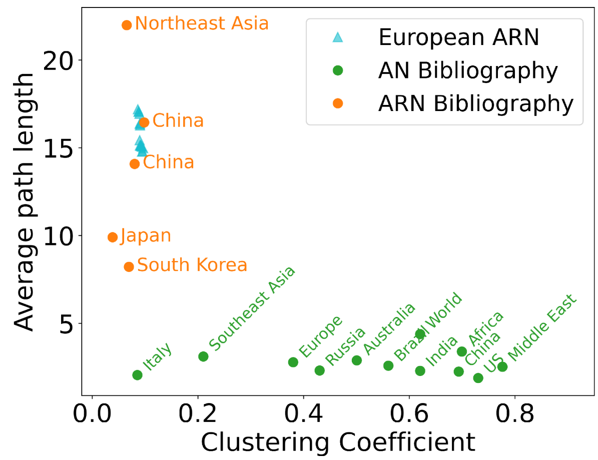

Fig. 1. Comparison of the average shortest path length and clustering coefficient for some key airport networks (AN) and air routes networks (ARN) reviewed in Section II. See Section III-B for definitions of the two topological metrics.

The analysis of airport networks from the complex network viewpoint has a long history, dating back to the first works formalising the latter theory; this is probably due to the relative easiness with which data can be obtained, and the social and economic relevance of the results. To the best of our knowledge, the first work on the topic was proposed by Li-Ping and coauthors [18], extracting some topological metrics from the US flight network, and firstly observing a power-law behaviour in the degree distribution. This was followed shortly afterward by Ref. [19], focusing on the structure of Chinese flights; and by the well-known work of Guimera et al. [7], on the world-wide aviation network. Since them, many additional research works have been proposed, whose complete review is outside the scope of this contribution - the interested reader can refer, for instance, to Refs. [8], [9]. It is nevertheless interesting to observe the wide diversity in their geographical scope: they range from the world-wide scale [20]; multiple continents [11], [21]; individual continents, like Europe [14], [22] or Asia [23]; down to individual countries, e.g. US [24], [25], [26], [27], [28], China [13], [29], [30], [31], [32], Brazil [33], [34], [35], Australia [36], [37], India [38] or Italy [39]. Researchers have also used different extensions of the complex network methodology, including weighted [24], [38] and multi-layer representations [22], [40].

Moving to the proper air route networks, to the best of our knowledge, the first work on the topic is [13], focusing on the analysis of the topology of the Chinese air route network. This was followed by a set of works [15], [41], [42] comparing the topology of the networks corresponding to different countries. More recently, some contributions have studied more specific aspects of these networks, like the centrality of nodes and links [43], [44], [45], [46], their vulnerability [47], the multi-scale and modular structure of the network [48], and the relationship between the route network and the flights operating on top of it [16], [49]. Additionally, it is worth citing a set of works that have analysed the structure of route networks of the Chinese airspace, aimed at identifying bottlenecks for traffic, and proposing ways to optimise the structure [50], [51], [52],

[53]. It is finally worth highlighting the work of [14], in which the evolution of the air transport topology is evaluated between 2011 and 2013; the focus is nevertheless on how aircraft actually use the airways, and how this use varies over time, as opposed to how the airways themselves change over time.

As in any analysis based on real data, it is important to take into account that the scope and completeness of these can have a major impact on the obtained results. To illustrate this point, Fig. 1 reports the average shortest path length and clustering coefficient reported in some of the aforementioned research works - these two topological metrics will be defined in detail in Section III-B. A great variability in the results can be appreciated, mostly due to the spatial scale heterogeneity of the networks - from single countries, up to whole continents. Yet, even for the four works focusing on the European air route network, i.e. [14], [15], [41], [48], substantially different values of the average shortest path length are reported.

III. Materials and Methods

A. Airspace Structure and Traffic Data

Airways are designated routes through which aircraft generally have to fly (with the exclusion of RNAV, or Area Navigation regions), designed to facilitate navigation and to help air traffic controllers by providing more organised trajectories and thus reducing the risk of accidents [54]. The historical origin of airways can be traced back to the United States Postal Service's Contract Air Mail routes, composed of successions of flashing lights between cities that guided pilots flying at night. Nowadays, airways are defined as segments between pairs of navigational aids (such as VHF Omnidirectional Range stations, VORs, or Non-Directional Beacons, NDBs) or similarly defined points in space, with an assigned minimum altitude and corridor width. They can thus naturally be mapped into networks, in which nodes represent these intersection points, pairwise connected when a segment connects them.

The data used in this study have been extracted from the EUROCONTROL's R&D Data Archive, a public repository of historical flights made available for research purposes and freely accessible at https://www.eurocontrol.int/dashboard/rnd-data-archive. It includes information about all commercial flights operating in and over Europe, completed with flight plans, radar data, and associated airspace structure. Note that, at the time of performing this analysis, the dataset was limited to four months (i.e. March, June, September and December) of four years (2015-2018); the choice of the 2015-2018 time window is thus not a decision of the authors, but rather a constraint of the available data.

More specifically, the route structure of the European airspace has been obtained from the "route" files. Each one of these files corresponds to a single AIRAC (Aeronautical Information Regulation And Control) cycle, i.e. periods of 28 days used to synchronise all significant operational changes, and to notify all users about them. Within each file, each row represents a waypoint (i.e. a significant navigational point, defined through its latitude and longitude), and all waypoints composing a route are identified through a sequential number - see Table I for an extract. The structure of the airspace is then encoded in a network, where nodes represent waypoints, with pair of them being connected whenever they appear consecutively in the same route. For the sake of clarity, such network will be called Air Route Network (ARN) in what follows. This initial structure is then refined through three filters:

TABLE I
Extract of the File Defining the Airway Structure (I.e. the "route" File) for March 2015.

Route ID	Sequence Number	Latitude	Longitude
A1	1	48.40694	3.29472
A1	2	48.02583	3.91389
A1	3	47.62028	4.55639
	...		
A1	19	30.09222	31.38833
A10	1	37.55722	24.29861
A10	2	37.21	24.39333

- Waypoints not included within 35 and 70 degrees of latitude north, and 15 west and 30 east of longitude were deleted, in order to only include the core of the European airspace. Note that some airways described in the data set reached regions far away from continental Europe; and no trajectory data are available for them. Consequently, and for the sake of coherence in the analysis, those airways have been disregarded. This represented a deletion of approximately 25% of the nodes - for instance, 4,534 nodes of the original 18,155 were deleted for March 2015.
- Due to the previous filter, some small parts of the network can become disconnected from the main core; to solve this, the giant component of the resulting network has been extracted, and all other nodes have been deleted. Note that these isolated nodes are located outside the main core of the network, which has not been affected by this filter.
- As a final point, a few routes appear to include very long segments, with waypoints more than 500 km apart. After a manual examination, it has been determined that these instances correspond to pairs of routes that share the same name, and the corresponding waypoints are consequently reported into a single sequence. As an example, route A1 in AIRAC cycle 2015-03 actually corresponds to two routes, one crossing France and Italy, and a second one over Greece; waypoints from 1 to 12 correspond to the former, and the following ones to the latter. This has been solved by deleting any link of length > 500km; these represented a minimum share of the whole network, e.g. 191 for March 2015.

