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DISSERTATION

EUROPEAN AIR TRANSPORT TRANSFORMATION: NETWORK-BASED INSIGHTS INTO POST-COVID AND RESTRICTIONS-INDUCED ROUTE SHIFTS

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OLGA KURAIAN

SUPERVISION:
PROF. JOÃO TIAGO APARÍCIO
PROF. CARLOS J. COSTA

JURY:
PRESIDENT: PROF. MÁRIO JOSÉ BATISTA ROMÃO
RAPPORTEUR: PROF. CARLOS MANUEL PEREIRA CAPELA BERNARDINO
SUPERVISOR: PROF. JOÃO TIAGO APARÍCIO

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GLOSSARY

ADS-B – Automatic Dependent Surveillance–Broadcast.

COVID-19 – Coronavirus Disease of 2019.

CRISP-DM – Cross-Industry Standard Process for Data Mining.

EU – European Union.

EUROCONTROL – European Organisation for the Safety of Air Navigation.

GCC – Giant Connected Component.

ICAO – International Civil Aviation Organization.

MFW – Master’s Final Work.

POST-DS – Process Organization and Scheduling Electing Tools for Data Science.

PR – PageRank.

SQL – Structured Query Language.

WCC – Weakly Connected Component.

ABSTRACT

This dissertation examines the development of the European air transport network between 2019 and 2025 in the context of two major systemic disruptions: the COVID-19 pandemic and subsequent airspace restrictions affecting the region. Using flight data from the OpenSky network, the study applies network science methodology to analyze changes in the structure, connectivity, centrality of airports, and network resilience on quarterly and annual time scales.

Directed weighted graphs were constructed for each period, and centrality measures were used to quantify the importance of airports and assess changes in the network hierarchy. PageRank was chosen because it captures indirect connectivity and is widely used for ranking in directed graphs. To study long-term dynamics, annual PageRank trajectories were clustered using the K-means method, which revealed four distinct behavioral patterns among European airports. Network resilience was assessed using percolation experiments simulating both targeted and random node and edge removal.

The results show that COVID-19 caused a sharp structural collapse in 2020, followed by a gradual recovery and significant reorganization in 2022–2025. Traditional Western European transport hubs such as Frankfurt, Munich, and Amsterdam retained their influence but experienced relative decline. In contrast, several airports, such as Palma de Mallorca, Istanbul, Nice, Porto, and Krakow, have gained in importance, reflecting the rerouting of traffic flows and the rapid recovery of leisure and tourism-oriented routes.

Percolation tests showed that the 2021 network was the most fragile, while the 2025 network demonstrated the greatest resilience, indicating increased redundancy and a more distributed hub structure.

Overall, the European air transport network has not simply recovered to its pre-pandemic state; it has transformed into a more diversified, interconnected, and resilient system. The results indicate a gradual geographical rebalancing of European connectivity and provide a methodological framework for monitoring structural changes in complex transport networks.

KEYWORDS: Airport connectivity; Network; Resilience.

JEL CODES: C63; D85.

RESUMO

Esta dissertação analisa a rede europeia de transportes aéreos entre 2019 e 2025 em consequência de duas grandes perturbações sistémicas: a pandemia da COVID-19 e as subsequentes restrições do espaço aéreo regional. Utilizando dados de voo da rede OpenSky, o estudo aplica a ciência de redes na analise de alterações na estrutura, conectividade, centralidade aeroportuária e resiliência em escalas trimestrais e anuais.

Construíram-se grafos orientados e ponderados para cada período, utilizando medidas de centralidade para quantificar a importância dos aeroportos e avaliar a hierarquia da rede. O PageRank foi escolhido por captar a conectividade indireta, sendo ideal para a classificação nestes grafos. Para estudar a dinâmica a longo prazo, as trajetórias anuais do PageRank foram agrupadas via método K-means, revelando quatro padrões comportamentais distintos. A resiliência foi avaliada através de experiências de percolação que simularam a remoção direcionada e aleatória de nós e arestas.

Os resultados mostram que a COVID-19 causou um colapso estrutural abrupto em 2020, seguido de uma recuperação gradual e reorganização significativa em 2022–2025. Os nós tradicionais da Europa Ocidental, como Frankfurt, Munique e Amesterdão, mantiveram a sua influência, mas registaram um declínio relativo. Em contrapartida, aeroportos como Palma de Maiorca, Istambul, Nice, Porto e Cracóvia ganharam importância, refletindo o reencaminhamento de fluxos e a rápida recuperação de rotas turísticas e de lazer.

Os testes de percolação demonstraram que a rede de 2021 foi a mais frágil, enquanto a de 2025 revelou maior resiliência, indicando mais redundância e uma estrutura de nós mais distribuída.

Globalmente, a rede europeia não regressou simplesmente ao estado pré-pandémico; transformou-se num sistema mais diversificado, interligado e resiliente. Os resultados indicam um reequilíbrio geográfico gradual da conectividade europeia e fornecem um quadro metodológico para monitorizar alterações estruturais em redes de transportes complexas.

PALAVRAS-CHAVE: Conectividade aeroportuária; Rede; Resiliência.

CÓDIGOS JEL: C63; D85.

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1. Introduction

1.1. Motivations

Prior to the pandemic, global air transport carried 4.5 billion passengers (passenger journeys) in 2019 (International Civil Aviation Organization, 2024). Research shows a clear link between demand for airport services and a city's GDP, so airports also contribute to economic growth (Wandelt & Sun, 2015). Furthermore, better air connectivity might make regions more competitive worldwide and reshape passengers' travel choices (Burghouwt, 2017). Together, these factors highlight the importance of studying how airports operate in networks and how connectivity changes over time.

The past several years have emphasized the vulnerability of the air transport system to large-scale disruptions. The COVID-19 pandemic has caused a sharp decline in passenger traffic: PRR 2020 reports flights dropped as low as −88% in April 2020 in the EUROCONTROL area (Performance Review Commission, 2021). Just when the industry was beginning to recover, geopolitical restrictions – primarily airspace closures following military conflicts – changed routing strategies and further restructured European traffic flows. These disruptions not only reduced traffic volumes but also altered the network structure, weakening some hub airports and fragmenting established flows.

Understanding these transformations is crucial for policymakers, regulators, and industry stakeholders. It allows us to understand how air networks are adapting to high loads, which airports are gaining or losing strategic importance, and how to improve resilience to future crises.

1.2. Research Question and Objectives

The following research question guides this dissertation:

How did the European air transport network transform in response to COVID-19 disruptions and geopolitical airspace restrictions, and what are the implications for network structure, connectivity, and resilience?

To answer this question, the study has three key objectives: structural analysis, impact assessment, and resilience evaluation. During the structural analysis, I am going to examine the evolution of European air transport networks between 2019 and 2025, with a particular focus on changes in centrality and connectivity. The impact assessment will examine the influence of pandemic-related restrictions and geopolitical conflicts in Europe on network topology, airport roles, and route reconfiguration. Finally, resilience evaluation will explore how these transformations affect the adaptability of the European airspace, identifying new hubs, fragmentation, and changes in connectivity.

The analysis will be based on temporal flight data from OpenSky (Schafer et al., 2014; The OpenSky Network, 2025) and apply graph-theoretic and network-science methodologies to quantify these structural changes.

To answer these questions, the study uses analytical methods based on network science and data-driven time series analysis. Flight records from OpenSky are transformed into directed, weighted graphs in which airports represent nodes and the number of flights defines edge weights. The structural properties of these networks are evaluated using measures such as degree centrality, PageRank, and network density. Quarterly datasets and April snapshots are used to reveal long-term shifts in airport importance and support cross-sectional comparisons of network configuration, respectively. In addition, the study includes a percolation-based assessment of network resilience, examining how the removal of highly connected airports affects network fragmentation. Together, these methods provide a systematic approach to analyzing how the European air transport network adapted to pandemic and geopolitical shocks.

1.3. Structure of the Master's Final Work

This Master’s Final Work consists of five main chapters. The dissertation begins with an introduction that explains the motivation for the study, formulates the research question, and the objectives that guide the analysis.

The second chapter provides a literature review that examines existing research on the topic. It provides the theoretical and empirical foundations of the study, starting from network science methodologies and ending with its application to transport networks in general and airport networks in particular.

The third chapter, “Methodology”, explains the steps considered in this study, consistent with the CRISP-DM framework, including business understanding, data understanding, data preparation, modeling, and evaluation. This chapter describes the data collection methods, analytical techniques, and the rationale for choosing these methods.

The fourth chapter covers the results and discussion, presenting empirical findings from the network analysis and interpreting them in relation to observed disruptions and broader implications for European airspace resilience. It is leading to the final section – conclusion – which also discusses the limitations of the study and potential directions for future research.

2. LITERATURE REVIEW

2.1. Network Science

Network science is useful for studying systems where many elements are interconnected, such as social interactions, computer communication, disease spread, or transportation routes. Although these systems differ, the key idea is the same: connections between objects shape the behavior of the whole system.

According to Ted G. Lewis (Lewis, 2013), network science is the systematic study of networks using the scientific method. In simple terms, it helps explain how structure and function emerge from the way elements are connected. To describe networks formally, network science uses graph theory. A graph consists of nodes and edges, where nodes represent the objects in the system and edges represent the relationships between them (Lewis, 2013).

Many real-world networks also change over time, so they can be described as dynamic graphs, for example

$$G(t) = \{N(t), L(t), F(t)\}$$

where *N(t)* denotes the nodes present at time *t*, *L(t)* denotes the edges, and *F(t)* specifies how nodes are connected. Nodes and edges may appear or disappear, or their intensity may change. Lewis (Lewis, 2013) highlights this distinction by separating static networks, where the structure stays the same, and dynamic networks, where the graph evolves due to internal processes or external shocks.

Graphs can also be undirected or directed. In undirected graphs, edges represent mutual relationships, while in directed graphs each edge has an orientation. This distinction is especially important for air transport networks, since flights connect a specific origin airport to a specific destination (M. Newman, 2010).

Finally, edges can be weighted, meaning that the connection has an additional numerical value. In transport networks, weights often represent the number of flights, passengers, or another indicator of traffic intensity. This makes it possible to analyze not only whether a connection exists, but also how strong or important it is.

To understand how strongly the network is connected and which elements play the biggest role in keeping it functional, network analysis uses a set of structural measures that can be applied both to individual nodes and to the network as a whole (M. Newman, 2010).

The simplest and most basic property of a node is its degree. It shows how many edges are connected to that node. Nodes with a high degree are often called hubs, because they provide many connections and can make the network easier to navigate. At the same time, degree does not always fully represent importance. Some airports, for example, may have many direct routes but still not be essential for connecting different parts of the network (M. Newman, 2010).

To capture node influence more accurately, researchers use centrality measures (Freeman, 1978). Each of them highlights a different aspect of importance.

Degree centrality is closely related to degree and reflects strong local connectivity. Closeness centrality focuses on how quickly a node can reach all other nodes in the network. It is usually based on the average shortest-path distance from a node to the rest of the graph. If closeness centrality is high, the node is “well positioned” and does not need many intermediate steps to reach others (M. Newman, 2010).

Another important measure is betweenness centrality. It shows how often a node lies on the shortest paths between other nodes. Nodes with high betweenness often act as bridges between different parts of the network. Because of this, they can become critical bottlenecks, and their failure may cause strong fragmentation or connectivity loss (M. Newman, 2010).

A different way to measure importance is provided by eigenvector-based metrics, such as PageRank. Unlike degree or closeness, PageRank does not focus only on direct connections or distance. Instead, it evaluates node influence based on how important its neighbors are (Brin & Page, 1998). As a result, a node can have a high PageRank not only because it is well connected, but also because it is connected to other influential nodes. This approach is especially useful in hierarchical systems, where indirect influence can be as important as direct connectivity (M. Newman, 2010).

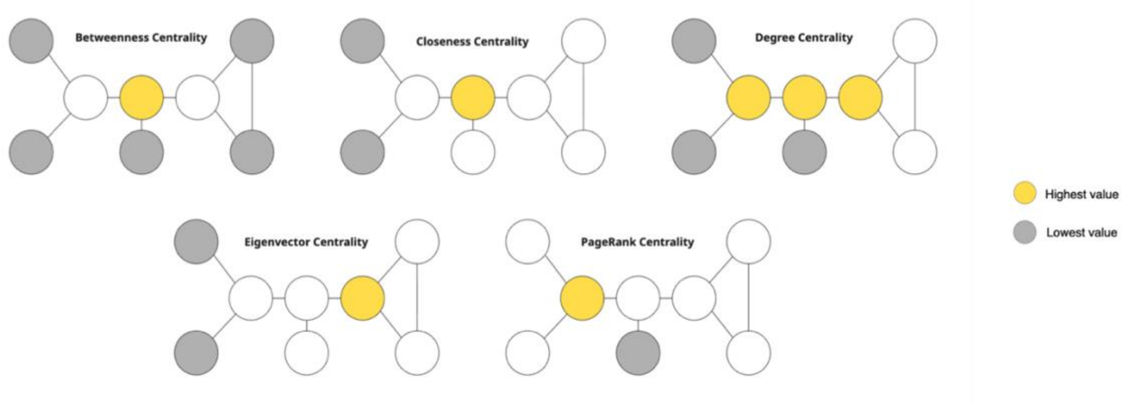

FIGURE 1 – Distinct characteristics of the centrality

The structure of the network as a whole can also be described through such concepts as path length and network diameter. The shortest path between two nodes indicates the minimal number of steps required to travel from one to the other. If the average shortest path length is low, the network usually works more efficiently. The network diameter is the longest shortest path in the graph. It represents how far apart the most distant nodes are in the network (M. Newman, 2010).

