MHEDAS 2024-2025

A3 - US AIR TRAFFIC NETWORK STUDY

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Group A

CONTENTS

1. INTRODUCTION

Air transportation networks are critical for the mobility of people, therefore being an important and interesting field for research. Over the years, the air transportation system has evolved into a complex and heterogeneous network, shaped by geo-spatial relations, socioeconomic factors and political constraints, among others [1].

The aim of this report is to analyse a longitudinal U.S traffic network [2] to gain insights into its structural properties, resilience, and temporal dynamics. This study seeks to address two main objectives, a resilience analysis and a temporal analysis.

The resilience analysis evaluates how the network responds to targeted attacks (the removal of critical hubs) and random failures (the loss of random nodes). These scenarios simulate real-world challenges such as disruptions to major airports due to extreme weather and technical failures, for instance, systematic random failures which could be due to economic downturns. By examining the network's fragmentation and the size of the giant component in these conditions, it is possible to understand the network's robustness and identify critical nodes which are essential for connectivity.

The temporal analysis, on the other hand, aims to perform a time-series analysis of the network to study how its structure evolves over time and how critical historical events affect its architecture and variance. The analysis of the historical events will serve as the case studies with which to compare the theoretical insights.

The chosen dataset contains real flight data from U.S commercial airports and originally comes from the Bureau of Transportation Statistics [3]. It contains yearly snapshots of flights among all commercial airports in the United States ranging from 1990 to 2020.

The network is represented as a directed graph where nodes correspond to airports and edges represent flight routes, with weights indicating passenger volume. The source would be the encoded departure airport, whereas the target corresponds to the encoded arrival airport. In addition, the data file contains many informative attributes such as the number of passengers, the distance, and time-related columns, among others. There is a complementary metadata file which maps each encoded airport to its real code and city.

By combining a resilience analysis with temporal insights, this study aims to bring valuable lessons for future challenges in air traffic management, as well as to contribute to the ever evolving research field of complex transportation networks.

2. DATA PREPROCESSING

The aim of this section is to prepare the data for the downstream analysis and to perform a first data exploration to reveal any useful insights.

First of all, the column names are reformatted and the categorical and numerical columns are further explored. It has also been assured that the targeted columns did not contain any null values.
Then, the data was grouped by year in order to calculate the number of flights and passengers per year. Year 2020 was excluded from the analysis since there was only data for one month and this would result in skewing the plots.
Figure 1 gives a first overview of the tendency of the number of flights and passengers over the years 1990 to 2019. To better understand these trends further analysis is conducted.

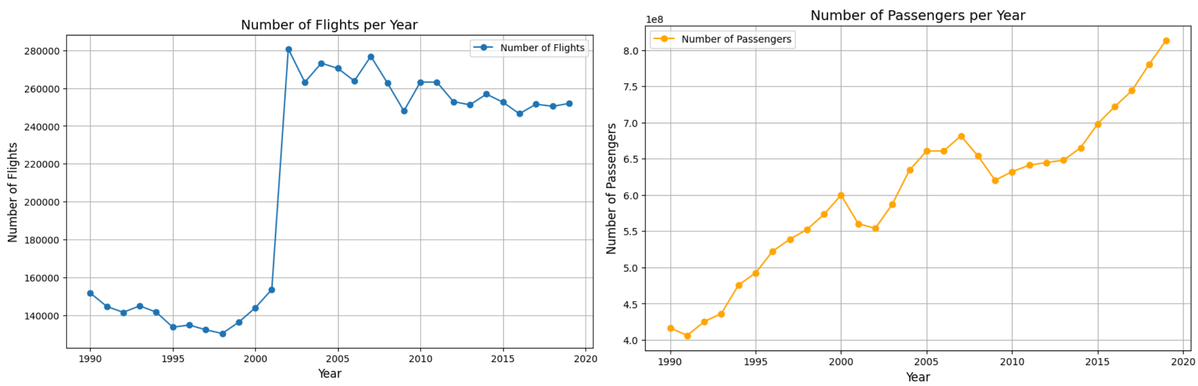

Figure 1.-Plot representing the number of flights per year (left) and the number of passengers per year (right).

Next, the data was filtered to remove redundant columns and outliers, such as the flights that contained 0 passengers.

The filtered data was aggregated by source, target and year. The number of flights with the same source and target for each year is stored in a new column named “total_flights”, whereas the column “total_passengers” represents the sum of passengers for each unique combination of source, target and year. By doing this aggregation, it has been possible to reduce the dimensions of the dataset and to obtain the weight for the network, which will be the number of passengers.

3. NETWORK CHARACTERISTICS

The present network is a mono-layered directed network, since each flight has a departure airport (source node) and an arrival airport (target node). It is also a unipartite network since all nodes represent airports and the edges represent flights between these airports.
In a weighted network, the edges carry additional information that reflects the strength or importance of the connection. For this network, it has been decided to use the number of passengers traveling on a route as the weight, because routes with higher passenger volumes are more critical for maintaining network efficiency and connectivity and therefore reflect the route importance.

The network used for this analysis contains a total of 2002 nodes and 74943 edges.

A directed graph was created using the networkx library. Then, some basic parameters and metrics of the network were obtained. *Table 1* contains a summary of these metrics.
In order to calculate the distance metrics like the radius, diameter and average shortest path length, it was necessary to use the largest strongly connected component (SCC). The SCC is a subgraph where every node is reachable from every other node following the direction of edges. It also identifies the most connected part of the network where bidirectional travel is possible.

Feature	Result
Number of nodes	2002
Number of edges	74943
Average degree	74.87
Number of nodes from the SCC	1838
Radius from the SCC	2
Diameter from the SCC	4
Average shortest path length from the SCC	2.89
Average clustering coefficient	0.53
Assortativity	0.05

Table 1. Basic features of the network.

The large number of edges indicates a dense network with significant connectivity between airports. The average degree indicates that airports, on average, are connected to approximately 75 other airports while the small radius and diameter indicates a highly connected and efficient core network, where even the farthest airports within the SCC are relatively close to each other in terms of connectivity.

Also, the average path length of approximately 2.9 reflects an efficient connectivity, meaning that passengers can travel between most airports in the SCC in less than three steps. To better understand this connectedness, *Figure 2*, shows a boxplot of the distribution of the nodes' betweenness. Betweenness centrality measures the frequency with which a node is on the shortest path between all pairs of nodes in a network. These between centrality represent values that have been aggregated by years and demonstrate that the majority of nodes have low values for betweenness likely attributed to regional airports whereas there are some that have significantly higher values which would represent airports that act as hubs for the network.