In order to understand how aircraft actually use those airways, all available aircraft trajectories (including planned and executed) have been mapped to them. As these trajectories are only defined through sets of spatial and temporal coordinates, each aircraft is considered to have flown over a waypoint when its distance was smaller than 0.6 NM, or approximately 1.1 km. This allows to detect both links defined in the ARN, and links included in planned and executed trajectories; note that the three networks may not coincide, as an aircraft flying a direct segment between two non-connected waypoints (i.e. skipping a third one) effectively creates a new link. While the threshold of 0.6 NM has been chosen arbitrarily, results weakly depend on it, with doubling this radius only leading to an increase of 3.9% in the number of matched waypoints. We further infer whether a segment in the ARN was directed or undirected, and the directionality in the former case, by checking the sequence of waypoints flown by each aircraft.

B. Network Analysis

The previously reconstructed data set of air routes can be interpreted as a complex network [5], [6], [17], i.e. a mathematical object composed of nodes, here representing waypoints, that are pairwise connected whenever a route segment connects them - or, in other words, if an aircraft can directly fly between these two waypoints. The network is formally represented by an adjacency matrix A, of size $N \times N$ (N being the number of nodes), where the element a_{ij} has a value of 1 to indicate that there is a directed link between nodes i and j, and 0 otherwise. We describe the resulting network through the following set of standard topological metrics:

- *Degree:* The degree of a node is simply defined as the number of connections departing or arriving to it, i.e. its number of neighbours. Mathematically, these two indicators can be represented for a node i as $k_i^{out} = \sum_j a_{i,j}$ and $k_i^{in} = \sum_j a_{j,i}$. As multiple nodes compose a single network, values are usually aggregated by considering the corresponding average, i.e. the average degree [55].
- *Clustering (CC):* Also called the global clustering coefficient, this metric is defined as the number of closed triplets of nodes (i.e. groups of three nodes completely connected between them) over the total number of triplets, both closed and open (i.e. groups of three connected nodes). It is mathematically defined as:

$$CC = \frac{3N_\triangle}{N_3}, \tag{1}$$

where

$$3N_\triangle = \sum_{k>i>j} a_{i,j} a_{i,k} a_{j,k} \tag{2}$$

is the number of closed triplets, and

$$N_3 = \sum_{k>i>j} (a_{i,j} a_{i,k} + a_{j,i} a_{j,k} + a_{k,i} a_{k,j}) \tag{3}$$

the number of connected triplets. The clustering thus indicates the tendency of nodes to cluster together, or to form closed triangles [56]. In the context of the ARN, these triangles represent redundant routes, i.e. alternative ways of reaching the same destination. To illustrate, an aircraft going from waypoint a to b may go directly, or through an intervening waypoint c, as the presence of a triangle implies that the three waypoints are connected. Such triangles are therefore important in defining the micro-scale resilience of the network.
- *Diameter:* The diameter of a network is defined as the length of the shortest path connecting the two nodes farthest away from each other; or, in other words, the maximum among the lengths of all shortest paths [55]. It thus indicates how many waypoints an aircraft has to cross to reach its destination in the worst case scenario. As waypoints represent intersections between different routes, and hence the intersection of different aircraft flows, a large diameter suggests the possibility of more complex interactions between flights.
- *Efficiency (Eff):* This metric assesses the easiness of moving through the network, or how efficient is the network in propagating information [57], [58]. Being $d_{i,j}$ the length of the shortest path between nodes i and j, and N the number of nodes in the network, the efficiency is defined as:

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{i,j}}. \tag{4}$$

Note that the efficiency is defined between zero and one, corresponding respectively to a completely disconnected (i.e. with no links) and a completely connected (all possible links are present) network. As in the previous case, small values of the efficiency imply the necessity of crossing multiple waypoints, and hence the potential for a higher number of interactions between flights.
- *Assortativity:* The assortativity measures the preference of a network's node to attach to others that are similar to it, in terms of the number of connections they have [59]. It is defined as the average Pearson's linear correlation between the degrees of nodes at the ends of each link. Positive values of assortativity indicate that highly connected nodes tend to connect between themselves, and hence to form a "rich club". On the other hand, negative values suggest that highly connected nodes are linked to small ones, thus forming a star-like structure.
- *Modularity:* Modularity refers to the tendency of nodes to organise themselves into communities (or modules), where communities are groups of nodes densely connected between them, but sparsely connected with the rest of the network [60], [61]. Specifically, given a partition of the network into communities, the modularity Q is defined as the fraction of links that connect nodes belonging to the same community, minus the expected number of such links for a random graph with the same node degree distribution as the given network. The community structure of the network has here been calculated through the celebrated Louvain's algorithm [62]. Note that, as this algorithm has a stochastic component (i.e. it does not always yield the same result), the modularity is here reported as the average over 100 independent realisations.
- *Information Content (IC):* A measure assessing the presence of mesoscale structures, as for instance communities, based on the identification of regular patterns in the adjacency matrix of the network, and on the calculation of the quantity of information lost when pairs of nodes are iteratively merged [63]. A low Information Content indicates the presence of regular structures, while a large value is obtained for irregular or random networks.

It is worth clarifying that the metrics here presented refer to the topological structure of the network, disregarding the fact that this network is embedded in a geometric space. In other words, the shortest path between two nodes is the one involving crossing the minimum number of waypoints, but not necessarily the shortest one in terms of distance flown. As waypoints are the locations where different flows of aircraft can intersect, these topological metrics describe minimum complexity (or minimum interaction) paths. Additionally, this analysis is a topological one, i.e. it disregards how the air routes are used - that is, how many aircraft fly on each segment; the planned and executed traffic will nevertheless be taken into account in the analysis of the network vulnerability, see Section III-C.

It is further important to note that some metrics, specifically the clustering, the efficiency and the Information Content, depend on the number of nodes and links composing the network. To illustrate, a dense random network will have a higher efficiency than a sparse one, not because its topology is better designed, but just because of the presence of a larger number of direct paths. This implies that the values obtained by these metrics cannot be used to compare heterogeneous networks [64]. As a solution, we here normalise these values by considering, for each network, an ensemble of 10^3 equivalent random graphs, i.e. with the same number of nodes and links; the three metrics are then reported as $\mathrm{CC}/\mathrm{CC}_{ER}$, $\mathrm{Eff}/\mathrm{Eff}_{ER}$ and $\mathrm{IC}/\mathrm{IC}_{ER}$, where the subscript ER indicates the average value obtained in the random graphs. In all cases, values larger (smaller) than one indicate that the real network has a stronger (respectively, weaker) property than what expected in a network without structure.

C. Vulnerability Analysis

Vulnerability, as usually defined in complex network theory [65], [66], [67], refers to the ability of the system to maintain its structure and function when one (or more) of its elements is (are) deactivated. We here evaluate the resilience of the ARN in terms of the additional flown distance caused by the deactivation of a link on one hand, and the deactivation of an entire airspace on the other. While these events are highly infrequent, they may be caused by extreme adverse weather phenomena, or by technical failures. Note that other alternatives also exist, as for instance approaches based on algebraic connectivity [68], [69], [70], or on node and link centralities [71]; the reader should be aware that what here presented is only one of many possible definitions of network vulnerability.