Many large networks are not completely uniform. Instead, they often contain smaller subgroups called communities or modules (Girvan & Newman, 2002). These groups are characterized by stronger connections inside the group than with the rest of the network. The strength of this division can be measured with modularity. High modularity indicates well-defined clusters with strong internal cohesion and relatively few external links. This is important because community structure can affect how disruptions spread and how resilient different parts of the network are during failures or targeted attacks.

Another property related to network organization is assortativity, which describes the tendency of nodes to connect to others with similar characteristics. In assortative networks, highly connected nodes tend to link with other highly connected nodes. In disassortative networks, hubs more often connect with nodes of lower degree. Infrastructure networks, including transportation systems, frequently display disassortative patterns, reflecting hierarchical flows between central hubs and smaller peripheral nodes. Both assortative and disassortative tendencies may appear in different parts of the same network (M. Newman, 2010).

2.1.1. Resilience Analysis Techniques in Networks

Resilience is an important concept in network science. It describes how well a system can keep functioning when it faces failures, disruptions, or deliberate attacks. In complex networks, resilience depends not only on how many elements fail, but also on what happens to the overall connectivity afterwards (Albert et al., 2000). This is especially relevant for infrastructure systems, because even a local problem can sometimes cause large-scale fragmentation and reduce performance.

A common way to study resilience is to remove nodes or edges step by step and observe how connectivity changes. The central object of interest here is the giant connected component (GCC). GCC can be defined as the largest group of nodes that are still connected to each other, meaning they remain mutually reachable[1]. As long as the GCC contains a large part of the network, the system can still operate at a global level. If the GCC declines very quickly, the network is vulnerable. On the other hand, if the decline is slower, the structure is usually more stable (Callaway et al., 2000).

Percolation theory provides a formal framework for studying these processes. Percolation theory was originally developed in statistical physics, but now it is widely used in network studies. The main idea is simple: to examine how global connectivity appears or collapses when elements of a system are removed. In network terms, percolation shows how the structure changes when nodes or edges are disabled. There are two main types – site and bond percolation. Site percolation refers to the removal or failure of nodes, while bond percolation focuses on the removal of edges. In both cases, the fundamental question is whether a large connected part of the network can still exist after a part of the elements has been removed (M. Li et al., 2021).

A crucial concept in percolation-based analysis is the percolation threshold. It represents the critical point at which the GCC breaks down into many smaller disconnected parts. Below this point, most of the network remains connected, so the system can continue functioning. Once a threshold is reached, connectivity quickly breaks

[1] Here GCC refers to the largest weakly connected component (WCC) (i.e., ignoring direction for connectivity)

down, and large-scale movement across the network becomes difficult. The exact position of this threshold depends on the network structure (Rong et al., 2022). Homogeneous networks, where nodes have similar degrees, tend to lose connectivity gradually, whereas heterogeneous networks with strong hubs can fragment suddenly even if a small number of key elements is removed (Albert et al., 2000).

Percolation processes can be implemented using different removal strategies, each representing a distinct type of disruption. Random removal models non-specific failures, where each node or edge has an equal probability of being disabled. This scenario is relevant for disruptions such as random technical failures or weather-related events. In contrast, targeted removal focuses on eliminating the most important elements first, typically identified through degree or betweenness centrality. Such strategies simulate intentional attacks, hub closures, or highly localized constraints. Empirical and simulation-based studies show that targeted removals are usually far more damaging than random failures, particularly in networks with strong hierarchical or hub-and-spoke structures (Holme et al., 2002).

Different targeted removal strategies represent different definitions of importance within the network. For example, degree-based removal focuses on nodes with the highest number of direct connections and models situations where highly connected hubs become unavailable. Betweenness-based removal targets nodes or edges that appear on many shortest paths. These elements often act as bridges between different parts of the network, so their removal can strongly reduce connectivity (Holme et al., 2002).

PageRank-based removal follows a similar idea but also considers the importance of neighboring nodes (P. Zhang et al., 2022). In this case, a node is ranked higher not only when it has many links, but also when it is connected to other influential nodes. In weighted networks, weight-based removal focuses on edges or nodes that carry the highest traffic volumes, frequencies, or capacities. This approach represents disruptions that mainly affect high-load routes rather than elements that are structurally central in the graph (M. E. J. Newman, 2004).

Targeted percolation strategies also differ in whether node or edge importance is recalculated as the network degrades. In static strategies, elements are ranked according to their importance in the initial network, and removals follow this fixed order. This approach assumes that the original structure is sufficient to represent vulnerability throughout the disruption. It is often used to model planned attacks or failures that do not adapt to changes in the system. In contrast, adaptive strategies update measures after each removal step, making it possible to reflect how network structure changes over time and how flows may shift after key elements are removed. Under this approach, each step targets the most critical element in the current, already degraded network. Previous studies have shown that adaptive strategies are typically more destructive than static ones, as they continuously exploit emerging vulnerabilities rather than those present only in the original configuration (Holme et al., 2002).

Both static and adaptive strategies can be applied to node-based and edge-based percolation processes. Node removals represent the failure or closure of entire entities, such as airports or stations, while edge removals model disruptions to connections, routes, or services between them. Evaluating resilience under these different combinations of removal type and strategy allows for a more comprehensive assessment of how structural importance, traffic concentration, and adaptive reconfiguration jointly shape the robustness of complex transportation networks (Holme et al., 2002; M. Li et al., 2021).

Resilience is closely connected to how importance is distributed across the network. In networks where connectivity is concentrated in a small number of nodes or edges, the removal of these elements can dramatically increase path lengths, isolate entire regions, and cause a rapid decrease in the size of the GCC. In contrast, networks with higher redundancy, more alternative paths, or modular organization can sustain greater levels of damage before global connectivity collapses. Instead, it emerges from the overall structure of the network (Albert et al., 2000; Holme et al., 2002).

In addition to connectivity, percolation-based approaches can also evaluate resilience using performance-related measures. When a network starts to fragment, transport or communication efficiency often declines even before full disconnection occurs. Shortest paths become longer, traffic is rerouted through less optimal routes, and bottlenecks emerge. For this reason, tracking indicators such as average path length or efficiency together with the size of the GCC provides a more detailed view of how functionality decreases under stress (Zhou & Wang, 2018).

Percolation analysis is especially useful in transport and mobility systems. Airports, railway stations, and road intersections often differ greatly in their topological importance, and disruptions rarely affect all components equally (X. Zhang et al., 2015). Percolation-based resilience analysis makes it possible to identify critical nodes and edges, assess how failures propagate through the system, and compare the robustness of different network configurations or time periods. As a result, it is widely used as a standard method for assessing vulnerability and adaptive capacity in large-scale transport networks.

2.2. Network Science for Transport Systems

A central insight from the literature is that transport networks, much like other complex systems, display strong heterogeneity in their structure. In their seminal analysis of the global aviation network, Guimerà et al. (Guimerà et al., 2005) demonstrated that air transport exhibits the hallmarks of a scale-free and small-world system, characterized by a few highly connected hubs and a large number of peripheral nodes. Similar patterns have been documented in railway and subway networks, where degree distributions are heavily skewed, and clustering levels are high (Derrible & Kennedy, 2010; Zanin & Lillo, 2013). While such configurations support efficient large-scale connectivity, they also increase systemic vulnerability, as the removal of a single highly connected hub can trigger widespread fragmentation.

Beyond their structural properties, transport networks are inherently dynamic. As Barthélemy (Barthélemy, 2011) argues, mobility infrastructures evolve through incremental growth, demand-driven rewiring, and adaptive reorganization, making temporal analysis essential. In urban mobility systems, peak-hour demand reshapes flows and alters effective connectivity, whereas in aviation networks, seasonal scheduling, airline strategies, and market fluctuations continuously modify the availability and weight of routes. Temporal network theory provides tools to analyze these processes. Holme and Saramäki (Holme & Saramäki, 2012) note that incorporating time into network models allows researchers to capture causality, time ordering of interactions, and rhythm, elements that are crucial for understanding real transport behavior.

Network science also offers a robust framework for evaluating resilience in transport systems, as transportation networks have been shown to be particularly sensitive to targeted disruptions. In this context, percolation-based resilience analysis has been widely applied across different types of transportation networks. In studies of urban rail systems, Derrible and Kennedy (Derrible & Kennedy, 2010) used progressive node and link removal to examine how metro networks fragment under both random failures and targeted disruptions, interpreting the loss of connectivity as an indicator of robustness. Similar techniques were adopted by Aparício et al. (Aparicio et al., 2022) in their assessment of multimodal transport resilience in Lisbon, where the evolution of connected components under simulated disruptions was used to compare vulnerability across transport modes and to capture interdependencies between them. Percolation theory has also been explicitly applied to road traffic systems under extreme events. Yao and Chen (Yao & Chen, 2023) proposed a percolation-based framework to analyze the resilience of an urban traffic network during a snowstorm, identifying critical thresholds beyond which large-scale connectivity collapses and targeted interventions are required to restore functionality.

These findings are supported by theoretical work showing that networks with hub-and-spoke architectures are particularly fragile under targeted attacks. Callaway et al. (Callaway et al., 2000) demonstrated through percolation models that the removal of high-degree nodes leads to rapid network collapse, highlighting the structural vulnerability of transport systems dominated by central hubs. This insight is especially relevant for air transportation, where connectivity is strongly concentrated in a limited number of airports.

In the context of air transportation, analogous techniques have been employed to study the robustness of airport networks. Several studies simulate random failures and targeted removals of airports or routes and assess resilience through the evolution of the giant connected component and related performance measures. Lordan et al. (Lordan et al., 2014) analyzed the vulnerability of the global air transport network under different attack strategies, while Sun and Wandelt (Sun et al., 2017) compared multiple robustness metrics to evaluate how airport networks respond to structural degradation. More recent work has extended percolation-based analysis to temporal airport networks, demonstrating that connectivity undergoes critical transitions over time and that resilience depends not only on topology but also on the ordering and persistence of connections (Liu et al., 2020).

These results align with a broader body of literature indicating that aviation networks are especially vulnerable to directed attacks or hub closures, underscoring the importance of redundancy and modular organization for maintaining functionality (Sun & Wandelt, 2021; Zanin & Lillo, 2013). Subsequent studies further confirm that resilience in air transport systems depends on the availability of alternative routes, structural diversity, and the extent to which communities within the network can operate autonomously following a disruption (Zhou et al., 2021).

The modular nature of many transport systems has significant implications for network performance. Newman and Girvan (M. E. J. Newman & Girvan, 2004) established that community structure influences both the diffusion of flows and the propagation of failures. In transport contexts, modules often correspond to regional or operational clusters – for example, airline alliances, geographic zones, or intermodal hubs. High modularity can localize disruptions, preventing system-wide collapse, whereas low modularity increases the risk of cascading effects. This insight has been applied in public transport studies, where modular organization has been shown to enhance operational robustness (Dinh et al., 2012).

Finally, transport systems frequently exhibit disassortative mixing patterns, in which high-degree nodes tend to connect with low-degree nodes. Such patterns are characteristic of infrastructure networks because major hubs must serve a large number of smaller peripheral nodes. In air transportation, this structural hierarchy results in efficient large-scale connectivity but also in pronounced dependency on hubs, reinforcing the need for resilience-focused analysis (Diop et al., 2021).

Overall, the application of network science to transport systems provides a powerful lens through which to analyze their organization, efficiency, and vulnerability. By integrating structural, temporal, and resilience-based perspectives, researchers can better understand how transport networks evolve and adapt under both normal and disrupted operating conditions.

2.3. Air Transport Networks

Network theory is now widely used in air transport research. It provides a clear way to describe flight systems as networks, where airports are nodes and routes are connections between them. Based on graph theory, this approach helps study airport connectivity, route efficiency, and overall system resilience at different spatial and time scales (Guimerà et al., 2005; Zanin & Lillo, 2013). Research on both global and regional networks shows that air transport often has small-world and scale-free characteristics. In practice, this means that a small number of central airports carry a large share of traffic flows and play a dominant role in keeping the network connected (Barabási & Albert, 1999; Wandelt & Sun, 2015).

Network analysis of air transportation relies on a wide range of metrics. Among the most common are degree centrality, betweenness centrality, and PageRank, which quantify an airport's importance within the network. Degree centrality captures the number of direct connections, while betweenness centrality measures the role of airports as bridges in the system. PageRank extends this by considering indirect connectivity and influence within the network (Huynh et al., 2024; Z. Li et al., 2023; Xu et al., 2017). In addition to centrality measures, other studies use clustering methods, motif analysis, and community detection. These techniques are useful for exploring network modularity and identifying spatial structure in air transport systems (Lehner & Gollnick, 2014; Milazzo et al., 2022; Rocha, 2017).