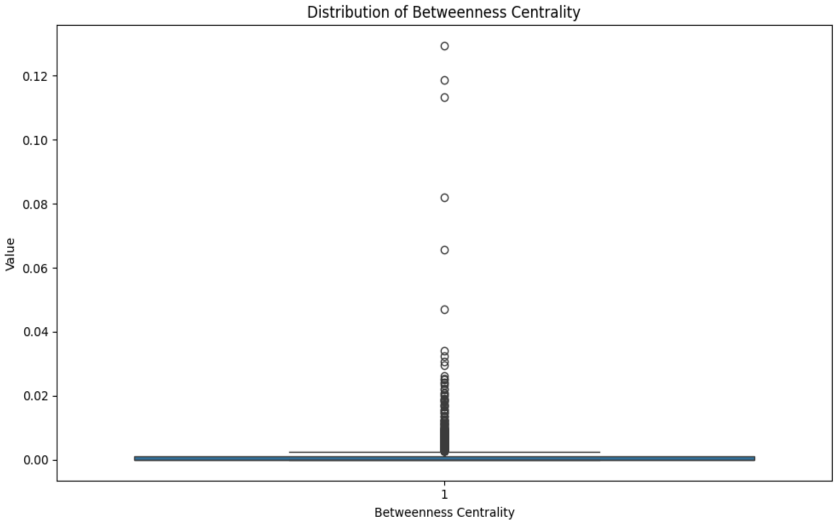

Figure 2.- Distribution of the betweenness centralities

In *Table 2* below, the betweenness centralities are shown for the top 10 of the values in the above box plot.

Node	City	Betweenness Centrality
110	Anchorage, AK	0.129323
208	White Plains, NY	0.118687
196	Fairbanks, AK	0.113229
133	Burbank, CA	0.081975
444	Teterboro, NJ	0.065568
185	King Salmon, AK	0.047126
55	Burlington, VT	0.034179
247	Seattle, WA	0.032486
135	Chicago, IL	0.030790
109	Juneau, AK	0.029428

Table 2.- Top 10 nodes with the highest betweenness centralities in the network aggregated by year

Just as an example, node 110 represents the Ted Stevens Anchorage International Airport. According to the airport's website:
"Anchorage's strategic location just 9.5 hours from 90% of the industrialized world cements its position as a pivotal global supply chain hub, handling not only passenger traffic but also serving as North America's second busiest cargo airport and fifth busiest in the world."

This shows us that the betweenness values of airports (nodes) can accurately depict its importance within the network .

Figure 3 visualises the air traffic network:

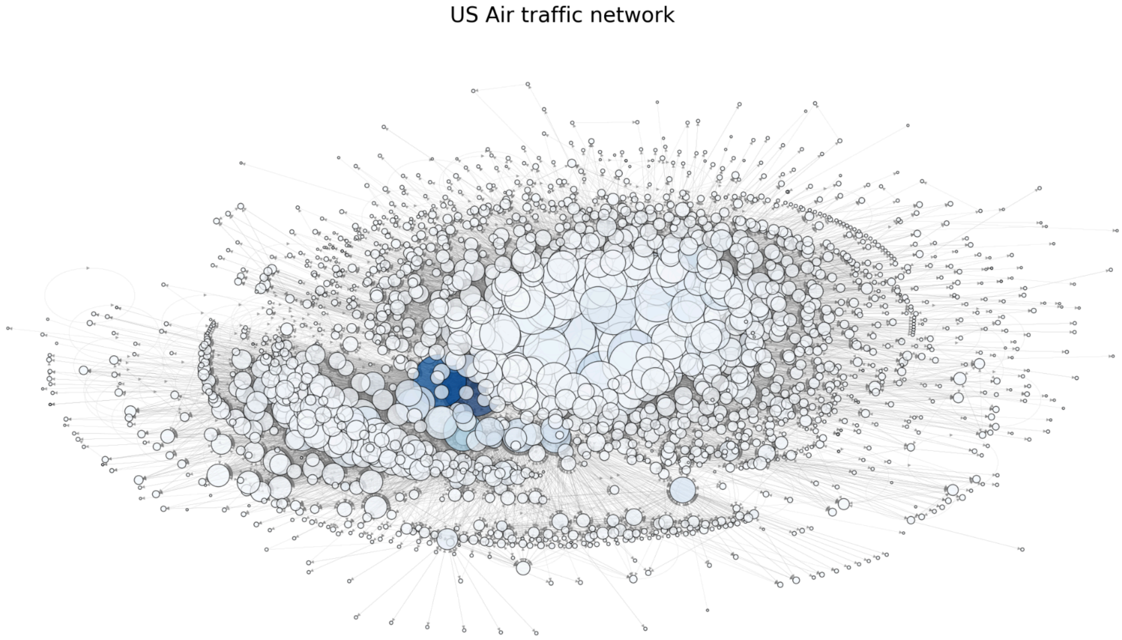

Figure 3.- Visualization of the U.S Air traffic network with the node size being representing the magnitude of the degrees and the node color intensity representing the betweenness.

Figure 4 below represents a degree distribution plot for the U.S. air traffic network.

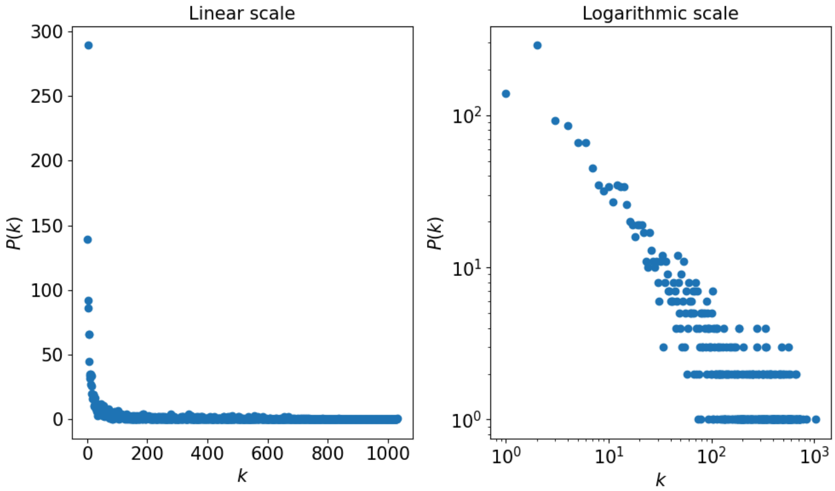

Figure 4.- Visualisation to test for scale free behaviour

The following plots, in *Figure 5*, are used to test the scale-free nature of the network by examining if the degree distribution follows a power-law. Scale-free networks are characterised by the presence of a few highly connected nodes (hubs) and many nodes with low connectivity, resulting in a degree distribution that decays linearly on a log-log plot. The visualisation provides insights into whether the network exhibits this behaviour, which is often typical of complex networks related to transportation and communication systems.

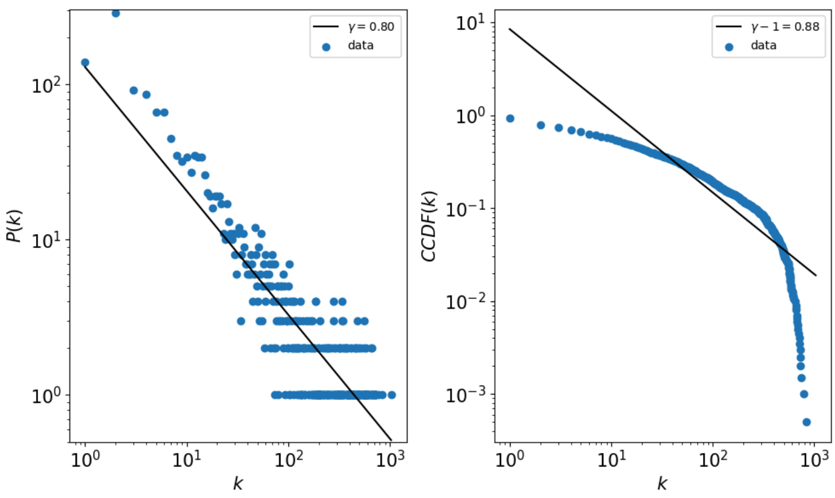

Figure 5.- Visualisation to test for scale free behaviour

The observed pattern, in *Figure 5,* shows a tendency indicative of the presence of hubs and scale free behaviour; however, in the cumulative plot there is heavy-tailed distribution suggesting that further statistical tests are needed to confirm the power-law distribution and establish whether the network can be definitively classified as scale-free.