When one or more links are deactivated, two different situations may arise. On one hand, some flights may have to be cancelled, as no suitable trajectory can be found - for instance, if the affected airspace involves the departure or arrival airport. These cancellations are unavoidable, and are therefore not considered in this work. On the other hand, some trajectories may have to be rerouted, leading to a rerouting cost. Such cost is estimated by re-evaluating the shortest path length between the first and last point of each flight, respectively denoted by u and v, such that:

$$\Delta d_i(u,v) = d'_i(u,v) - d_i(u,v) \geq 0, \tag{5}$$

with $d_i(u,v)$ being the length, in nautical miles, of the original trip of aircraft i, and $d'_i(u,v)$ the length after the corresponding set of links has been removed. In other words, we suppose that the aircraft is always looking for the best trajectory, in terms of flown distance, between the initial and final points; and that the cost of link deactivation is proportional to the difference between the best available alternative and the originally planned trajectory. The global rerouting cost due to the failure of a local set of links is given by the sum over all flights i:

$$\Delta D = \sum_i^N \Delta d_i. \tag{6}$$

ΔD integrates information about both the structure of the network, and the volume of traffic passing through the affected region. Due to the high variability in traffic between different seasons and years, and in order to be able to compare results from different AIRAC cycles, we also consider a normalised rerouting quantity using the total optimal distance D_{TOT},

$$\Delta \widetilde{D} = \frac{\Delta D}{D_{TOT}} = \frac{\Delta D}{\sum_i^{N_{traj}} d_i}. \tag{7}$$

It is worth noting that both metrics are approximations of the real values. First of all, they suppose that aircraft always minimise the total flown distance; while this is generally true, other aspects are also taken into account, like heterogeneous navigation taxes, other operational considerations, or local weather phenomena - see [72], [73], [74], [75] for examples of more complex rerouting strategies. Secondly, we do not allow for rerouting outside the existing ARN, e.g. through direct trajectories between otherwise unconnected nodes. Thirdly, traffic data has been obtained by integrating all flights included in an AIRAC cycle, while the disturbance to the system may last substantially less time.

Finally, we evaluate the vulnerability of the system under two conditions: the deactivation of one link at a time, and of all links in a specific region. In the latter case, the European airspace has been divided into non-overlapping regions of size $\Delta\phi = 1.0^\circ$ of latitude and $\Delta\lambda = 1.5^\circ$ of longitude, i.e. approximately 60×60 NM; and all links crossing them have been deactivated at the same time. Therefore, while the former case corresponds to a localised disruption, the latter is designed to capture the interdependencies between neighbouring airways.

IV. Results: Network Topology and Its Evolution

As is to be expected, the structure created by airways in Europe is a complex one, comprising more than 17,000 nodes and 31,000 links - see Fig. 2 left panel for a graphical representation. In order to put these numbers in context, around 20,000 flights cross the European airspace every day; the system thus comprises more airway segments to organise aircraft flows, than aircraft using such infrastructure. Node degrees and the length of each link are organised according to a distribution resembling an exponential one - see central and bottom right panel of Fig. 2, respectively depicting the cumulative probability of links as a function of their length, and of nodes as a function of their degree.

Note that this is at odds with some results suggesting that both distributions follow a power law [15], or showing an almost

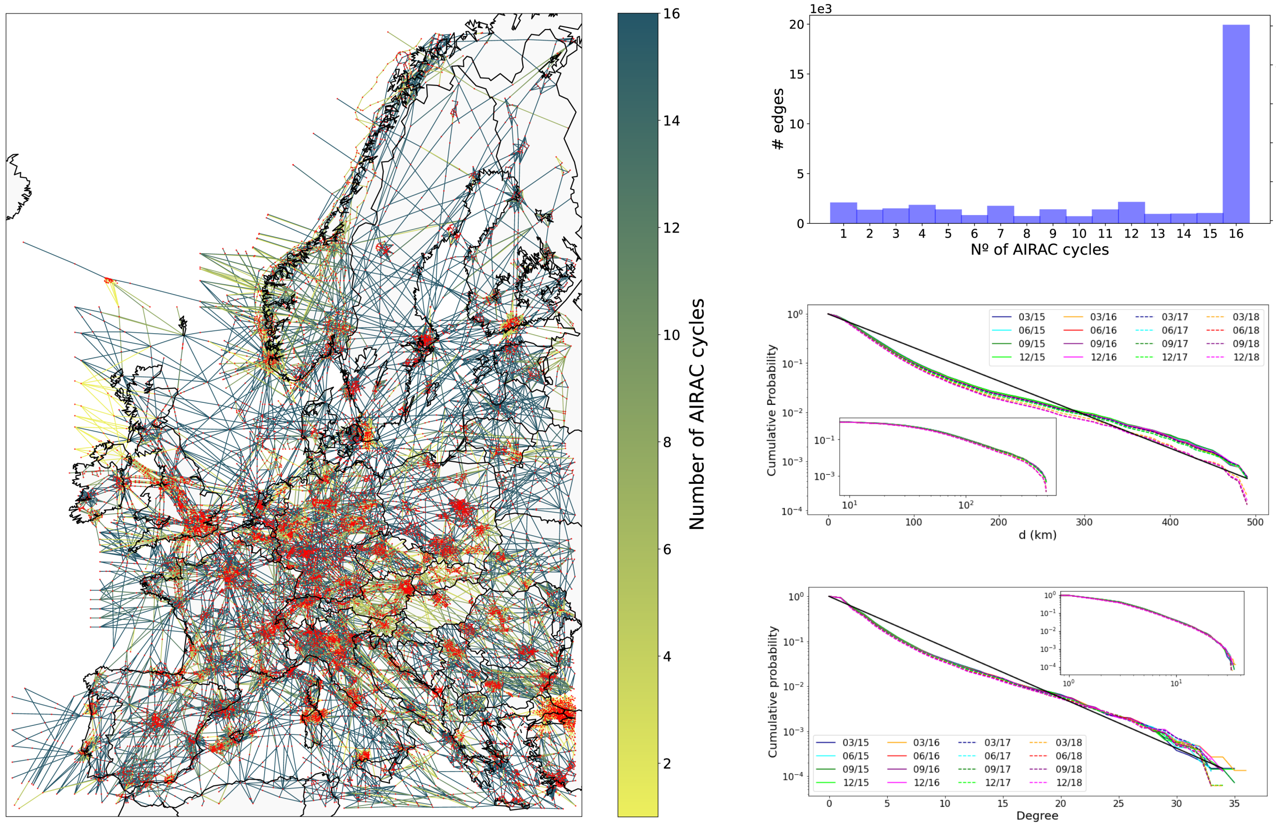

Fig. 2. Macro-scale properties of the airways network. (Left) Graphical depiction of the network. Nodes are marked in red, and the colour of links corresponds to the number of times (AIRAC cycles) they appeared in the data set - see right colour bar. (Top right) Histogram of the number of links, as a function of the number of networks they appear in. The right axis reports the same values as a percentage over the total number of edges. (Middle right) Cumulative probability distribution of links as a function of their length, in km. (Bottom right) Cumulative probability distribution of nodes as a function of their degree. In the middle and bottom right panels, insets depict the same distributions in a log-log scale.

perfect fit to an exponential distribution [13], [48]. This difference is easily explained by the fact that the complete transnational network is here considered, as opposed to individual national networks. Due to the larger size of the transnational network, a power-law distribution would require having nodes of higher degree, i.e. waypoints where a large number of routes converge; this is nevertheless avoided operationally, as such waypoints would generate high controller workloads, and hence a reduction in safety. It is further theoretically known that a reliable estimation of the scale-freeness of a network requires the availability of multiple orders of magnitude in node degrees [76]; hence, claims about a power-law distribution in the degree of nodes in small national networks should be interpreted with caution. The top right panel of Fig. 2 further shows the number of times each edge appears in the network. As a first hint to the non-stationarity of the system, almost half of the links are not always present in the network, suggesting a substantial evolution.