In recent years, particular attention has been paid to the dynamic evolution of air transport networks. This includes changes in airport roles, shifting traffic patterns, and the overall transformation of network structure. To capture these dynamics, temporal centrality analysis and evolving graph models have been introduced (Wandelt & Sun, 2015; Zanin & Wandelt, 2023). Such approaches are particularly useful when studying periods of disruption and recovery, since they help track not only whether connectivity returns, but also how the network reorganizes in the longer term.

2.4. Related Works

Many scientific papers in recent years have been devoted to studying the impact of the COVID-19 pandemic on air transport networks. For instance, Li et al. (S. Li et al., 2021) analyzed the European network and found that total connectivity dropped by over 80% in April 2020, with secondary hubs and peripheral airports experiencing the greatest losses. Vossen et al. (Vossen et al., 2023) also reported significant changes in the importance of airports such as Istanbul and Warsaw. Zhou et al. (Zhou et al., 2021) proposed a layered network efficiency measure to evaluate how connectivity changes under different levels of disruption. Sun et al. (Sun et al., 2022) focused on recovery trajectories, and showed that the recovery was uneven across regions and airport types. In a broader perspective, Zanin and Wandelt (Zanin & Wandelt, 2023) presented an overview of the evolution of centrality over a ten-year period, with the pandemic serving as a major turning point. Together, these studies show that the pandemic not only reduced traffic but also changed the network topology, with long-term consequences.

While many of these studies have addressed to global airspace, several have specifically focused on the European air transport network. The study from Vrije Universiteit Brussel and EUROCONTROL (Vossen et al., 2023) applied GraphWave embeddings to detect role changes among airports between 2019 and 2022. The results highlighted emerging hubs and shifts in clustering structure. Similarly, (Milazzo et al., 2022) analyzed the networks of 50 European airlines and showed clear differences between hub-and-spoke and point-to-point configurations. Another example is "In the Flow of Connectivity" (Kölker et al., 2025), which provides a dynamic view of Europe's top 20 airports by tracking their centrality trajectories over time and showing how their roles depend on each other.

In addition to the pandemic, geopolitical events also had a strong impact on European air transport. In particular, airspace restrictions related to military conflicts and diplomatic sanctions forced airlines to modify their routing strategies. This affected the structure of the European network, especially in Eastern and Central Europe. For example, Dannet et al. (Dannet et al., 2025) showed that Russian airspace closures redirected traffic through Turkey and Central Asia. This increased emissions and also strengthened Istanbul's position as a key hub. Vossen et al. (Vossen et al., 2023) also described how these reroutings contributed to fragmentation and reduced integration between parts of the network. Together, these findings reveal the combined effect of pandemic-related shocks and geopolitical constraints, both of which contribute to a reshaping of the air transport landscape in Europe.

This dissertation aims to contribute to this discussion by analyzing how the European air transport network evolved between 2019 and 2025 under the influence of both health-related and geopolitical shocks. Using temporal network analysis, with a focus on centrality metrics and structural shifts, the study will examine which airports gained or lost strategic importance, how network connectivity changed, and what these developments mean for the resilience and adaptability of European airspace.

3. METHODOLOGY

In this study, I used the CRISP-DM methodology (Shearer, 2000), complemented by selected elements of the POST-DS framework (Costa & Aparicio, 2020). This combination helped me follow a clear and reproducible workflow throughout the whole research process. As a result, each analytical step – from defining the research objectives to interpreting the outcomes – was organized in a logical way and remained aligned with the aims of the dissertation.

The CRISP-DM model includes six iterative phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. In my dissertation, these stages were adapted to analyze how the European air transport network transformed between 2019 and 2025 *(Figure 2)*.

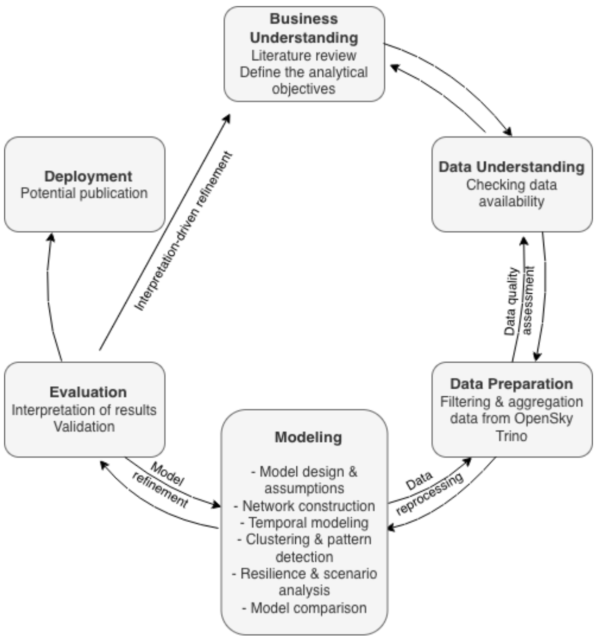

FIGURE 2 – Workflow of Research

3.1. Business Understanding

During the Business Understanding phase, I defined the main purpose of the study and clarified what exactly should be analyzed and why. The focus of this work is the European air transport network and the way it changed between 2019 and 2025 under two major disruptions: the COVID-19 pandemic and the later geopolitical airspace restrictions.

At this stage, I formulated the central research question and the main objectives of the study. The key goal was to understand how these shocks affected the structure of the network, the roles of individual airports, and the overall level of connectivity across Europe. It is very important from a practical perspective because changes in air connectivity influence economic links between regions, mobility, and the stability of transport systems.

Based on this problem definition, I decided to treat European air transport as a complex network. Airports were considered as nodes, and direct flight connections as edges. I also defined the time frame of the analysis, covering the period from 2019 to 2025, in order to compare the pre-pandemic situation, the crisis phase, and the recovery period. Particular attention was given to identifying whether the network returned to its previous structure or developed new patterns after the disruptions.

In summary, the Business Understanding phase was used to define the research scope, select the network perspective, and specify the key questions that guided all later stages of the analysis.

3.2. Data Understanding

In the Data Understanding stage, I focused on identifying what data was available for the analysis, what it contains, and what limitations it has.

The dataset is obtained from the Trino OpenSky platform, which provides open historical air traffic information derived from ADS-B signals, automatic broadcasts transmitted by aircraft that contain real-time information about their position, velocity, and identification. The raw records were processed using SQL to extract flight origin and destination airports, date and time information, and basic aircraft-related metadata.

After reviewing the structure of the dataset, I selected two time perspectives. The first one was the quarterly aggregates for the period 2019–2025. This helped capture long-term changes while keeping seasonal patterns visible. Second, I extracted the flight data for each April of the years 2019–2025. April is a good reference point to catch the network state just after the major disruptions, as the peaks of both COVID-19 and geopolitical restrictions happened in February and March.

All the flights were filtered to keep only rows where both origin and destination airports are located in Europe. Records were first pre-filtered at the database level using the prefixes “E-“, “L-“, “U-“, “B-“ for the airport codes and then limited to a specific list of countries. The country list used for this step was curated and cross-checked with the *OpenFlights airports.dat*. The final list of countries included Albania, Andorra, Armenia, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom. In this study, the European air transport network definition follows the EUROCONTROL regional footprint. Therefore, South Caucasus nations (Armenia and Georgia) are retained due to their full membership in EUROCONTROL, reflecting their integration into the European aviation functional airspace blocks (EUROCONTROL, 2025).

Finally, I performed a preliminary data exploration – checked overall completeness, looked for outliers or unusual values, and verified that coverage remains reasonably consistent across time. All described manipulations resulted in 8 CSV files, prepared for further analysis described in the section 3.3.

3.3. Data Preparation

The third phase involved transforming raw flight records into structured datasets suitable for network analysis.

The data were cleaned to remove duplicates and incomplete records and aggregated by airport pairs with frequencies used as edge weights. Airport codes were standardized and temporal alignment across quarters was verified. The outcome of this phase is a set of directed, weighted graphs, each representing the European air transport network for a given time period. This process resulted in both quarterly networks for dynamic metrics and April networks for structural visualization and evolution assessment.

A range of computational tools was employed to support data management and network analysis. All processing was conducted in Python, using the NetworkX library

(Hagberg et al., 2008) to construct directed weighted graphs, compute structural and centrality metrics, and perform the connectivity analyses described in the subsequent sections. In addition, the "airports.dat" dataset was used to retrieve standardized information on airport identifiers, locations, and metadata, ensuring consistency across the assembled datasets.

The full analysis workflow, including the Jupyter notebook and the aggregated datasets, is publicly available at https://github.com/okuraian/MFW.

3.4. Modeling

The Modeling phase of CRISP-DM usually focuses on applying analytical and computational techniques to the prepared data. In this study, the modeling process applies network science and machine-learning techniques to represent and analyze the European air transport system across multiple temporal snapshots. Each directed, weighted graph models the system as a set of nodes, representing airports, and directed edges, representing scheduled routes. Edge weights correspond to the number of flights on each route, capturing route intensity and enabling differentiation between low- and high-frequency connections. These graphs are constructed for several periods – pre-pandemic baseline, COVID-19 disruption, and various recovery stages – to assess how the structure and function of the network evolve over time.

To characterize the network at each time snapshot, a range of structural metrics is computed. The number of nodes and edges provides a direct indication of the network's size and coverage: reductions in these values reflect decreases in active routes or temporarily inactive airports, whereas increases indicate expansion or recovery. The average degree measures how many connections an airport maintains on average and is calculated as the total number of incoming and outgoing links divided by the number of airports. Higher average degree values suggest denser connectivity and more active interaction across the system.

Network density further contextualizes these properties by quantifying how full the network is relative to the maximum number of possible directed links. A sparse network, with density close to zero, indicates that only a small fraction of potential connections are realized, whereas higher densities reflect increasingly saturated route structures.

To identify key nodes and understand the distribution of influence across the system, centrality-based metrics are employed. Degree centrality measures the number of direct connections an airport maintains and captures its local structural prominence. However, degree alone does not account for the importance of neighboring airports. For this reason, the study adopts PageRank as the principal centrality measure. Originally developed to rank webpages by considering both the number and the prestige of incoming links, PageRank can be naturally applied to air transport systems by viewing airports as nodes and flights as directed links. An airport becomes influential not only by having many connections, but by receiving traffic from other well-connected airports – that is, it can act as a “hub of hubs”. This quality makes PageRank particularly suitable for the hierarchical hub-and-spoke structures typical of European aviation.

From a dynamic perspective, PageRank provides a robust indicator of structural influence as the system undergoes disruptions, rerouting, and recovery. Unlike simple degree-based metrics, it captures how the importance of an airport changes when the connectivity of its neighbors changes. PageRank values in this study are computed using a damping factor of 0.85 and weighted by route frequency. Rankings derived from these values enable comparative analysis of airport influence across the years, revealing how major hubs gained or lost importance during the pandemic and subsequent geopolitical constraints.

Beyond static structural analyses, the modeling phase incorporates unsupervised learning to uncover broader behavioral patterns across airports. K-means clustering is applied to the PageRank time series for each airport, treating the temporal trajectory from 2019 to 2025 as a multidimensional vector. After normalization and standardization, the clustering groups airports according to the shape of their temporal evolution rather than the magnitude of their centrality values. This makes it possible to identify distinct behavioral categories – such as sustained decline, sharp COVID-related disruption followed by recovery, or long-term resilience with stable or increasing centrality. The validity of the resulting clusters is assessed using silhouette scores to ensure that the chosen number of clusters reflects meaningful underlying structure in the data.

To evaluate the robustness and adaptability of the network, resilience is assessed through percolation-based analysis. In this simulation, airports are sequentially removed from the network, and at each step, the size of the largest connected component is recalculated. This process is repeated under several removal strategies: targeted removals based on PageRank (removing the most influential airports first), targeted removals based on degree centrality, and random removals representing non-specific failures. The fraction of nodes remaining in the giant component serves as a measure of global connectivity. Sharp declines under targeted removals reveal structural vulnerabilities, while slower declines indicate higher resilience. By comparing percolation curves across different years, the analysis captures how the network's robustness changed before, during, and after major disruptions, highlighting shifts in redundancy, the emergence or disappearance of critical hubs, and broader structural fragmentation or recovery.

Together, these modeling approaches provide a comprehensive view of how the European air transport network's structure, connectivity, and hierarchy evolved between 2019 and 2025 (*Table 1)*.

TABLE 1 – ANALYTICAL FRAMEWORK FOR CORRESPONDING RESEARCH QUESTIONS

Research question	Analytical strategy	Methods and metrics	Temporal scope
Structural analysis: Investigate how European flight networks evolved between 2019 and 2025, with a focus on changes in centrality and connectivity.	Calculate structural and centrality metrics, build time-series plots, and conduct comparative temporal analysis	Number of nodes, number of edges, average degree, network density, NCC, betweenness centrality, eigenvector centrality, PageRank.	- Quarterly aggregates (2019–2025) - Annual aggregates (2019–2025) - April snapshots (2019–2025)
Impact assessment: Examine the influence of pandemic-related restrictions and geopolitical conflicts in Europe on network topology, airport roles, and route reconfiguration.	PageRank-based analysis, clustering analysis (for behavioural patterns identification)	PageRank, **Δ**PageRank, K-means	- Quarterly aggregates (2019–2025) - Annual aggregates (2019–2025) - April snapshots (2019–2025)
Resilience evaluation: Explore how these transformations affect the adaptability of the European airspace, identifying new hubs, fragmentation, and changes in connectivity.	Percolation-based resilience analysis	Random vs targeted attacks, giant connected component size	- April snapshots (2019–2025)

The integration of graph metrics, temporal centrality analysis, clustering methods, and resilience simulations enables the identification of key airports, the detection of long-term patterns in hub importance, and the assessment of network vulnerability under stress. These findings serve as the foundation for subsequent interpretation and policy discussion concerning the stability, adaptability, and future planning of the European air transport system.