4. RESILIENCE ANALYSIS

The goal of this section is to test the resilience of the air traffic network by simulating random failures and targeted attacks on its nodes. The metric to define the network resilience is the size of the giant component, which represents the largest connected subset of nodes (airports) that remain functional after the disruption.

A large giant component indicates that most of the nodes can still interact with each other - in this context that passengers can travel between airports. However, a small giant component may indicate that the network is fragmented into isolated clusters, making travel significantly more difficult.

The variable that represents the fraction of nodes to keep in the graph after the attack is called “occupation probability”. This variable can range from 0 (all nodes are removed) to 1 (no nodes are removed).

In a random attack, nodes are removed randomly, trying to simulate natural disruptions that could be related to weather conditions or maintenance, for example. Scale-free networks like this one are expected to be highly robust to random failures because most of the nodes have a low connectivity, so their removal will not significantly affect the giant component.
In order to simulate the random attack, a function loops through all the nodes in the graph and generates a random number for each node. If the random number is greater than the defined occupation probability *(occ_prob)*, that node is targeted for its removal. In summary, the function removes a fraction of nodes to mimic a random disruption, and then returns the updated graph.

On the other hand, in a targeted attack, nodes with high centrality are removed, so the attacks are performed to critical hubs (important airports). In contrast to random attacks, scale-free networks are very vulnerable to targeted attacks, since these small but important numbers of hubs hold the network together.

A function was used to calculate the degree of each node using G.degree() and sort the nodes in descending order by degree. Then, the nodes which are the most connected (and therefore have the highest degree) are removed following the occupation probability. In this case, the output is the graph with the most connected nodes removed.

For both attacks, an occupation probability of 0.7 was set, which means that 70% of the nodes are retained, and 30% of the nodes are removed from the network. This value was arbitrary and was useful to assess a quick overview of the giant component size after the attacks.

After a random attack under the mentioned conditions, the giant component size was 1214 nodes, whereas for the targeted attack it was 391 nodes. This supports the statement that the network is more vulnerable to targeted attacks.
Figure 6, analyzes the network behavior over a wider range of occupation probabilities.

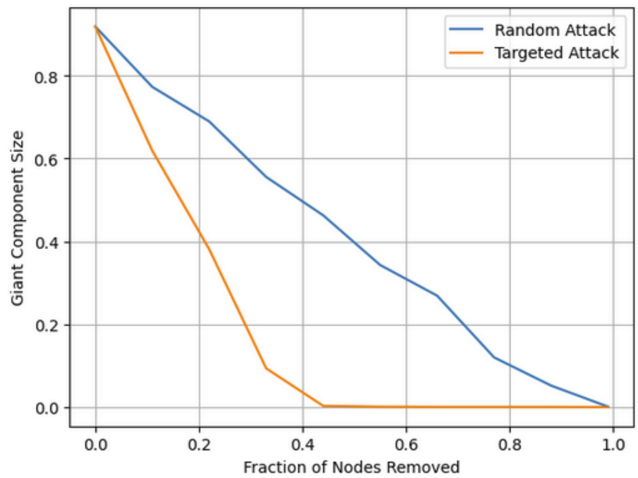

Figure 6.-Network behaviour and resilience over the different occupation probabilities.

From *Figure 6*, it is possible to observe that the giant component size gradually and smoothly decreases as the nodes are randomly removed. Even after removing 50% of the nodes, a relatively large giant component exists, which highlights the robustness of the network against random failures.

In contrast, in the targeted attack the giant component size decreases abruptly when the first few nodes are removed, and the network becomes almost completely fragmented after removing only 20-30% of the nodes. This demonstrates the vulnerability of the network to targeted attacks.

The percolation threshold is the critical fraction of nodes removed at which the giant component collapses. Below this threshold the network is fragmented, with no giant component or connectivity at all. For the random attack, the threshold is very high, around 0.8, but for the targeted attack it is only around 0.3.

5. TEMPORAL ANALYSIS

4.1. Metrics Analysis Over Time

This section focuses on analysing the evolution of key network metrics over the time, more specifically between the 1990-2020 period. The studied metrics are the number of nodes and edges, and the clustering coefficient and average shortest path length.

Figure 7 illustrates the number of nodes and edges in the network over time. It is possible to see that there is an initial stability between 1990 and 2000, reflecting a steady growth in the air traffic network. However, there is a rapid expansion between years 2000-2005, likely reflecting a surge in air transportation routes, the introduction of new airports as well as the offering of lower cost air travel.

After the expansion phase, the network stabilizes between 2005 and 2019, with minor annual variations in both metrics.

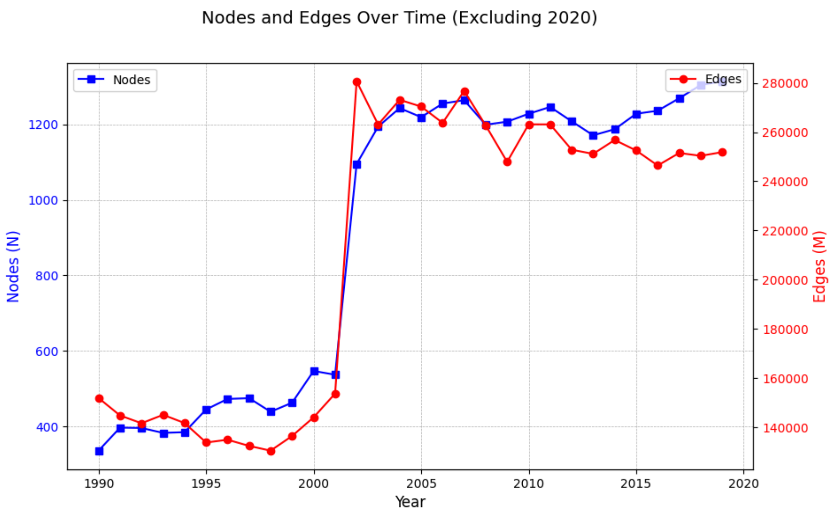

Figure 7.-Number of nodes (blue curve) and edges (red curve) in the network over time.

The clustering coefficient measures how likely it is that two neighbors of a node are also neighbors themselves. In this context, a high clustering coefficient may indicate a strong regional connectivity, where airports within the same area are well-connected (for example, regional hubs connecting smaller airports).

On the other hand, the average shortest path length measures the average number of steps required to travel between any two nodes in the network. For this network, shorter path lengths indicate better efficiency, since it allows passengers to travel between airports with fewer stops.

Figure 8 shows the average clustering coefficient and the average shortest path length plotted over time.