The size of the network, and specifically the evolution of the number of nodes and links composing the Largest Connected Component (LCC) of the network across the four years, is presented in Fig. 3. Note that three different networks are here considered: (i) the one created by airways, as originally defined; (ii) the one comprising only nodes and links included in the flight plans of flights operating during that time period; and (iii) the one comprising only nodes and links actually used during operations. As is to be expected, a small but significant part of the network is not used in planning the flights, as may for instance correspond to airspace shared with military users. At the same time, note that the network corresponding to the executed trajectories can be underestimated, due to the limited temporal resolution of trajectory data. Finally, the number of isolated components, i.e. of nodes not composing the core of the network, also comprises waypoints that were deleted as part of the network geographical preprocessing, hence the large value. From a general perspective, it can be appreciated that the network has increased in size. Additionally, the number of links for executed flights almost doubled from 2015 to 2017; as these are substantially more than those encoded in the airway network, this increment has to be interpreted as a more frequent use of "direct routing," i.e. when one aircraft is allowed to fly outside an airway to reduce delays. This trend seems nevertheless to be reversed starting from mid-2017, with values returning to levels seen in mid-2015.

Delving deeper into this evolution, Fig. 4 reports how links were added or deleted between different networks. Specifically, the two panels correspond to comparing each available network with the one preceding it (sequential comparison, left panel), and to comparing each network with the first one available, i.e. March 2015 (cumulative comparison, right panel). The four lines correspond to: (i) the total number of links in the network (black

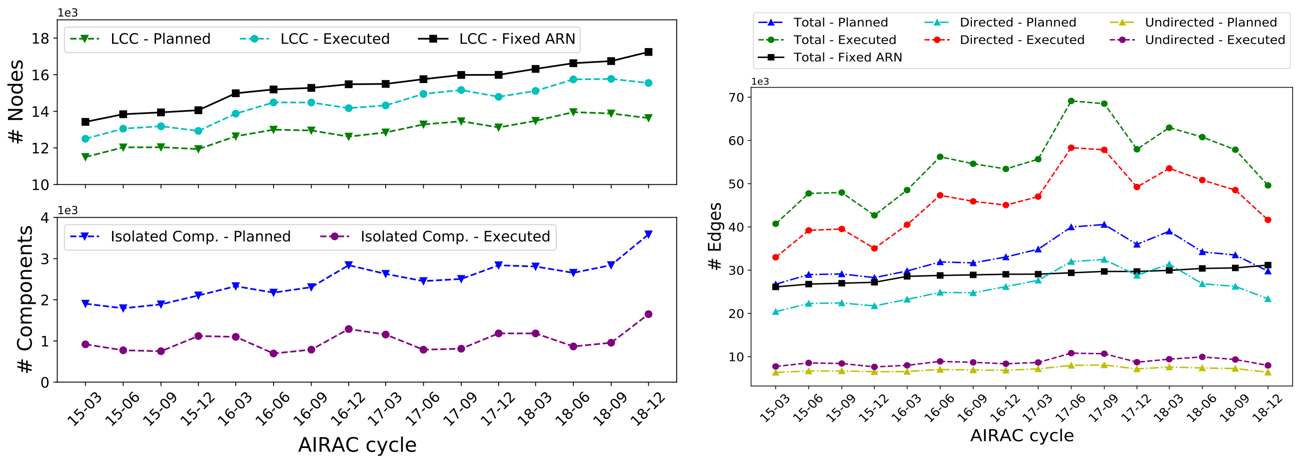

Fig. 3. Evolution of the network size. Panels report the evolution of the number of nodes composing the largest connected component (LCC) (top left); the number of isolated components (bottom left); and of the number of links in the LCC (right panel) as a function of time. Results are reported for the published airway network, and for the networks created by planned and executed trajectories. Additionally, in the right panel, links are divided into directed and undirected ones.

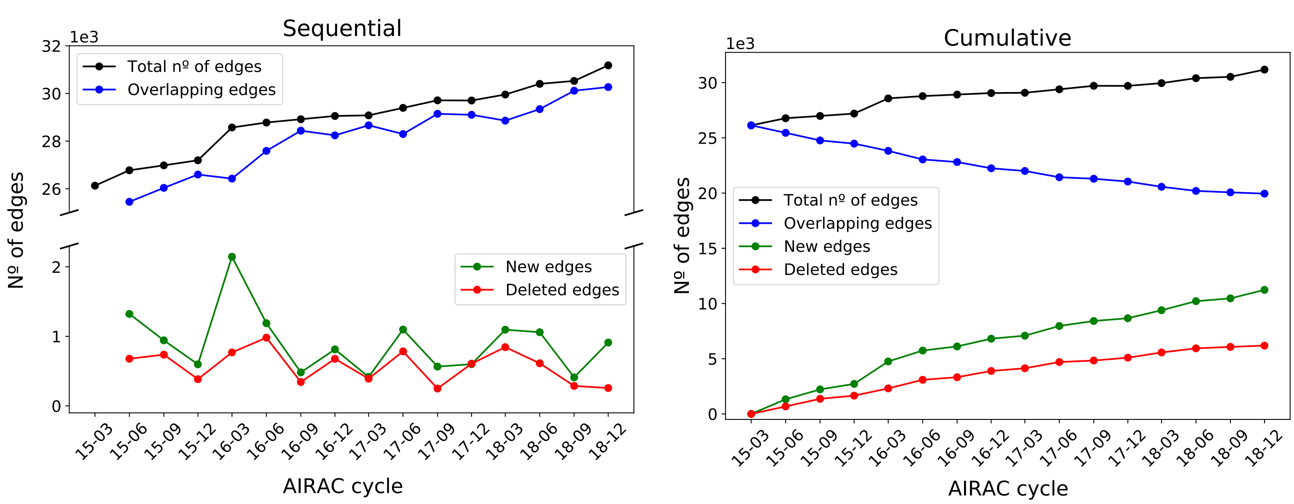

Fig. 4. Creation and deletion of links. The left and right panels depict the evolution of the number of links that have changed, respectively between consecutive pairs of networks (left panel) and with respect to the first one (right panel). Lines represent: the total number of links (black), the number of overlapping (or preserved) links (blue), and the number of new and deleted links (green and red).

lines); (ii) the number of links that were present in the reference network (blue lines); (iii) the number of new links, i.e. links that were not present in the reference network (green lines); and (iv) the number of links that have disappeared (red lines). It can easily be appreciated that changes across these four years were not minor. For instance, comparing the last (December 2018) and first (March 2015) networks, approximately 12,000 of the final 32,000 links were not the same, corresponding to an overlap of $\approx 63\%$; of these, more than 10,000 links were new additions, and 5,000 were deleted. More generally, a constant trend can be seen, in which links are always added more than deleted - on an average pace of 1,000 new links and 500 deleted links per AIRAC cycle.