3.5. Evaluation

During the evaluation phase, the results were checked to confirm that the analysis is consistent and that the main patterns are reliable.

First, the centrality measures were compared. Major European hubs such as Amsterdam Schiphol, Frankfurt, and Charles de Gaulle remained highly influential across the whole period. This was visible in PageRank, degree, and betweenness centrality. In contrast, airports affected by closures or restrictions, such as Berlin Tegel and Sheremetyevo, showed a clear decline in all indicators. The agreement between different centrality metrics suggests that PageRank is a reliable measure for tracking temporal changes and that the observed trends reflect real shifts in connectivity rather than random noise.

The clustering analysis was evaluated through silhouette scores and interpretability. The silhouette values supported the four-cluster solution, and the final groups were possible to interpret. They reflected clear patterns, such as stable major hubs, airports with long-term decline, steadily growing southern airports, and airports with more volatile changes over time. This makes the clustering output meaningful in the context of European aviation.

Network-level indicators were checked across quarterly and annual aggregations. The results followed expected seasonality, with stronger connectivity in summer and weaker connectivity in winter. The structural collapse in 2020 and the gradual recovery after 2021 were also consistent across different time scales, which supports the robustness of the computed indicators.

The percolation experiments provided an additional layer of evaluation by testing resilience under simulated failures. The results were coherent across years: the 2021 network was the most fragile under targeted removals, while the 2025 network remained connected for longer and showed higher redundancy. This matches the observed transition from a constrained post-pandemic network to a more stable and adapted structure.

The key findings were consistent across centrality measures, clustering, structural metrics, and resilience tests. The weakening of Eastern hubs, the sustained dominance of Western European airports, and the growing importance of southern destinations appear repeatedly across all the methods. These outcomes also align with trends reported in previous studies and industry sources (Airport Industry Connectivity Report, 2025; Kölker et al., 2025; Zanin & Wandelt, 2023). This indicates that the modelling pipeline is stable, that the results are internally coherent, and that the network-science approach used in this study is appropriate for addressing the research question.

3.6. Deployment

Although this dissertation is academic in nature, the Deployment phase corresponds to the presentation, interpretation, and contextualization of analytical results. The findings are visualized through tables, graphs, and network maps that illustrate the evolution of European air connectivity. They are discussed in terms of their implications for policy and practice, particularly regarding airspace resilience, regional accessibility, and the identification of emerging strategic hubs.

In addition, the outcomes of this research may later be collected and developed into a separate publication. This would allow the main results and the applied methodology to be shared with a wider academic audience.

Thus, this stage supports both the academic contribution of the dissertation and the practical value of the approach, since the same framework can be reused for future network studies based on open flight data sources like Trino OpenSky.

3.7. Limitations

While network analysis provides valuable insights, certain limitations must be considered:

- As the OpenSky data is derived from ADS-B signals, coverage may be incomplete, especially for smaller regional airports or low-altitude routes.

- Network indicators capture structural rather than economic or operational dimensions (e.g., airline business models, passenger demand, or profitability).
- Temporal resolution is limited to quarterly aggregates and selected April snapshots, which may not fully reflect daily fluctuations or intra-monthly adjustments.
- The clustering results are subject to methodological limitations arising from the application of K-means. The algorithm's assumption of compact and equally sized clusters may not be suitable for complex airport data, resulting in uneven cluster sizes and partial overlap in airport behavior across clusters. Alternative approaches, such as hierarchical clustering based on correlation matrices, could potentially provide more nuanced groupings but are beyond the scope of the present study.

Despite these limitations, the methodological framework provides a robust foundation for understanding structural changes in European air transport amid the pandemic and geopolitical shocks.

4. RESULTS AND DISCUSSION

4.1. Overview of the European Air Transport Network (2019–2025)

The analysis examines how the European air transport network has changed between 2019 and 2025. It is based on flight data aggregated at various time scales, including quarterly and annual summaries, as well as data for April of each year.

The network was represented as a directed weighted graph: airports were considered nodes, and the connections between them were defined as active routes. Each route was assigned a weight equal to the total number of flights. Using this multi-scale structure allows long-term changes in the network to be separated from seasonal fluctuations and short-term disruptions.

4.2. Quarterly Network Evolution

The quarterly aggregation provides a more detailed understanding of short-term structural changes in the European air transport network between 2019 and 2025 *(Figure 3)*. The number of active nodes (airports) and edges (routes) shows clear seasonal fluctuations, usually reaching its highest levels during the summer quarters (Q2–Q3) and decreasing during the winter period (Q4–Q1).

The sharp decline in the second quarter of 2020 reflects the impact of COVID-19 lockdowns, which led to reductions in both network size and connectivity. Following this shock, the network began to gradually recover during 2021.

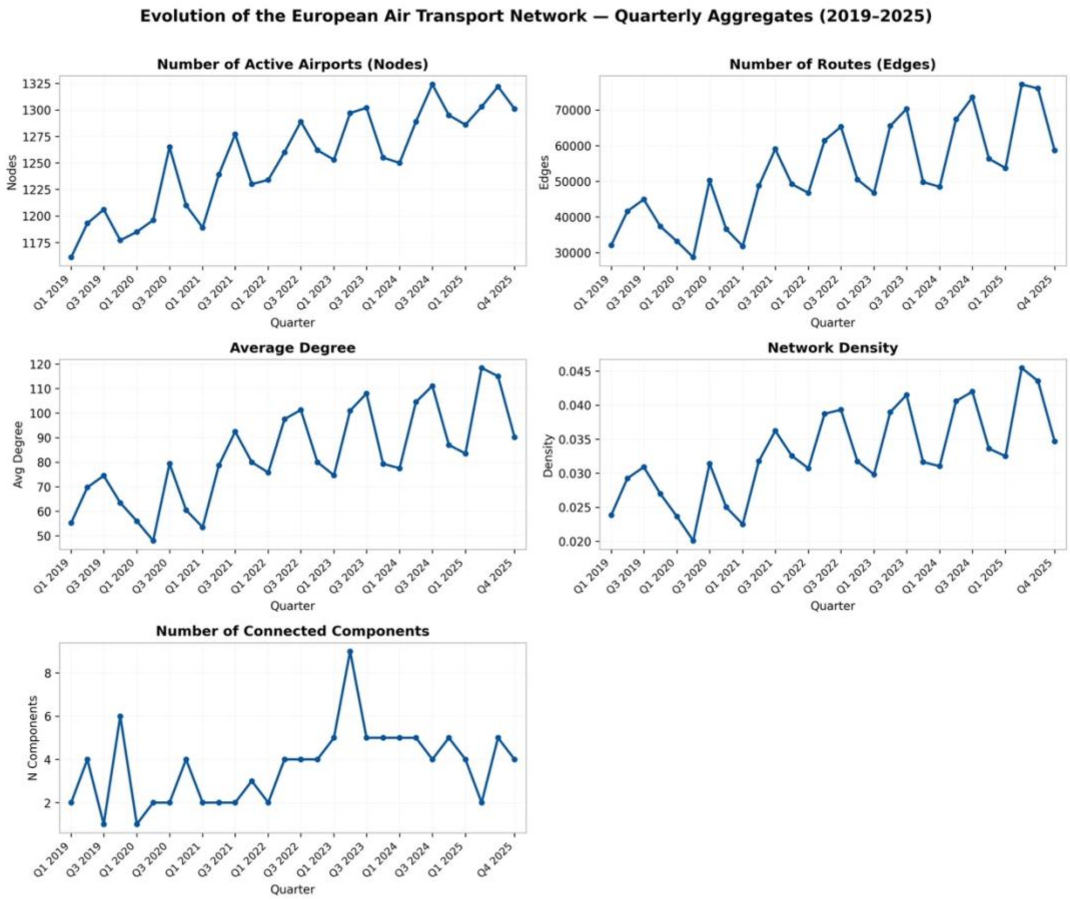

FIGURE 3 – Network metrics based on Quarterly Aggregates (2019–2025)

The increase in average degree and network density after 2021 indicates not only a recovery in traffic volume but also a trend toward more interconnected structures. This suggests an adaptive reorganization of air connections, with major hubs compensating for the loss of specific regional links.

4.3. Phase-Based Summary of Network Indicators

To better interpret the changes in the network indicators, the analysis was structured into five main phases (*Table 2).* During the Recovery phase, the average degree temporarily exceeded pre-pandemic levels, implying intensive route utilization among a smaller number of active airports. However, by the Adaptation phase, both density and degree became more stable. This indicates that the European air transport system had reached a new equilibrium under changed geopolitical and operational conditions.

TABLE 2 – PHASES OF NETWORK EVOLUTION

Phase	**Period**	**Key Characteristics**
Baseline	2019	Stable pre-pandemic structure, dense intra-European connectivity.
COVID Shock	2020 – Q1 2021	Collapse of flights and fragmentation of the network.
Recovery	2021	Rapid regrowth of domestic and regional routes.
Airspace Restrictions	2022 – H1 2023	Reconfiguration after closure of Eastern European and Russian corridors.
Adaptation	H2 2023 – 2025	Stabilization with a new, less centralized topology.

4.4. Annual Aggregates: Removing Seasonality

To reduce the impact of seasonal fluctuations during the year, the same indicators were also aggregated at the level of the entire calendar year *(*Figure *4)*. The results show a sustainable long-term recovery and gradual consolidation of the network structure.

Between 2019 and 2025, the number of active airports increased by approximately 5%, while the number of routes grew by more than 50% compared to the pandemic minimum. Since 2020, the average degree and network density increased almost every year. Both indicators reached their highest values in 2025. This shows that the network not only returned to normal activity, but its structure also changed after the crisis, and the system became more connected.

Annual aggregation helps reduce the effect of seasonality because summer and winter peaks are averaged out. When looking at the results this way, the recovery trend becomes clearer. By 2025, the network looks more complex than it was before the pandemic, so the changes cannot be explained as a simple return to the 2019 structure.

One especially interesting result is the sharp increase in the number of connected components in 2023. While most other indicators suggest that connectivity was improving, this rise points to a temporary fragmentation of the network. This may indicate that the recovery was uneven across all regions. It can be assumed that some airports and routes that were added or restarted during this period were not immediately integrated into the main network structure. Instead, they formed smaller subnetworks that were mostly connected locally. As a result, the network became more fragmented in the short term, even though connectivity within the largest component continued to improve. The reduction in the number of connected components in 2024–2025 suggests that these elements were gradually reintegrated into the main structure.

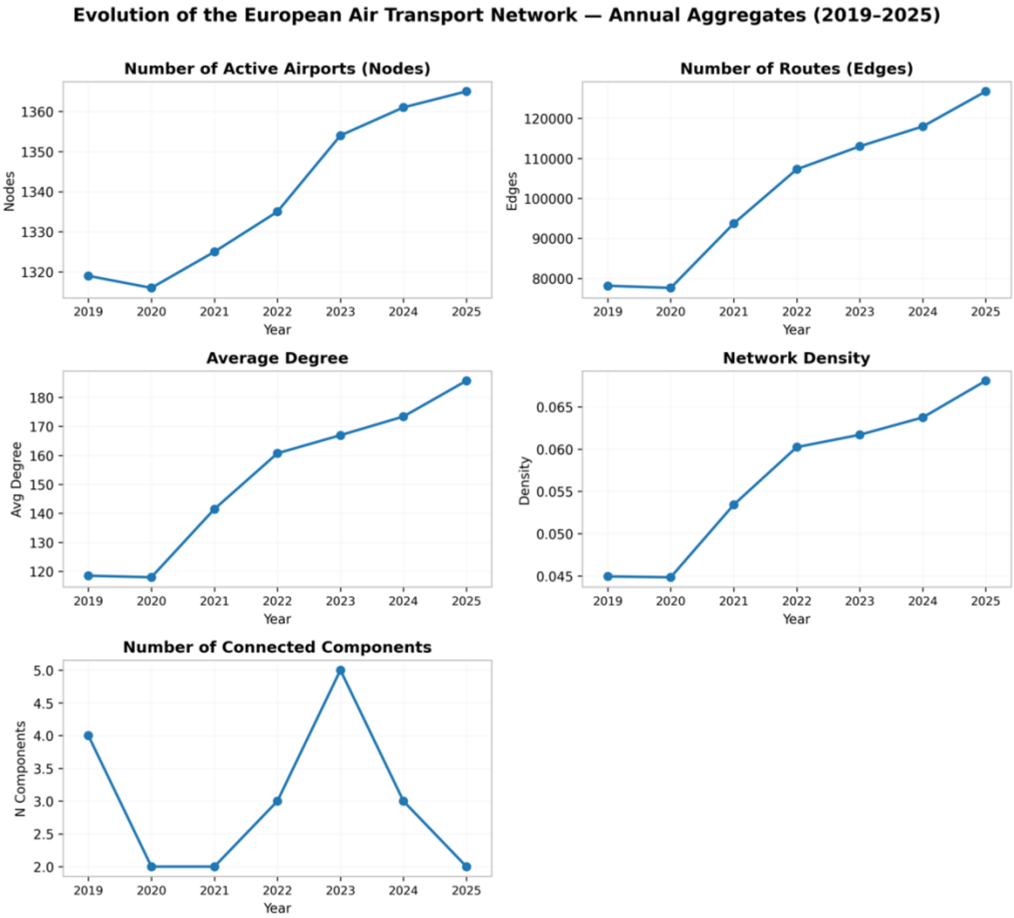

FIGURE 4 – Network metrics based on Annual Aggregates (2019–2025)

Centrality measures further support the interpretation of a structural transformation *(Figure 5)*. Both mean and maximum betweenness centrality decrease after 2020, implying a reduced dependence on a small number of highly critical transit airports. At the same time, eigenvector centrality and PageRank show a sharp drop in 2022, followed by partial recovery, but without reaching pre-2020 peak levels. This suggests a weakening of extreme hub dominance and a more distributed allocation of influence across the network. Taken together, the annual metrics indicate that the European air transport network evolved toward a denser and more balanced structure, with improved resilience due to reduced hierarchical concentration and increased connectivity redundancy.