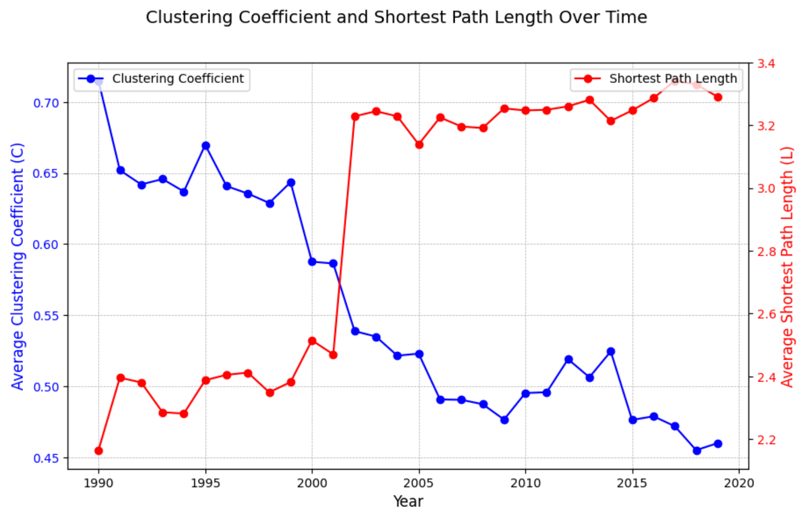

Figure 8.- Average clustering coefficient (blue curve) and average shortest path length (red curve) over time.

Following the plot in *Figure 8*, it is possible to observe that the clustering coefficient starts relatively high, indicating that the network had strong local connectivity. However, a gradual decline in the clustering coefficient is observed, especially after the 2000s, which could be the result of more direct routes and the improvement of commercial airlines. This critical period will be analysed in greater detail surrounding these events: the Dot-com boom (2000s), September 11 attacks (2001) and SARS Outbreak (2003).

The average shortest path length remained relatively stable and low before 2000, which means that passengers could efficiently travel between most airports with few steps. Then, it increased after the year 2000, stabilising around 3.2 recently. This may reflect an increase in the overall network size and a geographical spread, therefore resulting in longer travel paths. Despite the increase in the shortest path length, it still remains small, which highlights the network's efficiency.

The trends in these metrics reflect the dynamic nature of the air transportation network, influenced by economic growth and technological advancements. The observed stability and efficiency underscore the resilience and adaptability of the U.S. air traffic network, even in the face of significant challenges.

4.2. Temporality

Temporality, as defined in the paper *"Characterization of Interactions' Persistence in Time-Varying Networks"* [4], measures the consistency of interactions over time in dynamic networks, where relationships or communication patterns develop. A higher temporality value suggests that interactions occur in a stable, predictable order, while a lower value indicates more randomness or variability in the timing of these interactions. This concept is particularly useful for examining the stability of systems like transportation networks, since it allows us to compare their dynamics over time and understand the resilience to disruptions.

To calculate temporality, a function has been implemented based on the methodology presented in the paper. The process involves tracking the persistence of edges (flight routes) across consecutive snapshots of the air traffic network from 1990 to 2020. Additionally, a randomised version of the network has been created for comparison, since it helps to discover whether the observed temporality in the real network reflects meaningful structural patterns or just mimics a random behavior. This approach disrupts temporal correlations while preserving the number of nodes and edges per snapshot, serving as a baseline for random behavior.

The total network temporality for the real air traffic network, obtained by summing up the individual temporality values for each year interval, is 4.89. On the other hand, the temporality value for the randomized network was 1.988, significantly lower than the real network. This higher total temporality value compared to the randomised network implies that edges in the real network persist across snapshots much more than they would do by chance. This persistence may be due to the operational stability of airports, for instance, where major hubs remain active for decades and strategic connections may be influenced by passenger demand and geography, among other factors.

Figure 9 illustrates how temporality evolves over the timeline, for both real and randomised networks.

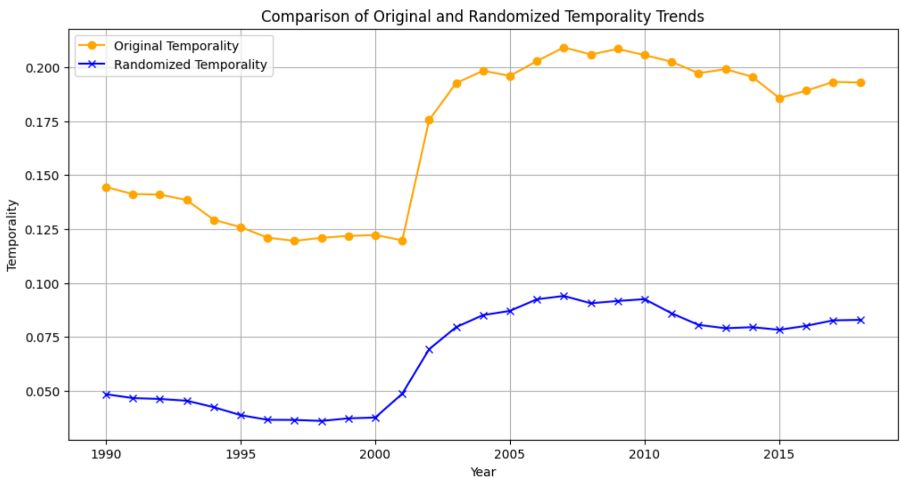

Figure 9. -Comparison of the real network and randomised network temporality.

In the early 1990s, the temporality of the air traffic network slowly went down, showing that interactions in the network became more unpredictable. This might have happened because the network was growing and adding more routes. By the late 1990s, temporality dropped sharply, hitting its lowest point just before 2000. This big decrease could be related to a period of rapid changes, expansion in air traffic. During this period there were also many significant events like the Dot-com boom (2000s) and September 11 attacks (2001).

After this low point, temporality quickly increased between 2000 and 2005, showing that the network was becoming more stable again. This recovery might have been influenced by the network adapting after global events like the Dot-com boom and the September 11 attacks, which disrupted air travel.

From 2005 to 2010, the network reached a stable period where temporality stayed high. This suggests that the network found a balance between growing and keeping routes stable. However, after 2008, temporality started to slowly decline again, possibly due to new challenges or changes in the network owing to the Global Financial Crisis (2008).

Despite this volatility, the network showed signs of recovery in the mid-2010s. By 2020, temporality had increased up to a normalized value of 0.18 per year, reflecting the network's ability to adapt and remain relatively stable despite changes and challenges.

6. IMPACT OF HISTORICAL EVENTS

This section examines how significant historical events have influenced the U.S. air traffic network by analysing its finer temporal dynamics. The analysis involves computing key network metrics over time on a more refined scale than the previous analyses. Instead of analysing the network on a yearly basis, this section completes the analysis on a monthly basis. These key metrics include density and the average clustering coefficient. Additionally, airports are depicted across a map of the U.S. over the months before, during and after the events. These maps also indicate the betweenness centrality for each airport (node). Betweenness centrality measures the frequency with which a node is on the shortest path between all pairs of nodes in a network and in previous sections has been established as a relevant indicator of the importance of each airport's (node's) connectedness to the whole network. These maps also offer insights into the network's stability over the time surrounding the events. Four events are addressed in this section: the Dot-com Boom (2000) vs the Global Financial Crisis (2008), the 9/11 attacks (2001), and the SARS outbreak (2003).

a. Dot-com Boom (2000) vs Global Financial Crisis (2008)

The graphs below, in *Figure 10*, illustrate changes in the network's density (top) and average clustering coefficient (bottom) during the Dot-com Boom (2000) and the Global Financial Crisis (2008).