In order to obtain a deeper understanding of the evolution of the topology of the network, beyond the previously observed increase in size, Fig. 5 reports the values of several classical topological metrics (defined in Section III-B) as a function of time. Several conclusions can be drawn. First of all, the increase in the number of links is not enough to compensate for the increase in the number of nodes; in other words, the network is getting larger and sparser - see the downward trend in the link density. Secondly, some metrics seem to be highly correlated, e.g. the clustering coefficient with the assortativity and the modularity (respectively 0.99 and 0.98 according to a Spearman's rank correlation test, p-values of respectively $1.09 \cdot 10^{-13}$ and $1.01 \cdot 10^{-10}$). Note that this is not the trivial result of changing the network size, as metrics have been normalised using the expected value in equivalent random graphs (see Section III-B); they therefore point towards a structural evolution of the network. When considering the simultaneous decrease over time of the link density and the increase of the clustering coefficient, the resulting picture is a process in which links are reconfigured to favour triangles, a configuration that is more resilient to disruptions and is also natural in planar graphs. This seems

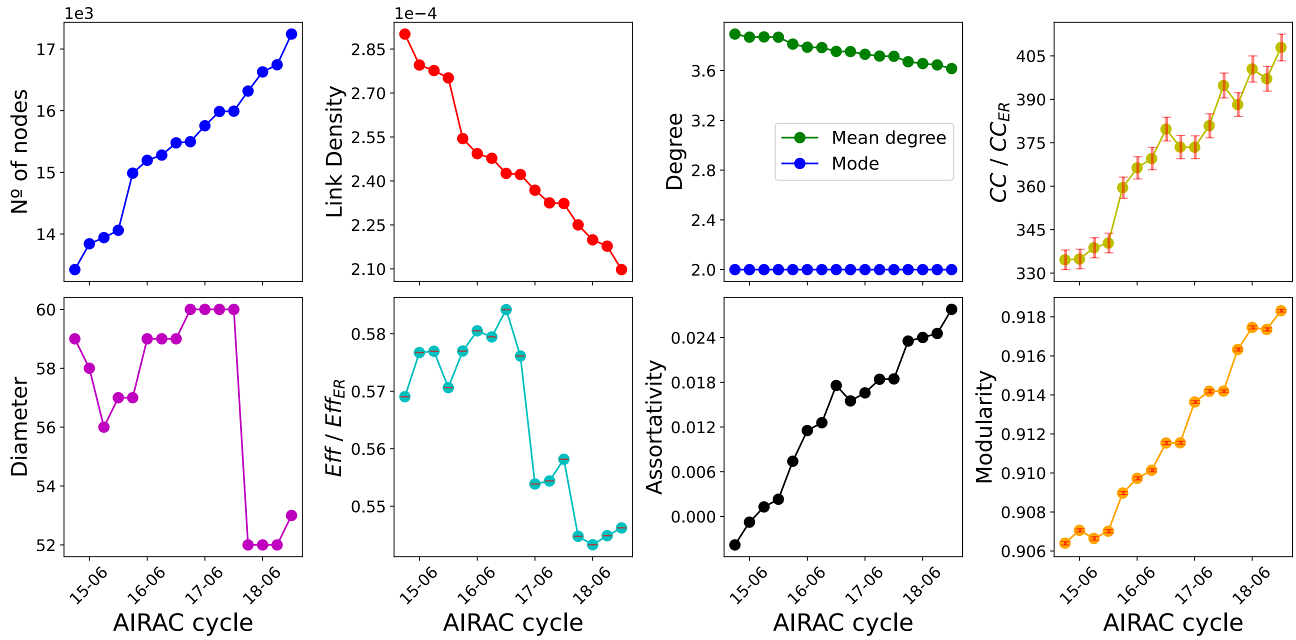

Fig. 5. Evolution of eight topological metrics of the airway network throughout time - see Section III-B for definitions. For the clustering coefficient and efficiency, reported values correspond to the normalisation using random networks, with error bars corresponding to the standard deviation obtained over 10^3 random realisations. The modularity is reported as the average of 100 realisations of Louvain's algorithm, with the error bars corresponding to the standard deviation.

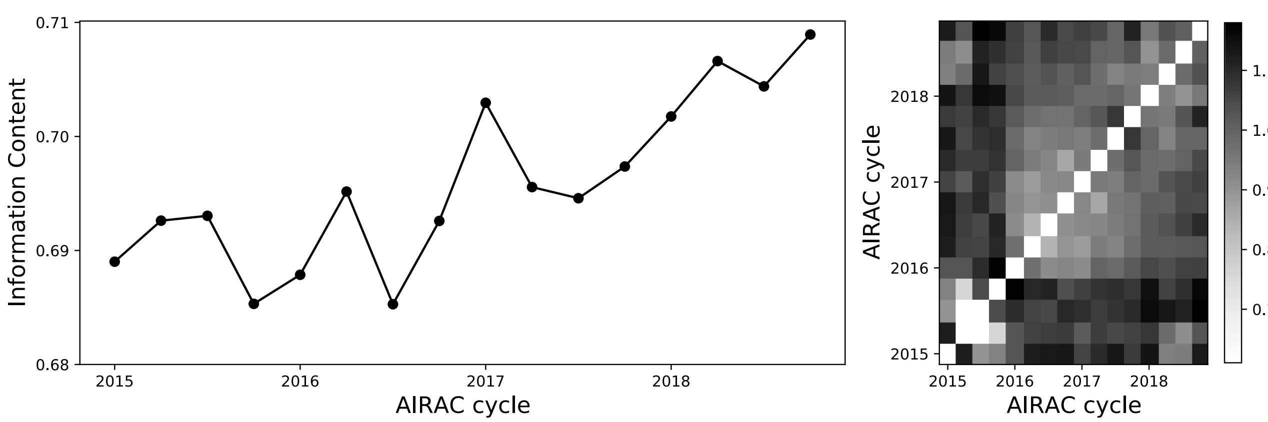

Fig. 6. Information Content of the ARN. (Left) Evolution of the normalised IC (see Section III-B for definitions) through time. (Right) Normalised IC when comparing pairs of networks. Smaller values (brighter colours in the right panel) indicate more regular structures.

to be further confirmed by the increase in modularity; in other words, short-range connections are favoured over long-range ones, these latter usually connecting distant communities of the network. Both the diameter and the efficiency suffered sudden changes, the first dropping from 60 to 52 in mid-2017, and the second dropping from 0.58 to 0.55 in mid-2016. While these drops are minor in absolute terms, they are substantially larger than the variability observed in other years; additionally, they are correlated with changes in the resilience of the network, as will be discussed in Section V.

We finally analyse the evolution of the IC of the network. Specifically, Fig. 6, left panel, reports the evolution of the normalised IC across time. Values are significantly smaller than 1.0, in agreement with the fact that the network is not random, but instead has an internal structure with some degree of regularity - also a consequence of being planar; still, a change can again be observed starting from year 2017. The right panel of the same figure shows the normalised IC obtained by comparing pairs of networks, in order to understand the degree of regularity in the difference between them [77]. Smaller values of the normalised IC, and brighter colours in the figure, indicate that the difference between the corresponding pair of networks is more regular; the appearance or deletion of a link is thus not independent from other changes, but is instead part of a global schema. This regularity is apparent between the four networks corresponding to year 2015. In other words, changes in the network through 2015 seem to have a clear structure; in contrast, differences between these four networks and all the others seem to be more local in scope, affecting a few links at the time, but without a common guideline.