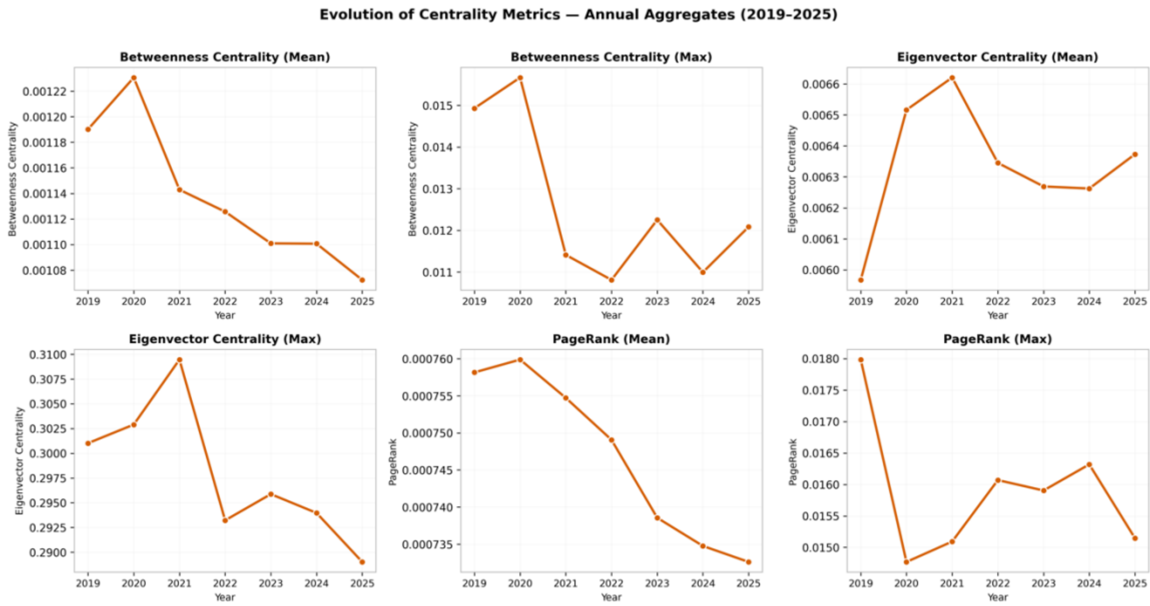

FIGURE 5 – Centrality measures for Annual Aggregates (2019–2025)

4.5. April Snapshots: Immediate Impacts and Turning Points

To capture short-term reactions to major disruptions, April data for each year (2019–2025) were analyzed separately. April was selected because both the pandemic lockdowns (March–April 2020) and the geopolitical airspace closures (February–March 2022) occurred immediately before this month. Thus, these snapshots actually reflect the state of the system immediately after major shocks.

In April 2020, all network indicators show a sharp decline *(*Figure *6)*. The number of active airports and routes drops to its lowest level, while average degree and network density also decline significantly. At the same time, the number of connected components reaches its maximum, indicating strong fragmentation of the network. This picture suggests that many airports have become isolated or remain weakly connected. This reflects the collapse of international connectivity and the disintegration of the previously integrated European air transport network during the initial period of the shock.

Since April 2021, the network started to recover in a more stable way. The number of airports and routes increases from year to year. Average degree and density also grow, which means that not only do more airports return to the system, but the links between them become stronger as well. At the same time, the number of connected components drops sharply after 2020 and then stays at a similar level in the following years. This suggests that parts of the network that were disconnected during the crisis gradually rejoined the main structure. By April 2025, the network looks more cohesive, with fewer visible gaps, even though it has not fully returned to its pre-2019 configuration.

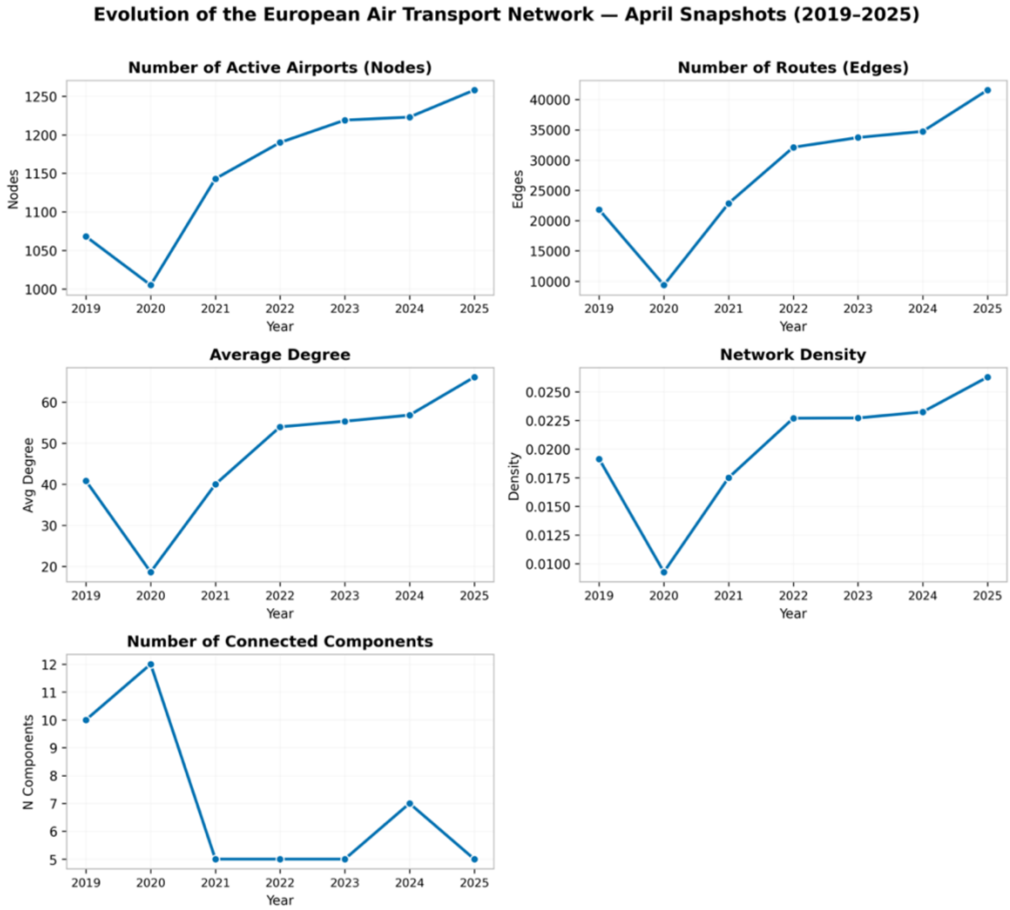

FIGURE 6 – Network metrics based on April Snapshots (2019–2025)

Centrality measures show the same general pattern. In April 2020, both mean and maximum betweenness centrality reached their highest values. This indicates that during the strongest shock period, only a small group of airports played a key role as the bridges in a fragmented system (*Figure 7).* Later, when connectivity improves, betweenness centrality becomes lower. This suggests that traffic flows are no longer concentrated around only a few airports and are spread across a wider set of nodes. Eigenvector centrality and PageRank show a similar trend. Both metrics show a peak or instability around 2020–2021, followed by lower and more stable values after 2022. This suggests a gradual reduction in extreme centralization and a shift toward a more balanced network hierarchy. Thus, the April snapshots highlight the transition from a highly fragmented and centralized system to a more resilient and diversified network structure by 2024–2025.

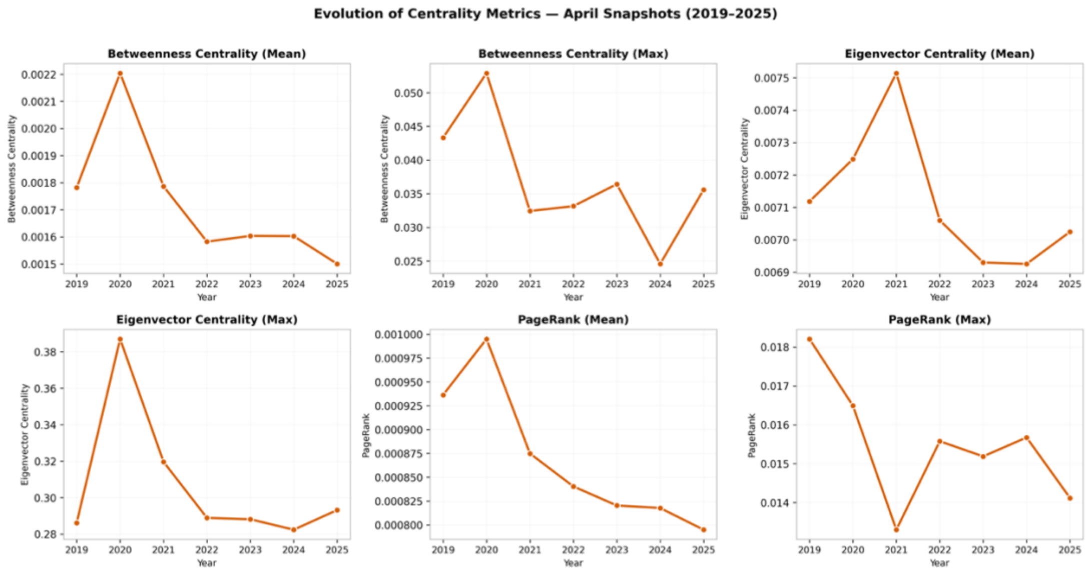

FIGURE 7 – Centrality measures for April Snapshots (2019–2025)

4.6. PageRank-Based Hub Centrality and Network Reconfiguration

To assess changes in the strategic role of individual airports, PageRank centrality was calculated for each April snapshot. Comparing the results for 2019 and 2025 shows how influence has shifted over time within the European air transport network.

The analysis of ΔPageRank indicates a clear reconfiguration of the European air transport network between 2019 and 2025, with some airports gaining structural importance while others losing it *(Figure 8)*. Several airports strengthened their positions, particularly Palma de Mallorca, Istanbul, Nice, Oslo, Porto, Prague, and Krakow.

This may reflect the recovery of tourist flows, the expansion of seasonal flights, and the growing role of secondary hubs. Palma de Mallorca Airport is a good example of this shift. In 2024, it reached a record high of 33.3 million passengers, a 7% increase over 2023. This growth was largely driven by international tourism and the expansion of its seasonal route portfolio (Aena, 2025). Nice Côte d'Azur Airport also strengthened its position, which can be attributed to the active recovery of Mediterranean destinations and the return of many intra-European flights. In the case of Oslo Airport (Lufthavn), the increase in PageRank can be attributed to the stronger integration of Scandinavian countries into the European network, as well as the development of both low-cost and long-haul options.

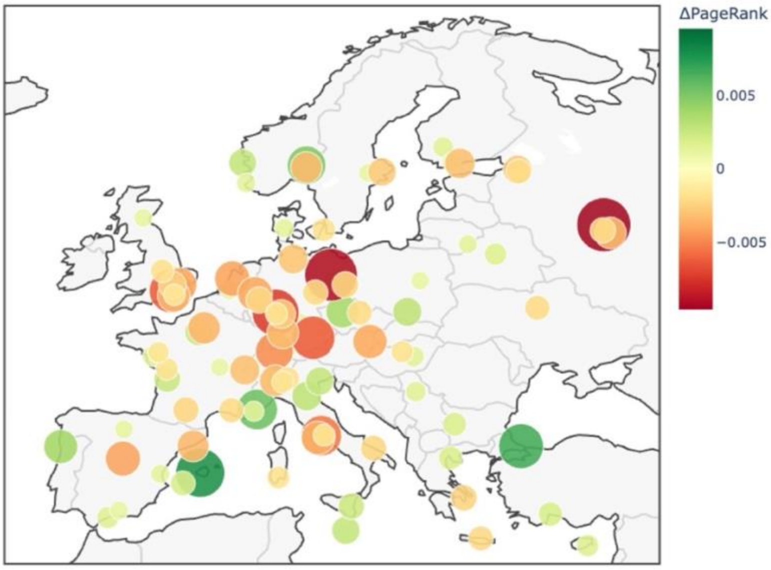

FIGURE 8 – Changes in the hubs by PageRank

However, the most notable growth was seen at Istanbul Airport. It significantly expanded its global hub network and improved by 59% compared to 2019. As a result, Istanbul overtook Frankfurt to become the most connected airport in Europe (Harding, 2025; Tasavvar, 2025).