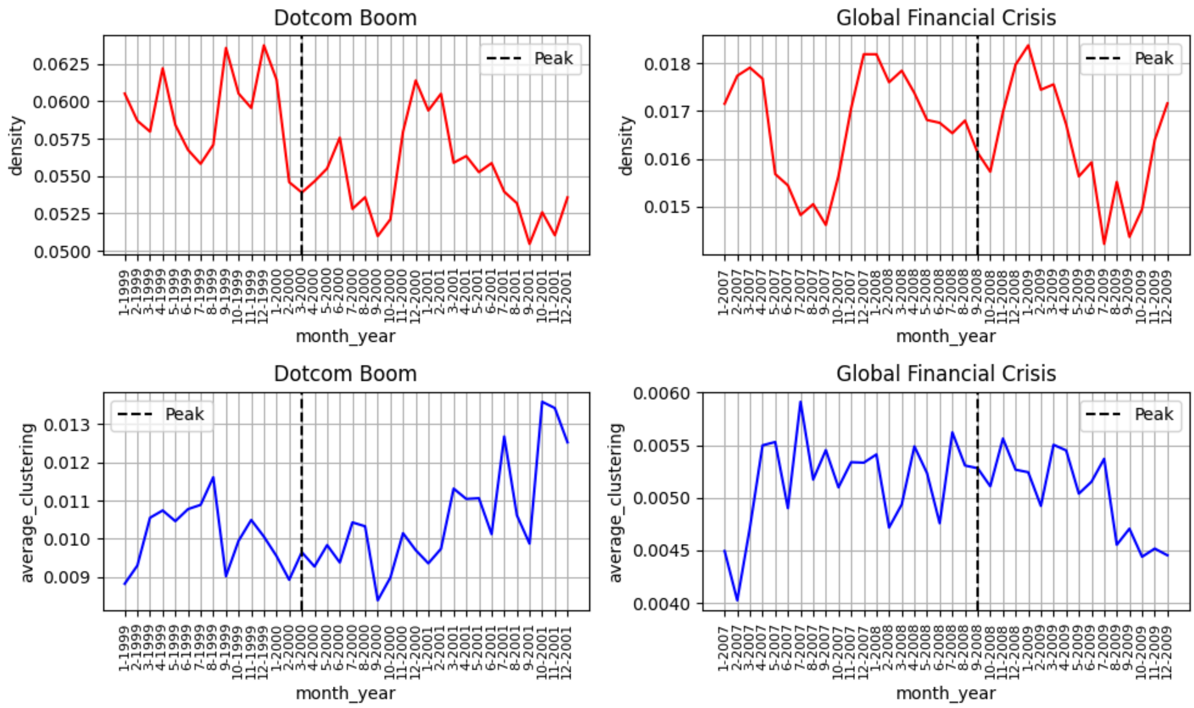

Figure 10. -Comparison of changes in the network's density (top) and average clustering coefficient (bottom) during the Dot-com Boom (2000) and the Global Financial Crisis (2008).

After the peak of the Dot-com Boom, there is a noticeable increase in density reflecting expansion in air routes and connectivity. During this period there was heightened economic activity and notable technological advancements. In contrast, the Global Financial Crisis (2008) shows a decline in density for a long period leading up to the peak of the crisis, indicating reduced activity within the network. This trend continues after the peak for a month. Also the average clustering coefficient shows significant fluctuations around the period of which signifies instability in the local connectivity and cohesion of the network.

The following maps, *Figure 11 to 14*, represent the U.S. air traffic network during key periods around the Dot-com Boom (1999–2000) and the Global Financial Crisis (2008). Each node represents an airport, with its size and colour indicating betweenness centrality.

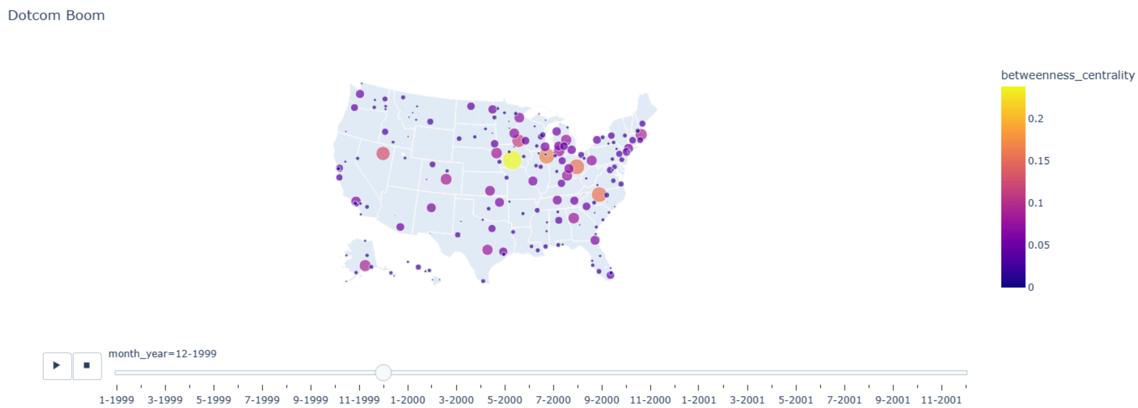

Figure 11. - Map of U.S. air traffic network for December 1999

This first map, *Figure 11* above, shows December 1999, three months before the Dot-com peak in March 2000. The network shows a high density of active nodes, particularly in major metropolitan areas for example Chicago and Columbus, and notable node activity on the east coast particularly near New York. Betweenness centrality is concentrated at key hubs, suggesting these airports were responsible for maintaining network connectivity during this economic expansion.

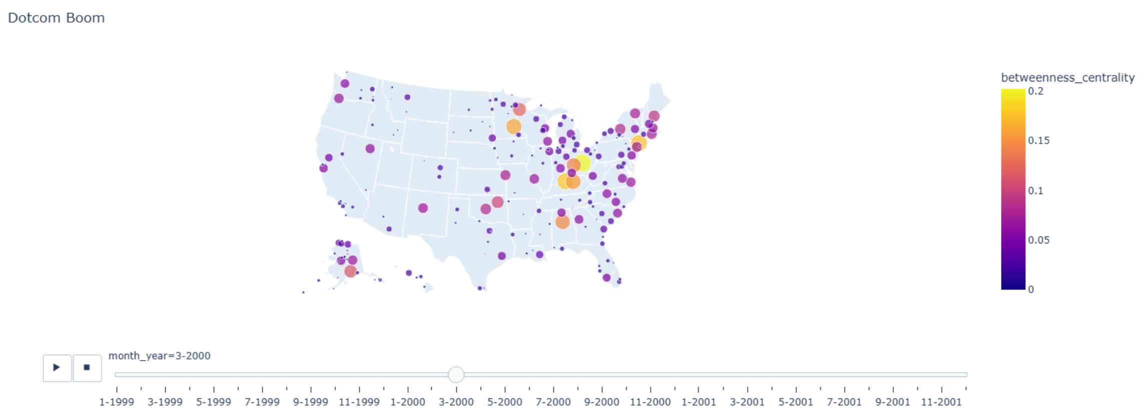

Figure 12. - Map of U.S. air traffic network for March 2000

The above map, *Figure 12*, at the peak of the Dot-com Boom in March 2000, shows the network expanded further with more routes and enhanced connectivity across both regional and major hubs. Betweenness centrality intensifies further across many nodes, representing growing importance as well as smaller airports becoming more connected. This expansion corresponds to increased economic activity and travel demand of this period.