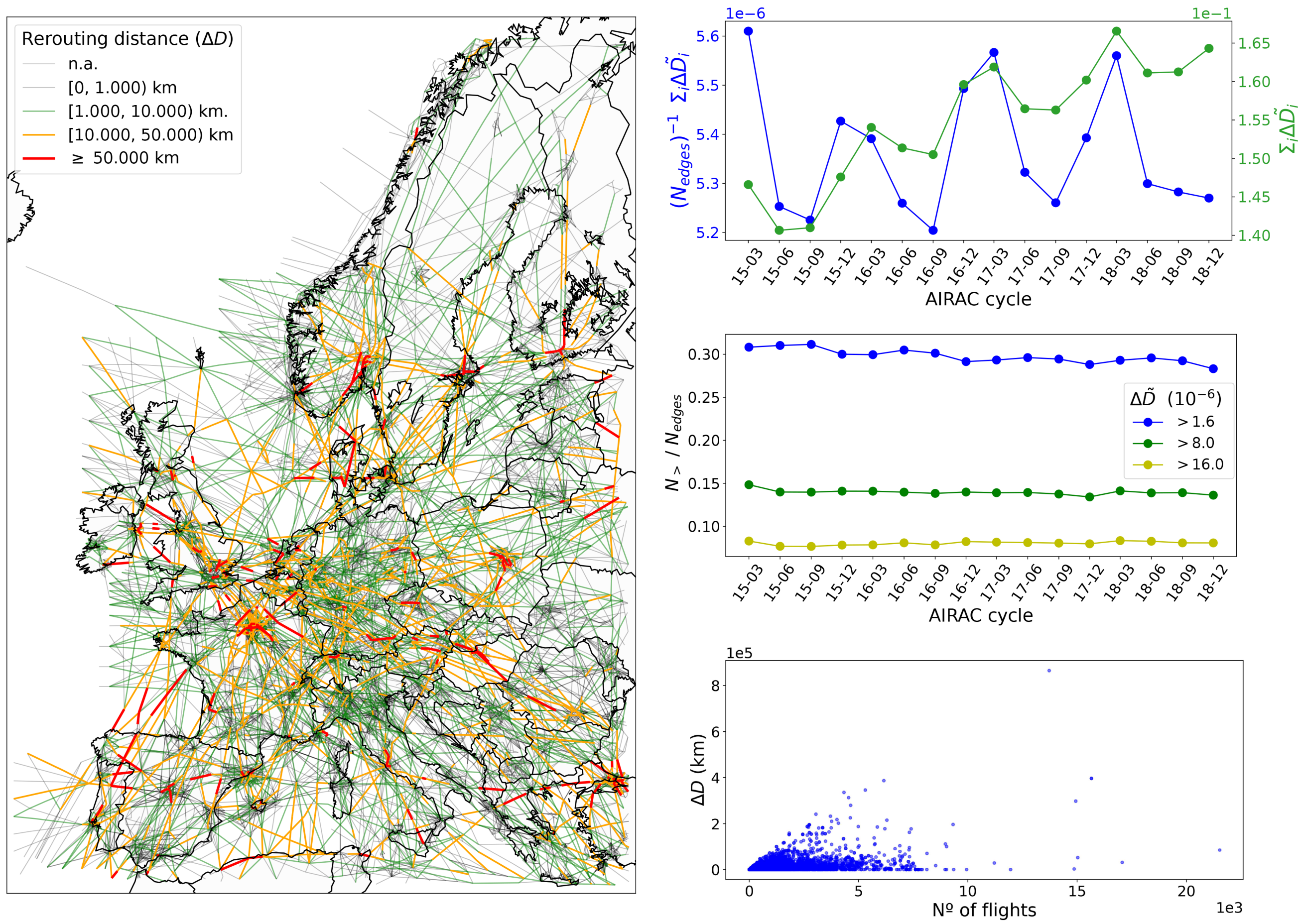

Fig. 7. Network vulnerability to link deactivation. (Left) Vulnerability of each link composing the network of March 2015, with colours indicating the additional distance to be flown if the corresponding link were deleted. (Top right) Evolution of the global vulnerability across time, in terms of the rerouting distance $\Delta\tilde{D}$ summed across all links ($\sum_i \Delta\tilde{D}_i$, green line, right Y axis) and the average rerouting distance per link ($\sum_i \Delta\tilde{D}_i/N_{edges}$, blue line, left Y axis). (Middle right) Evolution of the fraction of three categories of links over the total number; each category represents the fraction of the total rerouting distance that would be caused by their deletion. (Bottom right) Scatter plot of the rerouting distance caused by the deletion of each link, as a function of the number of flights through it flying.

V. Results: System Resilience

We then move to the analysis of the resilience of the network, using the metrics described in Section III-C, starting with the analysis of the resilience by route segments. Specifically, the left panel of Fig. 7 depicts the European ARN with colours indicating the vulnerability of each link, in terms of the additional distance that aircraft would have to fly if that link were deactivated. The evolution throughout time of the additional rerouting distance, summed over all links, is further presented in the top right panel of Fig. 7, green line. This measure increases with time, but such trend is mainly due to the increase in the size of the network; when the average additional distance per link is plotted (see the blue line), the trend is lost. It is nevertheless interesting to note that the vulnerability is lower in summer - and hence, the resilience is larger. This is not caused by changes in the topology of the system, which presents no seasonal trend - see Fig. 5. This trend is opposite to what may be caused by the increase in traffic volume typical of August and September, and is rather due to a change in the traffic flows, i.e. the only other element included in the calculation of the resilience. Consequently, it can be concluded that aircraft use more resilient parts of the network during the summer.

The middle right panel of Fig. 7 further represents the evolution through time of the relative share of links, when grouped into three categories according to their vulnerability. As may be expected from the previous results, the share of more vulnerable links (yellow line) slightly increases over time, at the expense of especially the least vulnerable ones (blue line). One may finally hypothesise that there may exist a correlation between the rerouting distance caused by each link, and the number of flights passing through it - in other words, that longer rerouting distances are only caused by the need of rerouting a larger number of flights. This is nevertheless disproven by the bottom right panel of the same figure, depicting a scatter plot between both quantities. No clear trend can be identified; significant rerouting can thus also be caused by less transited and less redundant links, as e.g. those crossing sea or peripheral regions.

We further study the resilience of the system to the deactivation of an entire region of the airspace, specifically of all links crossing it. Similarly to the previous case, the left panel of Fig. 8 depicts the European airspace, with colours indicating the