At the same time, a number of airports, including Sheremetyevo, Berlin Tegel, Frankfurt, and Munich, experienced significant declines in PageRank. These cases illustrate how geopolitical events and changes in competition can reduce the structural importance of traditional hubs. Sheremetyevo's ranking fell sharply after 2022, primarily due to the closure of European airspace to Russian carriers: on 28 Feb 2022, the EU introduced restrictions prohibiting Russian air carriers and Russian-controlled aircraft from landing, taking off from, or overflying EU territory (Council Regulation (EU) 2022/334, 2022). This reduced direct and indirect air connections to Russia by approximately 43% compared to previous levels (Airport Industry Connectivity Report, 2025; Mitchell, 2024). Berlin Tegel, by contrast, disappeared from the network due to its permanent closure in 2020 (Macola, 2021).

Finally, Germany's two main hubs – Frankfurt and Munich – also exhibited a relative decline in network centrality. Although passenger traffic recovered, its structural role weakened compared to faster-growing hubs. This trend may be related to regulatory restrictions and increased competition from airports such as Istanbul, which expanded more aggressively during the same period (Davitt, 2025; Koumelis, 2025).

To summarize, these results confirm that the importance of airports in the European air transport network depends not only on passenger traffic but also on strategic positioning, international accessibility, and the ability to remain resilient during major structural shocks.

4.7. Dynamic Analysis of Major European Hubs

To capture temporal patterns in airport influence, a dynamic clustering analysis was conducted using annual PageRank trajectories for all European airports from 2019 to 2025. First, the normalized PageRank values for each airport over time were represented as a feature vector. A K-means clustering algorithm was then applied to group airports that exhibited similar trends and changes over the years.

The results revealed four clusters representing distinct development patterns in the European air transport network. These clusters highlight that the recovery process was not uniform. Instead, airports responded differently to two major disruptions: the COVID-19 pandemic and subsequent airspace restrictions related to geopolitical conflicts *(Table 3)*.

TABLE 3 – CLUSTERS OF AIRPORTS BASED ON PAGERANK DYNAMICS

Cluster	Pattern
Cluster 0	A persistent decline in network centrality following both the COVID-19 disruption and subsequent geopolitical restrictions.
Cluster 1	Stable, resilient airports maintaining steady centrality levels after a short-term decline.
Cluster 2	Continuous growth after 2021, reflecting the diversification of European air connectivity.
Cluster 3	Airports with volatile trajectories, characterized by short-term spikes and later stabilization, suggesting temporary reallocation of traffic flows.

To make sure that the clustering results reflect meaningful structural differences, several values of *k* (from 2 to 7) were tested using standard validation methods. Two key criteria were used. The first was inertia (compactness within a cluster), assessed using the "elbow" method. The second was the silhouette coefficient, which measures how well clusters are separated from each other.

The inertia curve did not show a clear "elbow," making it difficult to directly determine the optimal value. However, the silhouette coefficient values reached their maximum levels at $k = 4$ and decreased significantly at higher values. This suggests that using too many clusters leads to less stable groups and weaker separation between them. Based on these diagnostics – and the fact that $k = 4$ yields clusters that are interpretable within the context of European air transport (declining hubs, resilient hubs, emerging hubs, and volatile regional airports) – the four-cluster solution was selected as the most robust and conceptually meaningful *(*Figure *9).*

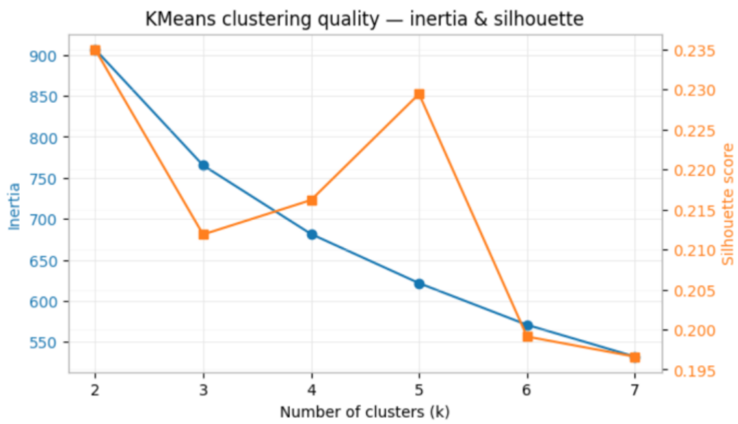

FIGURE 9 – Silhouette score and Elbow method results

Cluster 0 comprises airports that experienced a sharp and sustained decline in centrality, with little or no recovery by 2025. This group includes both closed or downgraded airports (e.g., Berlin Tegel) and those isolated due to airspace restrictions (e.g., Moscow Sheremetyevo). Airports in this cluster effectively lost their integration into the European network, either due to permanent traffic relocation or political disconnection.

Cluster 1 contains the largest and most resilient European hubs – such as Frankfurt, Amsterdam, Paris Charles de Gaulle, and London Heathrow – that maintained relatively high PageRank values throughout the study period. Although these airports experienced temporary declines in 2020–2021, they quickly recovered, demonstrating structural robustness and continued dominance in European air connectivity. Interestingly, this cluster also includes Palma de Mallorca, which, despite its regional and leisure orientation, reached comparable levels of network importance during the post-2022 recovery, highlighting the increasing relevance of Mediterranean destinations.

Cluster 2 represents a smaller set of emerging or steadily growing regional hubs, particularly in Southern and Eastern Europe (e.g., Istanbul, Nice, Porto, Kraków, Bologna). Their consistent upward trajectories reflect the gradual reorientation of European air traffic toward the south and southeast, supported by tourism recovery, expanded low-cost operations, and the redistribution of traffic flows following the closure of Eastern European airspace.

Cluster 3 includes airports with short-term volatility – typically smaller regional facilities that experienced brief surges during the early recovery period (2021–2022) but failed to sustain long-term growth. These fluctuations may correspond to transient market opportunities or temporary demand shocks rather than structural network shifts.

Comparative trajectory plots further illustrate these dynamics *(Figure 10)*. The Top-10 "gainers" – airports with the highest growth, including Palma de Mallorca, Istanbul, Nice, Oslo, and Porto – display consistent growth after 2021. This highlights the growing importance of leisure-focused, peripheral airports during the recovery period. In contrast, the Top-10 "losers" – airports with the lowest growth, such as Sheremetyevo, Berlin Tegel, Frankfurt, and London Heathrow – show continued decline or limited growth over time. This pattern may reflect structural downsizing, airport consolidation, or geopolitical isolation.

When comparing the top 10 airports in 2019 and 2025, the major Western European hubs remain largely central to the network. However, their relative dominance is weakening somewhat, creating more room for the increasing influence of southern and tourism-focused airports.

The dynamic clustering reveals a partial rebalancing of European air connectivity. Traditional hubs continue to play an important systemic role, but they no longer dominate the network's core. At the same time, the growing importance of southern airports points to a more diversified network structure, which could contribute to increased resilience through a more distributed connectivity model and stronger regional specialization.

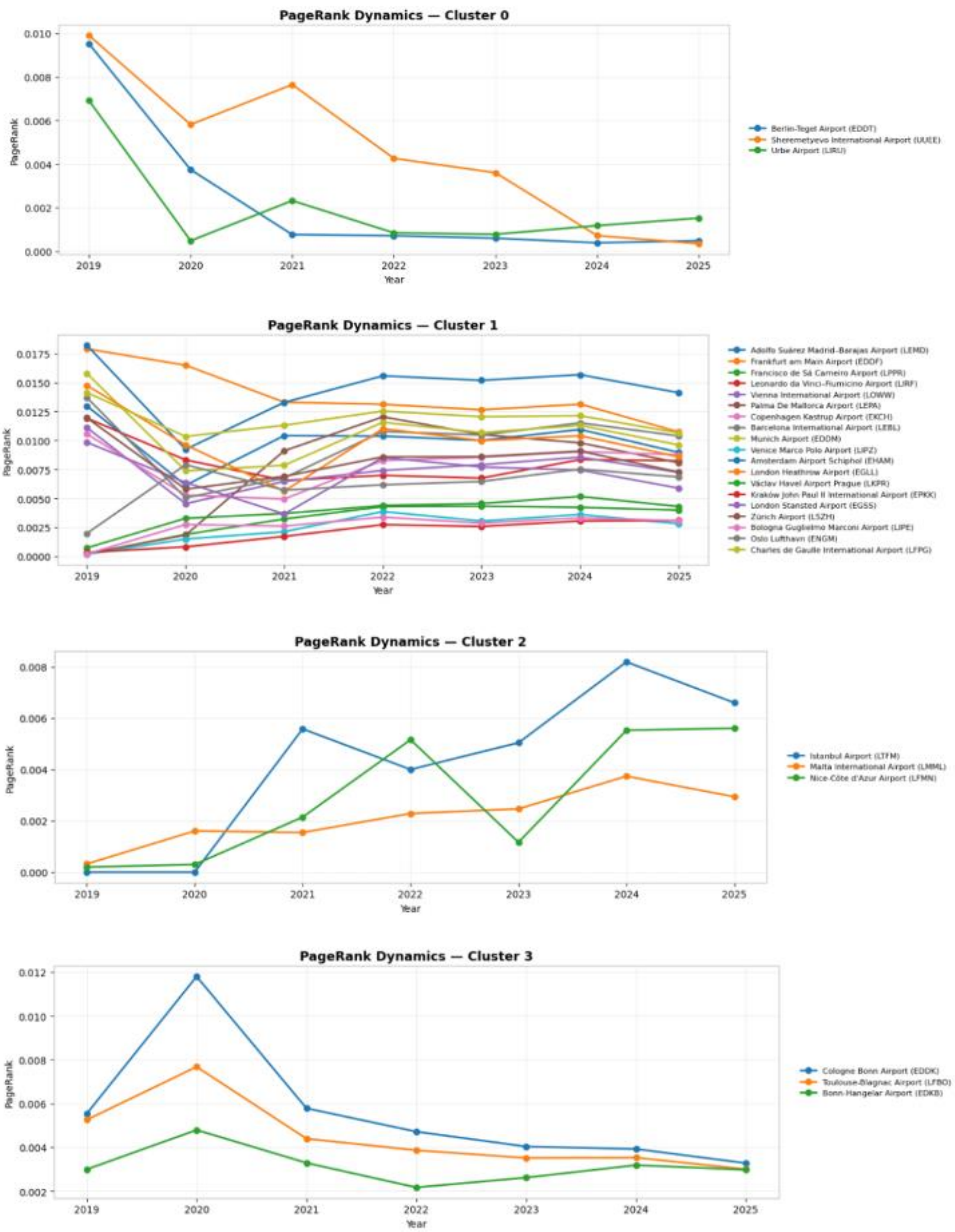

FIGURE 10 – PageRank Dynamics vs Clusters

4.8. Resilience of the European Air Transport Network

To understand how the structural changes influenced the robustness of the European air transport network, a resilience analysis based on percolation theory was implemented. The analysis uses April network snapshots for 2019, 2021, 2023, and 2025.

The main idea is to remove airports or routes step by step and observe how the network behaves. Robustness is measured by tracking the relative size of the giant connected component (GCC), which is the largest group of airports that are still connected to each other. If the GCC decreases quickly, the network becomes fragmented and can be considered less resilient. In contrast, a slight decrease suggests a more robust structure.

Both node removal and edge removal were considered. Node removal simulates airport failures, while edge removal simulates route disruptions. This difference matters for air transport systems, because problems can affect either airport infrastructure or the flight connections between airports. The methodological framework follows classical studies on attack vulnerability and percolation in complex networks (Albert et al., 2000; Holme et al., 2002), as well as recent applications to air transport systems.

For node removal, five strategies were analyzed: random failures and targeted removals based on degree, PageRank, betweenness centrality, and eigenvector centrality. For edge removal, four strategies were applied: random removal, removal by edge weight, edge betweenness, and node-product–based importance. Random strategies represent unsystematic disruptions such as technical issues or weather-related events. In contrast, targeted strategies simulate more critical scenarios, where the most important airports or routes are affected first.

4.8.1. Node removal resilience

The 2019 network exhibits the classical vulnerability pattern of a hub-and-spoke system. Targeted node removals based on degree, PageRank, and betweenness lead to a rapid collapse of the GCC. In particular, betweenness-based attacks are among the most destructive, confirming that airports acting as bridges between regions play a critical role in maintaining global connectivity. The GCC falls below 20% after the removal of roughly half of the most central airports, while random failures have a much weaker effect *(Figure 11).* This behavior is consistent with findings for scale-free and highly centralized networks, which are robust to random failures but fragile under targeted attacks (Albert et al., 2000).