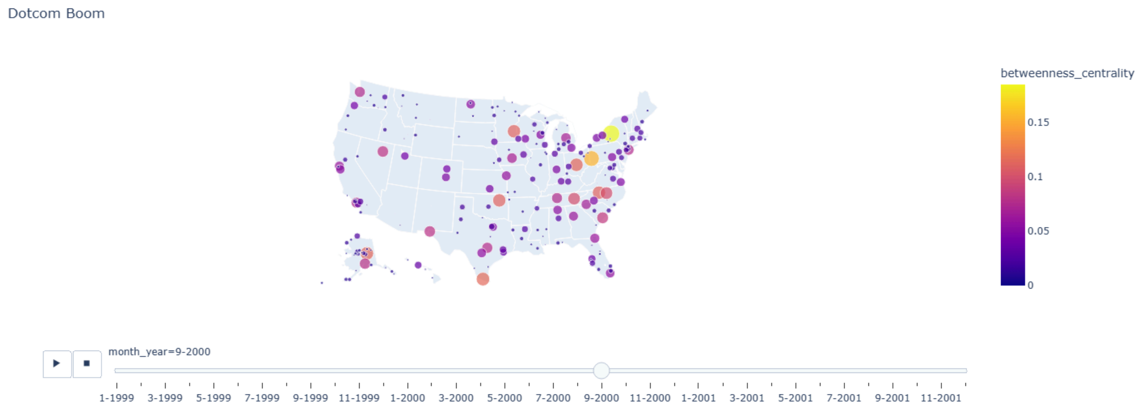

Figure 13. - Map of U.S. air traffic network for September 2000

In this last map of September 2000, *Figure 13* above, there is a slight reduction in the intensity of betweenness centrality at certain hubs, though the core structure remains intact. This snapshot at six months after the peak shows early signs of stabilisation as the effects of the Dot-com Boom began to subside, perhaps leading to reduced travel in some areas while major hubs maintained dominance. Also interestingly, the nodes in California, near Silicon Valley and Los Angeles, have become more established on the western coast - this aligns with expectations particularly for Silicon Valley as it was a prominent location during the Dot-com Boom.

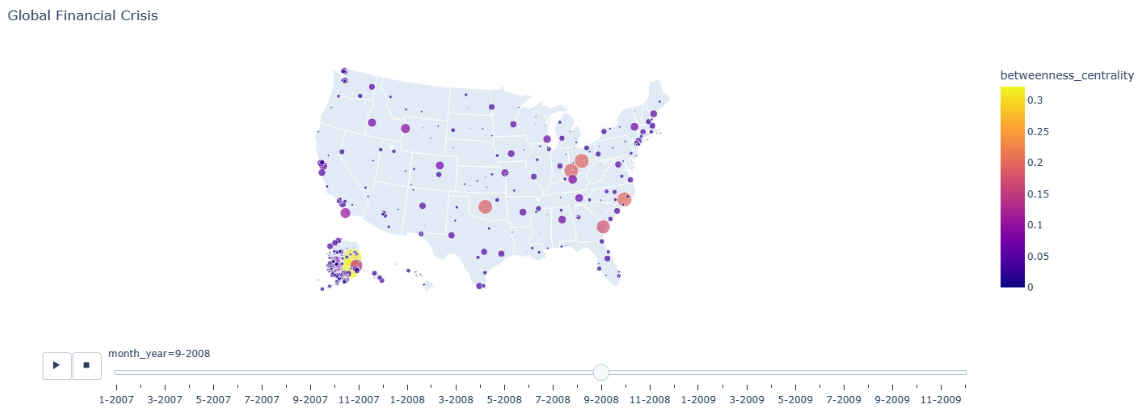

Figure 14. - Map of U.S. air traffic network for September 2008

In contrast, the above map for September 2008 at the peak for the Global Financial Crisis, *Figure 14*, displays a significant contraction in the network, with fewer routes and reduced betweenness centrality across many nodes. Key hubs become Cincinnati, Columbus and Oklahoma while the east coast and California still maintain higher centralities but their relative importance only increases due to the loss of connectivity at smaller and regional airports.This reflects the impact of economic constraints, as airlines focused on essential routes and high-demand hubs during the crisis.

The comparison shows the network's responsiveness to economic conditions, with greater connectivity during booms compared to fragmentation and instability during crises. The Dot-com Boom saw a broad network expansion with increased betweenness centrality at regional airports while the Global Financial Crisis caused a clear contraction, with reduced centrality and fewer active nodes as the airport network prioritised efficiency and cost-cutting.

b. 9/11 Attacks (2001)

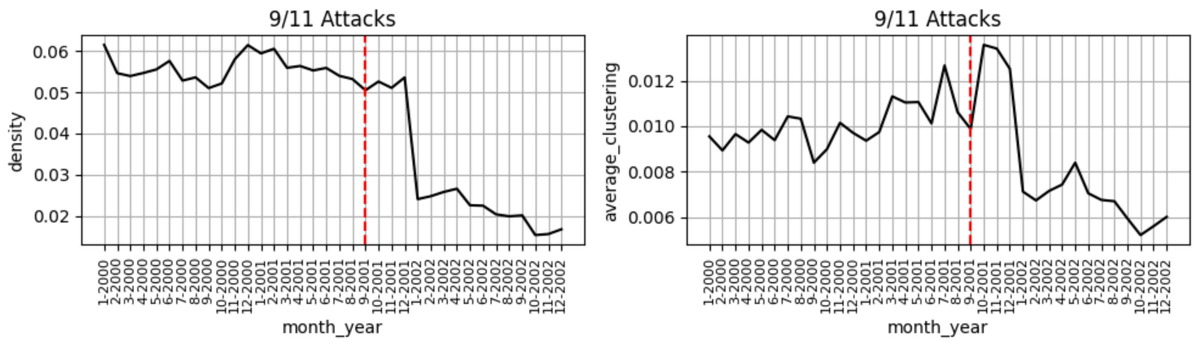

Figure 15.- Changes in the network's density (left) and in average clustering coefficient (right) following the 9/11 attacks in 2001

In *Figure 15*, the graph shows a sharp decline in the network's density (left) and in average clustering coefficient (right) immediately following the 9/11 attacks in 2001. The decrease in density indicates a fragmentation of the overall network, while the drop in the clustering coefficient highlights the loss of regional connectivity.

Over time, in the broader overview shown in previous sections, these metrics demonstrate a gradual recovery as the network adapted to new security protocols and regained passenger confidence. These two different views of the network trends highlight the network's vulnerability to sudden targeted shocks however also its capacity for subsequent resilience.