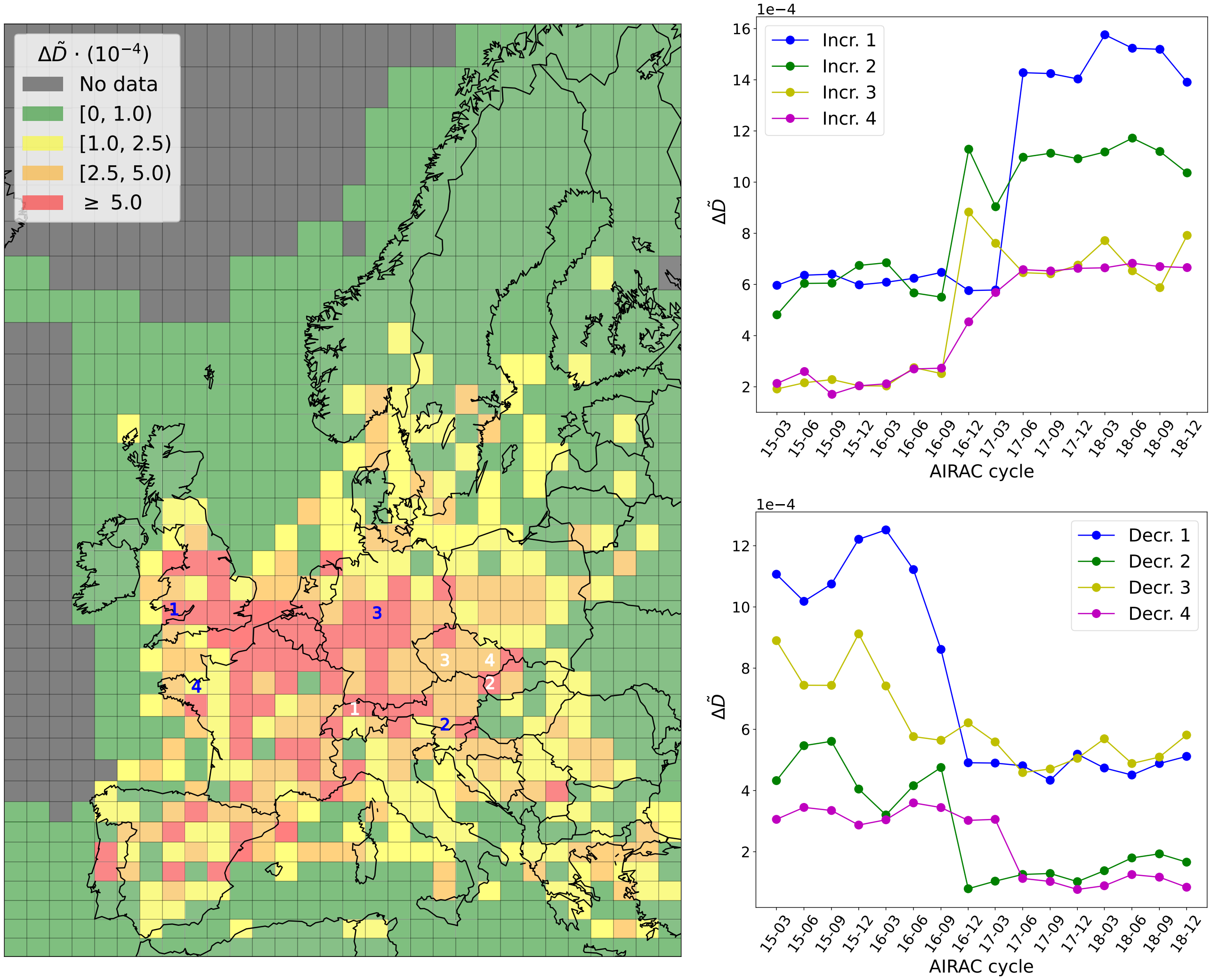

Fig. 8. Network resilience to region deactivation. (Left) Fraction of additional route length, when the considered section is deactivated, averaged over the four years. (Top right) Four regions with the highest increase in vulnerability (largest increment in route length) between 2015 and 2018. (Bottom right) Four regions with the highest decrease in vulnerability between 2015 and 2018.

fraction of additional distance needed to be flown. For the sake of clarity, regions for which data were not available (i.e. with no airways or no flights crossing them) are depicted in grey. It can be appreciated that most critical regions are located in the centre of Europe, something that was not evident from Fig. 7. When combined with results from the previous figure, this suggests that links in central regions are resilient because they can count on alternative nearby routes; yet, if all links in such regions are deleted, the damage is amplified by the many flights passing through them.

The two right panels of the same figure further report the evolution of the four airspace regions with the largest increase in vulnerability (top panel), and of the four with the largest decrease (bottom panel). The location of these eight regions is also indicated on the left map, respectively by white and blue numbers. In all eight cases, an important transition can be observed at the end of year 2016, with a substantial change in the vulnerability surrounded by more flat time periods. As previously seen, this has potentially been caused by a reconfiguration of the topology of the network (Fig. 5). Specifically, for the region with the largest increase in $\Delta\widetilde{D}$ (blue line in the top right panel of Fig. 8), this metric is both correlated with the assortativity and modularity (respectively 0.65 and 0.69 according to a Spearman's rank correlation test, p-values of respectively 0.0067 and 0.0028). Similar correlations, albeit with negative signs, are found in the case of the region with the largest decrease in $\Delta\widetilde{D}$ (blue line in the bottom right panel of Fig. 8). Such changes in the vulnerability are nevertheless local in nature, as no special trend can be seen in Fig. 7 for the end of year 2016. In other words, the reconfiguration of the network structure observed in 2016 may have positively and negatively affected different regions, for a zero net effect.

VI. Modelling the Evolution of the Network

In the previous sections, we have shown how the European airways network is not a static entity, but instead evolves through time in a complex way; one remaining question is what are the rules, or priorities, guiding such evolution. As it is not possible to directly extract these rules from the data alone, we here consider a different approach, based on comparing the prediction power of different evolutionary models. Specifically, we define a set of simple models that, given as input the network as observed in one time window, apply a set of rules and yield two lists of links, respectively ranking those with the highest probability of being removed, and those with the highest probability of being added to the system. We then check the rate of successful predictions, compared against a random null model; the best performing model is expected to be the one most similar to the real rules used to change the system.

We define three models for deleting links, as described below. In order to simplify the notation, and considering a direct route segment between waypoints i and j, we here denote by $a_{i,j}$ the availability of such segment; by $s_{i,j}$ the yielded score; by $d^g_{i,j}$ its geographical length, in NM; by $r^g_{i,j}$ and $r^t_{i,j}$ the length, respectively geographical (in NM) and topological (in terms of number of intervening waypoints), of the shortest alternative route connecting i to j; and by $v_{i,j}$ the number of aircraft that have crossed the segment. In all cases, links are deleted in decreasing order of score.

- *Strategy 1:* The score of each link is defined as the inverse of the number of flights crossing it, i.e. $s_{i,j} = 1/v_{i,j}$. In other words, those links that are underused are deleted first, as their deletion should suppose the smallest impact.
- *Strategy 2:* Link scores are defined as in Strategy 1, but are further divided by the length (in terms of jumps) of the shortest paths connecting the two ends of each link, when that link is deleted: $s_{i,j} = 1/(v_{i,j} \cdot r^t_{i,j})$. Therefore, links connecting waypoints that are otherwise poorly connected, and whose deletion would suppose a long rerouting, will have a lower score, and will be retained in the network.
- *Strategy 3:* Link scores are again defined as in Strategy 1, but are then divided by the difference, in nautical miles, between the original link length and the length of the alternative shortest route connecting the two ends of the link: $s_{i,j} = 1/[v_{i,j} \cdot (r^g_{i,j} - d^g_{i,j})]$. While similar to Strategy 2, this approach is more realistic, as it considers the additional distance that aircraft have to fly due to the deletion of that route segment. In other words, we prioritise the deletion of those links that are not contributing to the efficiency (in terms of distance flown) of the system.

In a similar way, two strategies are defined for link creation, where links are added in decreasing order of score:

- *Strategy 1:* Links can be created whenever three waypoints are connected forming an open triplet, i.e. one of the three possible links between them is missing, or, in other words, they form an incomplete triangle. This is known as "triadic closure" in social networks [78], [79]. The score for creating that missing link is defined as the reduction, in nautical miles, in the length to be flown to cross the triangle. Mathematically, the score is defined as $s_{i,j} = \max_k a_{i,k} \cdot a_{k,j} \cdot (r^g_{i,k} + r^g_{k,j} - r^g_{i,j})$. In synthesis, this is the opposite of the third deletion strategy, and links are created whenever they suppose a reduction in the flown distance.
- *Strategy 2:* Scores calculated in the previous strategy are further multiplied by the number of aircraft crossing the two existing links, i.e. $s_{i,j} = \max_k a_{i,k} \cdot a_{k,j} \cdot (r^g_{i,k} + r^g_{k,j} - r^g_{i,j}) \cdot (v_{i,k} + v_{k,j})$. In other words, priority is given to the completion of highly transited triangles, by weighting the previous score by the actual traffic crossing such triangle.