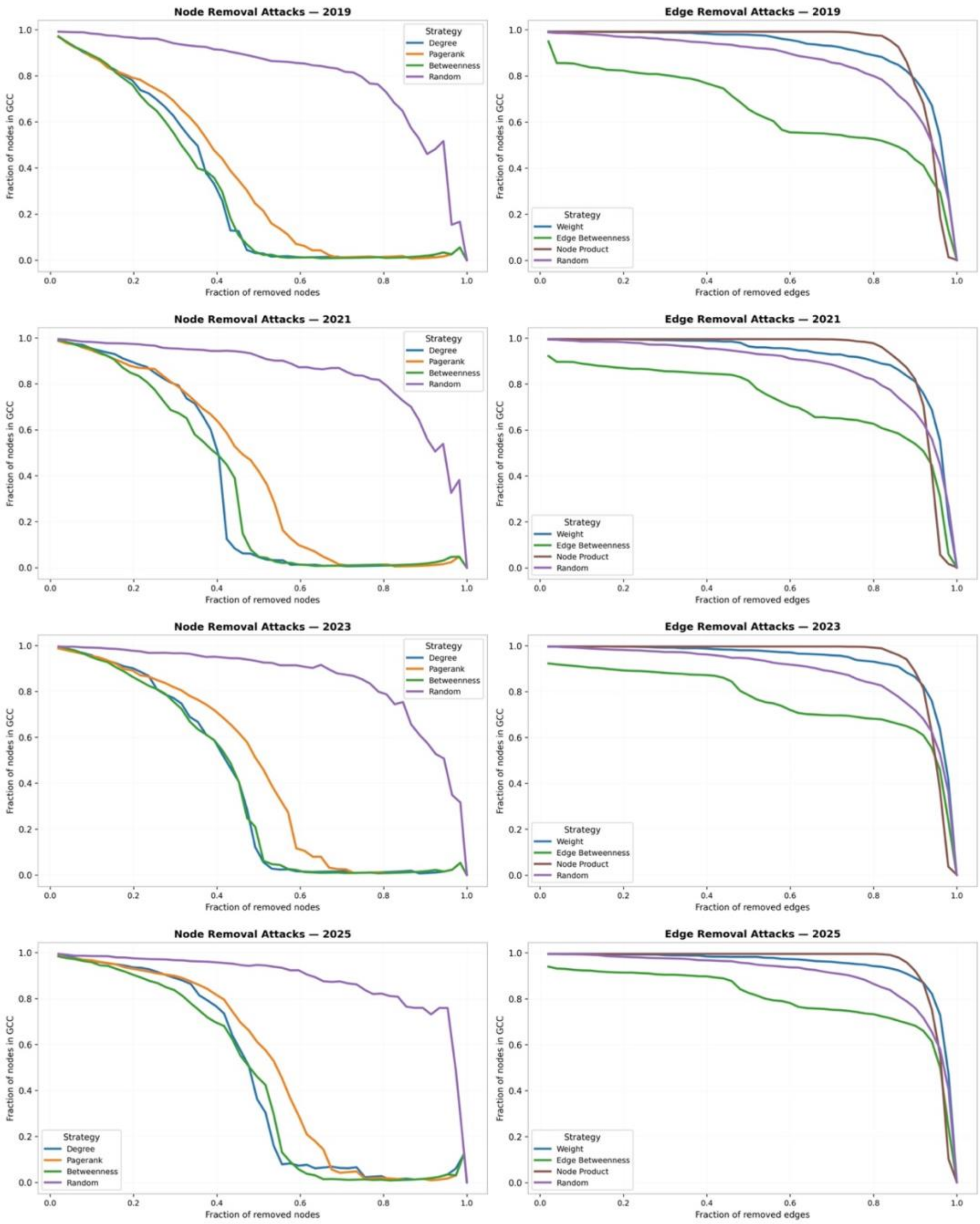

FIGURE 11 – Resilience of the airport network in 2019, 2021, 2023, and 2025

In 2021, the network became even more fragile under targeted attacks. The GCC collapses earlier than in 2019 for almost all centrality-based strategies, reflecting the fragmented topology of the system during this period. Reduced traffic volumes and the loss of redundant connections increase the importance of a small number of remaining hubs, making the network particularly sensitive to their removal.

By contrast, the 2023 and especially the 2025 networks display improved resilience. Although degree- and betweenness-based removals still outperform random failures in terms of damage, the decline of the GCC is noticeably slower. In 2025, the network retains a relatively large connected component even after a substantial fraction of high-centrality airports is removed. This suggests a more distributed structure, with connectivity supported by a broader set of secondary hubs. Eigenvector-based attacks show similar but slightly weaker effects than betweenness-based ones, indicating that global bridge positions remain more critical than pure influence within densely connected substructures.

4.8.2. Edge removal resilience

The edge removal experiments reveal a different but complementary perspective on network robustness. Across all years, random edge removals have a limited impact until a significant proportion of routes has been removed. This demonstrates that the European air transport network has high route-level redundancy, meaning that many routes can be lost without immediately disrupting the whole structure. However, targeted removal based on edge betweenness is the most damaging strategy. This highlights the importance of specific routes that act as critical “bridges” between different parts of Europe. It is important to note that these routes are not necessarily the busiest, but rather those that connect regions and support network integration.

In the 2019 and 2021 snapshots, removing edges with the highest centrality leads to early and gradual fragmentation of the GCC network. This indicates that the network relied heavily on a relatively small set of structurally important routes. At the same time, weight-based and node-product strategies are less destructive, suggesting that traffic volume alone is not a sufficient proxy for structural importance.

In 2023 and 2025, edge-based resilience improves markedly. The GCC remains stable over a wider range of removed edges, even under betweenness-based attacks. This indicates that critical inter-regional connections are no longer concentrated in a small set of routes but are distributed across multiple alternative paths, making the network more resilient to route failures.

4.8.3. Cross-Year Comparison

When comparing results across years, changes in resilience become apparent. The 2021 network was the weakest in both node and edge attacks. This demonstrates that the system was still constrained and had not fully recovered from the pandemic.

The 2019 network is larger and more interconnected, but it is also highly centralized. This makes it vulnerable to targeted hub removal. This is supported by the attack curves: in 2019 the GCC collapses already after removing about 40–45% of nodes under degree and betweenness attacks and 55–60% under PageRank and eigenvector attacks. By comparison, in 2025 a similar collapse typically occurred after 60–70% of removed nodes *(Figure 12).*

In 2023 and 2025, the network becomes more stable. The GCC decreases more slowly, even under targeted attacks, which suggests that the network started to rely less on a small number of major hubs and gained more alternative routes. In other words, there are more ways to remain connected even if some routes or airports are disrupted.

All these results show that the European air transport network has transitioned from a node-centric structure to a more balanced one. This makes the system less vulnerable to major disruptions and helps it cope better with local failures.

4.9. Interpretation and Broader Implications

The combined results from structural metrics, centrality measures, clustering, and the resilience analysis point in the same direction. The European air transport network gradually moved from a highly centralized hub-and-spoke system to a more distributed and adaptive structure. This shift did not happen instantly. Instead, the sequence of shocks during 2019–2025 caused not only short-term collapses in connectivity, but also longer-term changes in the way the network is organized.

The major hubs in Western Europe mostly kept their leading roles. However, their relative importance weakened over time, especially compared to the pre-pandemic structure. At the same time, several regional and secondary airports gained influence and started to work as alternative connectors within the network. This redistribution is important because it supports resilience: when the network has more routing options and relies less on a small group of airports, it becomes less fragile and can handle disruptions better.

The resilience results support this conclusion. Before 2020, the network was strongly centralized, and it was also very sensitive to targeted failures of key airports and routes. The weakest situation appears in 2021. In that year, both node- and edge-removal experiments show that the GCC breaks down quickly under targeted attacks, which suggests that the system still depended on a limited set of critical connections.

After that, the recovery period (2022–2025) looks different. Connectivity returns, but not only in terms of "more flights" or "more routes". The structure itself also becomes more robust. In 2025, the network shows higher redundancy, and the GCC declines more slowly even when important airports or routes are removed. This means that the network is less dependent on individual high-centrality hubs and can stay connected for longer.

From a policy and network management point of view, these findings highlight why flexible multi-hub strategies are important. If the system uses several regional connectors and has parallel routing options, it becomes easier to absorb shocks and maintain connectivity during crises. In general, the European air transport network appears to be moving toward a structure that is more resilient, more modular, and better prepared for future disruptions.

5. CONCLUSION

This dissertation examined how the European air transport network transformed between 2019 and 2025 under the influence of two major shocks: the COVID-19 pandemic and the later geopolitical airspace restrictions. Using a network-science framework, the study analyzed changes in structure, connectivity, airport centrality, and total resilience. The analysis was based on OpenSky flight data and used different time perspectives, including quarterly and annual aggregates, as well as April snapshots. By combining structural indicators, centrality metrics, clustering, and percolation-based tests, the dissertation provides a broad picture of how the network reacted, recovered, and reorganized during a highly unstable period.

The results lead to several main conclusions, which respond to the research question and the study objectives.

First, regarding the structural evolution of the European air transport network, the findings show that the period 2019–2025 was characterized by both short-term disruption and long-term reconfiguration. The pandemic created an exceptional disruption in 2020, when the number of active airports and routes dropped sharply, and the overall level of connectivity decreased. From 2021, the network started to recover gradually. The indicators then became more stable in the period 2023–2025. By 2025, key metrics such as density and average degree not only returned to pre-pandemic levels but also increased beyond them. This suggests that the network did not simply "go back" to its 2019 structure. Instead, it developed into a more connected and structurally diversified system. Seasonal patterns were still visible, but the long-term trends show stronger cohesion and wider integration across regions.

Second, the dissertation assessed how the two shocks influenced airport roles and the overall hierarchy of the network. The centrality analysis showed a clear redistribution of influence across European airports. Major Western hubs such as Amsterdam Schiphol, Frankfurt, Munich, and London Heathrow remained important, but their relative dominance declined over time. At the same time, several southern and southeastern airports increased their PageRank values, including Palma de Mallorca, Istanbul, Nice, Porto, and Kraków. This development can be linked to the recovery of leisure travel and to route changes caused by restricted air corridors in Eastern Europe. Some airports were directly affected by geopolitical constraints. Sheremetyevo is the most visible example, since it experienced a strong decline in centrality and became much less integrated in the European network. The clustering of PageRank trajectories also supported these findings, as airports followed different development patterns over time. Overall, the results show that external shocks changed not only traffic volumes, but also the internal balance of the European air transport system.

Third, regarding resilience, the study demonstrated that the European air transport network became more robust over time. Percolation experiments reveal that the 2019 system displayed classical hub-and-spoke fragility: removing a small number of highly central airports caused rapid fragmentation. The 2021 network was the most fragile in the entire series, when resilience dropped even further. This reflects a system that was still highly constrained, with fewer alternative routes and stronger fragmentation. From 2023 onwards, resilience steadily improved. By 2025, the network could tolerate the removal of a larger proportion of important nodes before the giant connected component collapsed. This outcome indicates a structural shift toward greater redundancy, more distributed hub functions, and a reduced dependency on a small group of dominant hubs, especially in Western Europe. The growing role of southern airports and the isolation of some eastern hubs also contributed to a more balanced network structure.

Taken together, these results allow us to answer the research question formulated in section 1.2: "How did the European air transport network transform in response to COVID-19 disruptions and geopolitical airspace restrictions, and what are the implications for network structure, connectivity, and resilience?" The European air transport network did not passively absorb the shocks of the pandemic and geopolitical disruptions; instead, it adapted through a process of structural transformation. Even though the immediate effects were severe, the long-term outcome was a network that became more distributed, more diverse, and more resilient. Connectivity recovered through new routing patterns, stronger roles for secondary hubs, and more parallel connections across regions. Traditional hubs did not disappear, but their influence became less concentrated because the network expanded around new centers. The stronger position of airports in southern and southeastern Europe appears to be one of the most important structural shifts in the 2019–2025 period.

This study contributes to the broader literature by demonstrating how multi-temporal network analysis can capture both disruption effects and structural adaptation in air transport systems. It confirms findings from earlier research about the impact of COVID-19 and geopolitical restrictions, while also providing evidence that resilience improved after 2022. The combined use of PageRank trajectories, clustering, and percolation analysis offers a replicable framework for monitoring resilience and identifying emerging hubs in evolving transport networks.

Several limitations must be acknowledged. ADS-B-based OpenSky data may under-represent certain regional airports, and the study focuses on structural connectivity rather than operational or economic performance. Despite these constraints, the analysis robustly reflects the major patterns observed across multiple data sources and aligns with documented developments reported by aviation authorities.

Future research could extend this work by incorporating airline-specific dynamics, passenger flows, or cost-based measures; by evaluating multilayer structures that include alliances or multimodal links; or by analyzing environmental and operational efficiency alongside network resilience.