Similarly to before, the following maps depict the U.S. air traffic network, showing the distribution of airports and their centrality before and after the 9/11 attacks. The first map, *Figure 16*, is for August 2001, one month before the attacks while the second image, *Figure 17*, is for January 2002, four months after the 9/11 attacks.

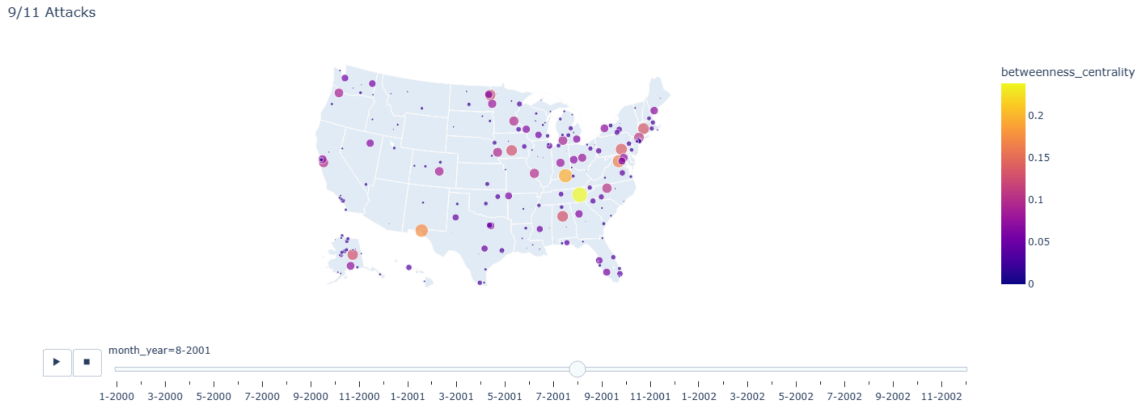

Figure 16. - Map of U.S. air traffic network for August 2001

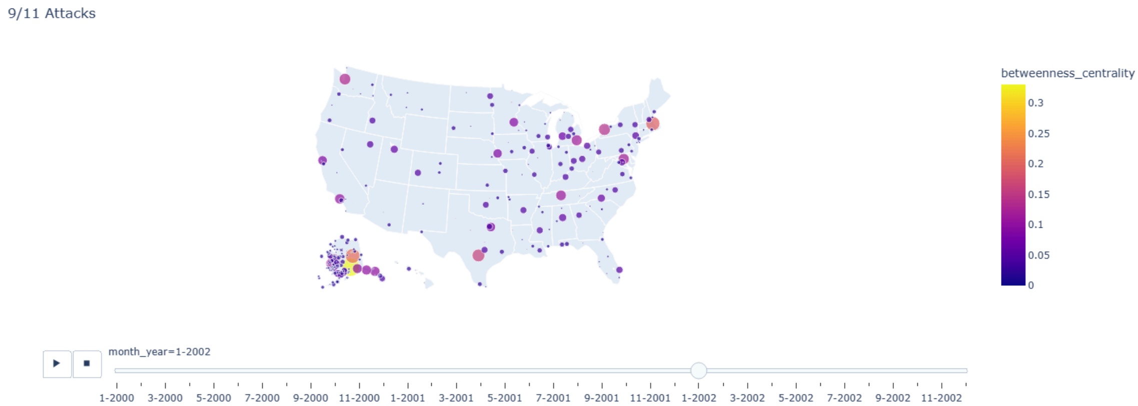

Figure 17. - Map of U.S. air traffic network for January 2002

After the 9/11 Attacks, the network shows a noticeable reduction in connectivity, with a smaller number of active routes. This reduction in connectivity likely represents the grounding of flights and closure of routes following the attacks. Betweenness centrality becomes more concentrated in a few major hubs, their role in maintaining the network during this period of disruption and indicating a shift in reliance on a few larger airports. Regional airports lose significance, as there is emphasised focus on essential routes and hubs while the network recovers. This aligns with the analysis of a targeted attack in the resilience analysis section as this example clearly demonstrates the vulnerability to targeted disruptions where core connectivity through major hubs is maintained, but the role of many regional airports is significantly reduced.

c. SARS Outbreak (2003)

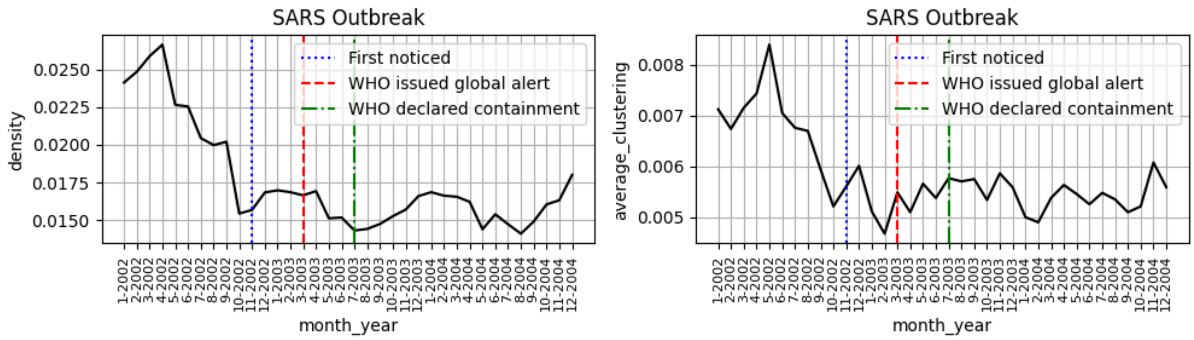

Figure 18.- Changes in the network's density (left) and in average clustering coefficient (right) following the SARS outbreak in 2003

The graphs, in *Figure 18*, highlight a temporary decline in the network's density (left) and average clustering coefficient (right) during the SARS outbreak in 2003. These trends reflect reduced travel demand and connectivity disruptions during the outbreak. The decrease in density points to a reduction in the overall connectivity, while the clustering coefficient fluctuations indicate disruptions to local network cohesion.

The provided maps show key phases of the SARS outbreak, focusing on the time points that correspond to the initial detection of the outbreak, the height of global concerns, and the post-containment period.