Both sets of strategies are compared against a null model, in which links are created and deleted at random. Results are presented in Fig. 9, for link deletion (left panel) and creation (right panel), as the number of links correctly predicted across the 16 networks as a function of the links added/deleted according to each strategy. The figure also includes the average result obtained in 200 realisations of the null model (solid back lines), and the corresponding 90 (solid grey lines) and 99 percentiles (dotted grey lines).

A couple of interesting conclusions can be drawn. First of all, it is easier (even for a random model) to correctly forecast deleted links than created ones. This is because no further geometrical restrictions (e.g. maximum length) have been imposed, and thus the number of disconnected pairs of nodes is much larger than the number of connected pairs; hence, the search space when creating links is much larger. Secondly, the third strategy for deletion, and the second one for creation, are better than the other ones; as may be expected, the number of flights affected by each change is a major concern for the network planners. Finally, while these two strategies outperform the null model on average, they yield a number of correct predictions below the 99 percentile; this suggests that, even if the modelled rules are important, these do not describe all the elements involved in the evolution of the network. While the real motivations driving the evolution of the air route networks are not public, we hypothesise that they may include demand and traffic forecasts, and therefore predicted changes in traffic flows; and the need of reducing the complexity (from the point of view of air traffic control) of some intersections. As data connected to those motivations are not currently available, more sophisticated models to test these hypotheses cannot be built at this time.

VII. Discussion and Conclusions

While complex network theory has frequently been applied to understand the structure and dynamics of the air transport system, much less attention has been devoted to the study of the topology of the technical system supporting it, i.e. the network of air routes. This is probably due to the fact that this network is not expected to radically change over time, as suggested by [14]: any modification in the structure can result in operational changes (and hence additional workload) for both airlines in planning their flights, and for air traffic controllers managing the traffic. In this work, we have tested this hypothesis against a large-scale data set of flights and air routes corresponding to the European airspace from 2015 to 2018. The air route structure has been represented through complex networks, in which intersection points (e.g. navigational aids) have been mapped into nodes, and air route segments into links. The resulting topology, its evolution over time, and its resilience to disrupting events have

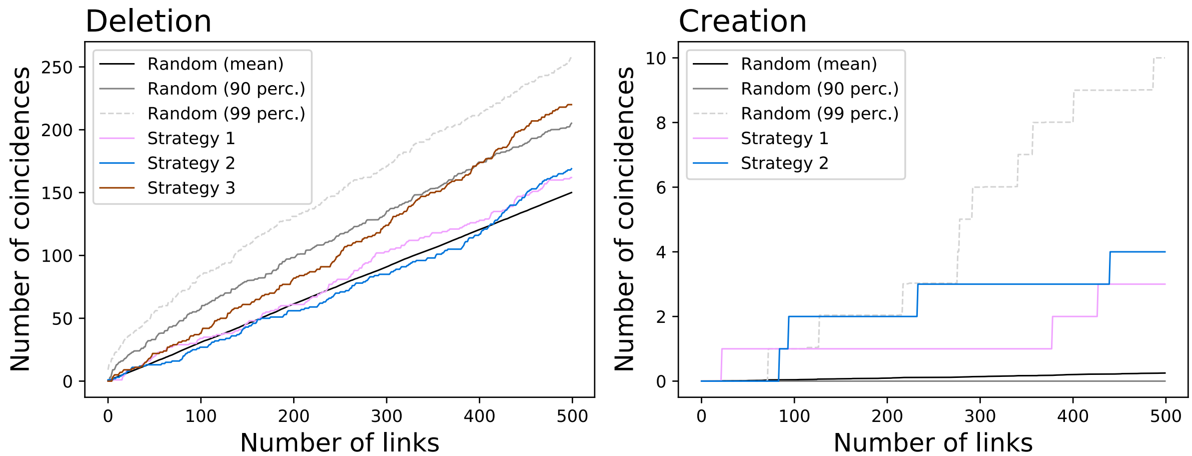

Fig. 9. Results of the synthetic model of network evolution. Left and right panels depict the number of correctly forecasted links, respectively deleted (left) and created (right), as a function of the number of modified links. Colours indicate different strategies and null model - see Section VI for details.

then been analysed using standard network theory metrics and techniques.

Results indicate a dynamic system, with only $\approx 63\%$ of the links being the same between the beginning and the end of the considered time period. The air route network has constantly been growing, both in terms of number of nodes (waypoints) and links (segments of airways) - see Fig. 3. Links have nevertheless not been added using a constant logic, resulting in a change in the topological characteristics of the network around year 2017 (Fig. 5). Most notably, the appearance of short-range connections, and specifically of triangular structures, seems to have been favoured over long-range connections. This resulted in a substantial change in the vulnerability of several parts of the airspace around that same year (Fig. 8). We have also shown that changes can be partly explained, but not completely, taking into account factors like redundancy of links and the volume of traffic on them (Fig. 9).

While the analyses here proposed are based on standard complex network concepts, the obtained results, and specifically the fact that the air route network is more dynamic than what initially suspected, have far-reaching consequences. For the sake of clarity, these will here be organised into three groups.

First of all, our results should be interpreted in the context of air transport research and literature. As here shown, the structure of the air route network is highly dynamic, and cannot therefore be taken for granted. This implies that the reproducibility of previous works, that neglected to report exact information about what period of time the data correspond to (see e.g. [47], [49]), is strongly hindered. In other words, our results should be interpreted as a warning call about the need of providing precise information about how the network has been obtained and analysed.

Secondly, the dynamic nature of the network opens new avenues for research. These may include the forecast of the future evolution of the network structure, in conjunction with the forecast of future market demand; and its optimisation, in terms of reduced flown distance, reduced workload for air traffic controllers [49], and increased robustness to disruptions [47]. Additional topics may include unveiling relationships between the structure of the network and operational aspects, e.g. the appearance and absorption of en-route delays; comparing the route networks of different countries/continents, again with the objective of identifying inefficient structures and optimising them; and the analysis of how the route networks of different countries/continents are connected. All these research topics would not be relevant if the network was not allowed to change, or if changes were only limited to a few links per AIRAC cycle; on the other hand, the assumption of the network stationarity is probably behind the lack of research works tackling these questions. It is also worth noting that the size of the system makes some of these analyses challenging from a computational point of view. To illustrate, the computation of the efficiency in the 16 networks (including the value in the 10^3 random equivalent graphs) required more than 260 hours; and the link and region vulnerabilities, i.e. Figs. 7 and 8, respectively 1250 and 1600 hours (total computation time using AMD Epyc2 7402 processors and 16 GB of memory for each core). The air route network can therefore be seen as an interesting case study for benchmarking new optimised algorithms.

Thirdly, results here presented highlight the need for more precise and recent data, in order to facilitate the aforementioned studies. Specifically, this contribution has been based on the EUROCONTROL's R&D Data Archive, the only official and public data source for air transport research in Europe - i.e. not considering those provided by private companies and organisations, and those made available by EUROCONTROL only to air navigation service providers and airline operators. Yet, the limitations of this data archive are evident, and the three years delay with which data are published is a major obstacle against timely research works. Additionally, as shown in Fig. 3, the structure substantially changes when considering the "published network," and when deriving links from planned and executed trajectories. While waypoints have here been associated with trajectories using a distance threshold, this process is prone to errors and is dependent on the precision of the trajectory information. More reliable associations, and hence more reliable results, would be possible if executed trajectories were actually described in terms of waypoints.

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