In conclusion, this dissertation shows that the European air transport network has emerged from a prolonged period of disruption, not simply restored but fundamentally reshaped – less centralized, more adaptable, and better prepared to withstand future crises.

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APPENDICES

TABLE 4 – TOP "GAINERS" AND "LOSERS" BY PAGERANK (2019–2025)

ICAO code	Airport name	City	Country	PR 2019	PR 2025	ΔPR
LEPA	Palma De Mallorca Airport	Palma de Mallorca	Spain	0.00021	0.00807	0.00786
LTFM	Istanbul Airport	Istanbul	Turkey	0.00000	0.00660	0.00660
LFMN	Nice-Côte d'Azur Airport	Nice	France	0.00020	0.00561	0.00541
ENGM	Oslo Lufthavn	Oslo	Norway	0.00197	0.00684	0.00487
LPPR	Francisco de Sá Carneiro Airport	Porto	Portugal	0.00018	0.00398	0.00380
LKPR	Václav Havel Airport Prague	Prague	Czech Republic	0.00072	0.00430	0.00358
LIPE	Bologna Guglielmo Marconi Airport	Bologna	Italy	0.00019	0.00307	0.00288
EPKK	Kraków John Paul II International Airport	Krakow	Poland	0.00033	0.00309	0.00276
LIPZ	Venice Marco Polo Airport	Venice	Italy	0.00017	0.00280	0.00263
LMML	Malta International Airport	Malta	Malta	0.00032	0.00294	0.00262
ENBR	Bergen Airport Flesland	Bergen	Norway	0.00000	0.00257	0.00257
LFPN	Toussus-le-Noble Airport	Toussus-le-Noble	France	0.00102	0.00355	0.00253
LEIB	Ibiza Airport	Ibiza	Spain	0.00016	0.00214	0.00198
LTAI	Antalya International Airport	Antalya	Turkey	0.00000	0.00192	0.00192
LBSF	Sofia Airport	Sofia	Bulgaria	0.00025	0.00214	0.00189
EDDP	Leipzig/Halle Airport	Leipzig	Germany	0.00020	0.00206	0.00186
LGTS	Thessaloniki Macedonia International Airport	Thessaloniki	Greece	0.00000	0.00186	0.00186
UWSS	Saratov Central Airport	Saratov	Russia	0.00000	0.00170	0.00170
LIMC	Malpensa International Airport	Milano	Italy	0.00370	0.00539	0.00169
LCLK	Larnaca International Airport	Larnaca	Cyprus	0.00023	0.00188	0.00165
LEMG	Málaga Airport	Malaga	Spain	0.00454	0.00617	0.00162
LFRS	Nantes Atlantique Airport	Nantes	France	0.00082	0.00231	0.00149
LYBE	Belgrade Nikola Tesla Airport	Belgrade	Serbia	0.00086	0.00228	0.00142
EFTP	Tampere-Pirkkala Airport	Tampere	Finland	0.00053	0.00194	0.00141
EDDB	Berlin-Schönefeld Airport	Berlin	Germany	0.00469	0.00603	0.00134
EDAQ	Halle-Oppin Airport	Halle	Germany	0.00018	0.00152	0.00134
LFMD	Cannes-Mandelieu Airport	Cannes	France	0.00018	0.00151	0.00133
ENZV	Stavanger Airport Sola	Stavanger	Norway	0.00022	0.00148	0.00126
EKBI	Billund Airport	Billund	Denmark	0.00030	0.00155	0.00125
EYVI	Vilnius International Airport	Vilnius	Lithuania	0.00025	0.00147	0.00122
LEVC	Valencia Airport	Valencia	Spain	0.00000	0.00121	0.00121
EDQF	Ansbach-Petersdorf Airport	Ansbach	Germany	0.00000	0.00119	0.00119
EFNU	Nummela Airport	Nummela	Finland	0.00048	0.00166	0.00118
LFPZ	Saint-Cyr-l'École Airport	Saint-Cyr	France	0.00020	0.00136	0.00116
LEBG	Burgos Airport	Burgos	Spain	0.00000	0.00115	0.00115
LSZR	St Gallen Altenrhein Airport	Altenrhein	Switzerland	0.00036	0.00150	0.00114
EDMS	Straubing Airport	Straubing	Germany	0.00030	0.00144	0.00114
EGPT	Perth/Scone Airport	Perth	United Kingdom	0.00027	0.00138	0.00111
EGXT	RAF Wittering	Wittering	United Kingdom	0.00035	0.00146	0.00110
ESOW	Stockholm Västerås Airport	Vasteras	Sweden	0.00032	0.00141	0.00109
UUBM	Myachkovo Airport	Moscow	Russia	0.00016	0.00125	0.00109
EPWA	Warsaw Chopin Airport	Warsaw	Poland	0.00506	0.00615	0.00109
LFLN	Saint-Yan Airport	St.-yan	France	0.00019	0.00124	0.00105
EGKR	Redhill Aerodrome	Redhill	United Kingdom	0.00309	0.00160	-0.00150
LFFI	Ancenis Airport	Ancenis	France	0.00170	0.00019	-0.00150
LIML	Milano Linate Airport	Milan	Italy	0.00580	0.00422	-0.00158
EDFE	Frankfurt-Egelsbach Airport	Egelsbach	Germany	0.00397	0.00239	-0.00158
LHBP	Budapest Liszt Ferenc International Airport	Budapest	Hungary	0.00581	0.00418	-0.00164
LFBN	Niort-Souché Airport	Niort	France	0.00226	0.00060	-0.00167
LIEE	Cagliari Elmas Airport	Cagliari	Italy	0.00184	0.00013	-0.00171
LIME	Il Caravaggio International Airport	Bergamo	Italy	0.00446	0.00268	-0.00178
EGNX	East Midlands Airport	East Midlands	United Kingdom	0.00327	0.00149	-0.00178
EKCH	Copenhagen Kastrup Airport	Copenhagen	Denmark	0.01055	0.00876	-0.00179
LKPD	Pardubice Airport	Pardubice	Czech Republic	0.00241	0.00039	-0.00202
ULLP	Pushkin Airport	St. Petersburg	Russia	0.00224	0.00020	-0.00204
UKBB	Boryspil International Airport	Kiev	Ukraine	0.00205	0.00000	-0.00205
LGIR	Heraklion International N.Kazantzakis Airport	Heraklion	Greece	0.00206	0.00000	-0.00206
UUWW	Vnukovo International Airport	Moscow	Russia	0.00487	0.00280	-0.00207
EDAM	Merseburg Airport	Muehlhausen	Germany	0.00241	0.00034	-0.00208
LIBD	Bari Karol Wojtyła Airport	Bari	Italy	0.00221	0.00000	-0.00221
LFBO	Toulouse-Blagnac Airport	Toulouse	France	0.00525	0.00300	-0.00225
EDDK	Cologne Bonn Airport	Cologne	Germany	0.00554	0.00328	-0.00226

EDCD	Cottbus-Drewitz Airport	Cottbus	Germany	0.00241	0.00015	-0.00226
LGAV	Eleftherios Venizelos International Airport	Athens	Greece	0.00568	0.00338	-0.00229
EGGW	London Luton Airport	London	United Kingdom	0.00647	0.00396	-0.00251
ESSA	Stockholm-Arlanda Airport	Stockholm	Sweden	0.01034	0.00771	-0.00264
EDFC	Aschaffenburg Airport	Aschaffenburg	Germany	0.00396	0.00127	-0.00268
ULLI	Pulkovo Airport	St. Petersburg	Russia	0.00333	0.00052	-0.00280
EDDH	Hamburg Airport	Hamburg	Germany	0.00759	0.00470	-0.00289
LSGG	Geneva Cointrin International Airport	Geneva	Switzerland	0.00777	0.00478	-0.00299
EFHF	Helsinki Malmi Airport	Helsinki	Finland	0.00326	0.00019	-0.00307
ENKJ	Kjeller Airport	Kjeller	Norway	0.00413	0.00089	-0.00324
UUDD	Domodedovo International Airport	Moscow	Russia	0.00349	0.00023	-0.00326
EDDS	Stuttgart Airport	Stuttgart	Germany	0.00595	0.00266	-0.00328
LEBL	Barcelona International Airport	Barcelona	Spain	0.01369	0.01038	-0.00331
EGKK	London Gatwick Airport	London	United Kingdom	0.00937	0.00591	-0.00346
LFPG	Charles de Gaulle International Airport	Paris	France	0.01412	0.01064	-0.00348
LIRF	Leonardo da Vinci–Fiumicino Airport	Rome	Italy	0.01191	0.00824	-0.00367
LOWW	Vienna International Airport	Vienna	Austria	0.01110	0.00724	-0.00385
EDDL	Düsseldorf Airport	Duesseldorf	Germany	0.00812	0.00422	-0.00390
EGSS	London Stansted Airport	London	United Kingdom	0.00983	0.00588	-0.00395
LEMD	Adolfo Suárez Madrid–Barajas Airport	Madrid	Spain	0.01297	0.00895	-0.00402
EHAM	Amsterdam Airport Schiphol	Amsterdam	Netherlands	0.01821	0.01412	-0.00409
LSZH	Zürich Airport	Zurich	Switzerland	0.01194	0.00726	-0.00468
LIRU	Urbe Airport	Rome	Italy	0.00691	0.00152	-0.00539
EGLL	London Heathrow Airport	London	United Kingdom	0.01474	0.00858	-0.00616
EDDM	Munich Airport	Munich	Germany	0.01578	0.00960	-0.00618
EDDF	Frankfurt am Main Airport	Frankfurt	Germany	0.01790	0.01072	-0.00718
EDDT	Berlin-Tegel Airport	Berlin	Germany	0.00952	0.00048	-0.00904
UUEE	Sheremetyevo International Airport	Moscow	Russia	0.00990	0.00035	-0.00955

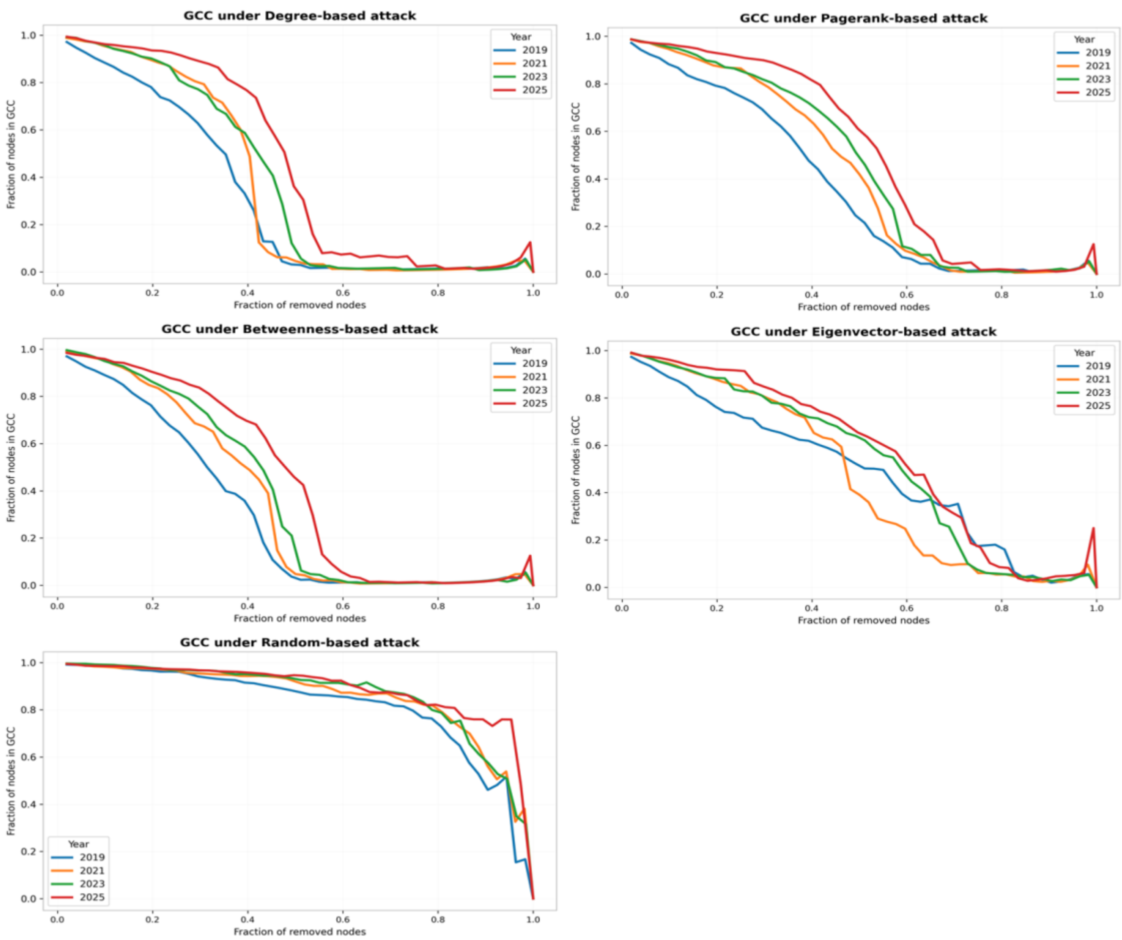

FIGURE 12 – GCC under different types of attacks