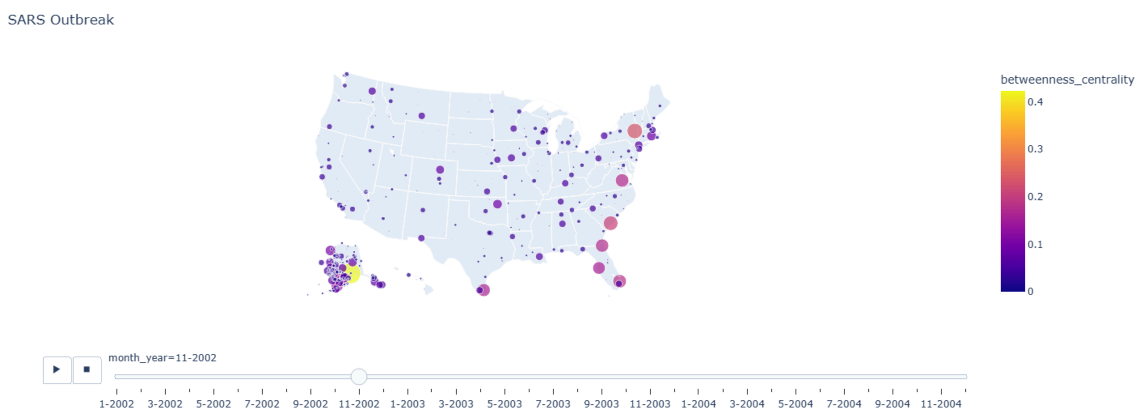

Figure 19.- Map of U.S. air traffic network for November 2002

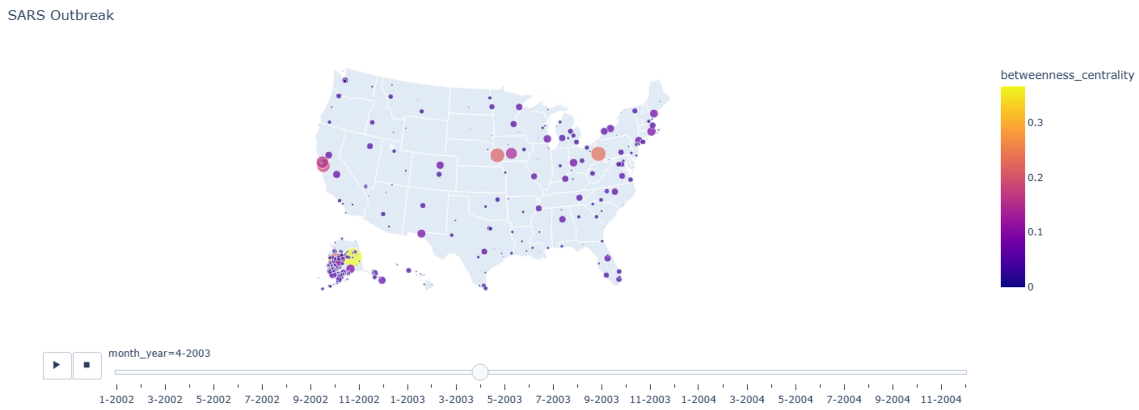

Figure 20.- Map of U.S. air traffic network for April 2003

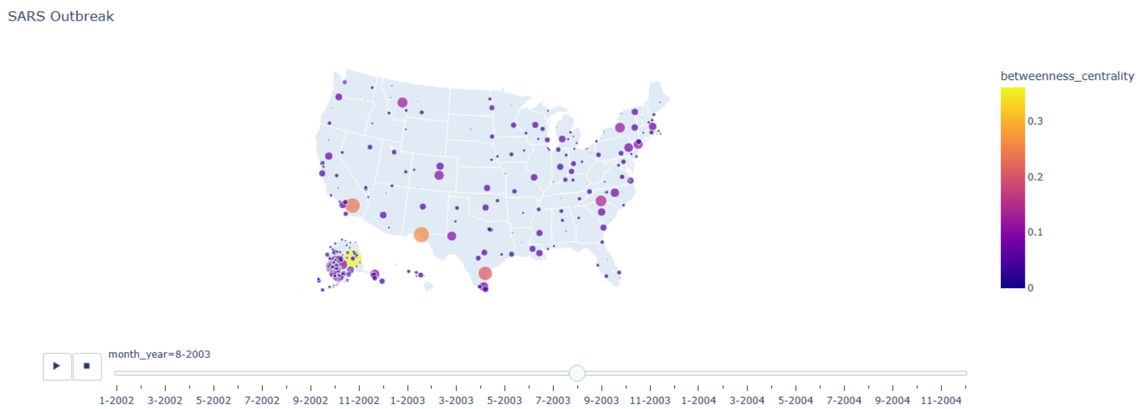

Figure 21.- Map of U.S. air traffic network for August 2003

In *Figure 19*, the map depicts the network for November 2002, when the SARS outbreak was first noticed in China. The network is largely unaffected at this stage, with consistent centrality across major hubs, particularly along the east coast and regional airports remaining active, contributing to a well-distributed network taking into consideration that the network was less active at this point independent of the disease outbreak.

However, in *Figure 20*, in April 2003, one month after the World Health Organisation (WHO) had issued a global alert, a decline in the number of active routes was visible, particularly affecting regional airports. The overall network becomes more centralised, relying more heavily on a few key nodes for connectivity.

And finally, *Figure 21* for August 2003, one month after WHO declared containment, the map shows the beginning of a gradual recovery of the network, with regional airports re-establishing their roles and overall distribution of centrality is more balanced compared to April 2003, reflecting a return to normal operations.

Compared to the 9/11 attacks, the SARS outbreak had a less severe and more geographically constrained impact, with metrics stabilising more rapidly. This illustrates the network's ability to withstand regional disruptions while maintaining its core structure, however it also once again emphasises the vulnerability of the network to a targeted attack.

7. FINAL REMARKS AND CONCLUSION

The analysis of the U.S. air traffic network from 1990 to 2020 revealed important insights into its structure, resilience, and changes over time. The network consisted of 2,002 nodes (airports) and 74,943 edges (routes), demonstrating a highly interconnected system. Key metrics such as the average degree, the radius or the average shortest path length, among others, have highlighted that the network is a highly connected and efficient system..

Its "scale-free" structure, in theory, makes the network strong against random failures, but more vulnerable when critical hubs are disrupted. This theory was tested in the resilience analysis which showed the network's ability to handle random failures and targeted attacks. In the case of random attacks, the network gradually fragmented, providing evidence for its resilience. However, targeted attacks on high-degree nodes fragmented rapidly, emphasising the network’s vulnerability to disruptions at key hubs. Understanding these vulnerabilities is important for improving air traffic management and planning.

The temporal analysis showed that interactions within the network remained stable during the 1990s, with a noticeable decline during the expansion period. Nevertheless, after 2005, the interaction pattern stabilised. Over time, the network has changed in response to economic growth and new technology. From 2000 to 2005, it grew and became more varied. After 2005, it stabilised, finding a balance between growth and staying efficient. Evidence for this efficiency and the crucial roles of major hubs was provided by comparing the temporality of the air traffic network to that of random models.

The analysis of historical events provided valuable insights into the U.S. air traffic network's dynamics. The Dot-com Boom showcased rapid expansion, while the Global Financial Crisis demonstrated its vulnerability to economic downturns, with regional airports losing connectivity. The 9/11 attacks highlighted susceptibility to targeted disruptions, shifting reliance to major hubs, and the SARS outbreak, though less severe, illustrated the network's resilience and quick recovery post-containment.

In conclusion, the U.S. air traffic network exhibits efficiency and resilience, driven by its scale-free structure and reliance on major hubs. However, this centralisation also represents a vulnerability during targeted disruptions, as evidenced by the resilience analysis and historical event case studies. To ensure future robustness, the network could benefit from strategies that decentralise connectivity and reduce reliance on these key nodes. This project has shown the complex interaction between the network structure and external factors, providing a foundation for improving air traffic management and preparing for future challenges in the transportation network.

Future research could focus on:

- Making the network more resilient by spreading connections more evenly and reducing reliance on major hubs.
- Exploring how new technologies, like drones and autonomous systems, might change the network.
- Creating strategies to deal with targeted attacks and large disruptions to keep operations running smoothly.

8. BIBLIOGRAPHY

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