Dynamic Flight Network Analysis: A Temporal Study of Airports and Passenger Flows

Roua Sabbagh
York University
Toronto, Canada
sabbagh0@my.yorku.ca

Jason Mcniece
York University
Toronto, Canada
jasonwes@my.yorku.ca

Sean Gould
York University
Toronto, Canada
sgould79@my.yorku.ca

Antonio Cedrone
York University
Toronto, Canada
antc16@my.yorku.ca

ABSTRACT

Air travel is a major contributor to the economy and allows people to move across the globe. Yet, the dynamics of domestic flight networks are subject to external shocks, such as the COVID-19 pandemic. In this report, we perform a temporal analysis of the United States flight network focusing on the effects of COVID-19 by employing algorithms used on weighted directed graphs.

We aim to uncover the impact of COVID-19 on the air travel network by way of metrics such as passenger flow and airport importance over varied time frames. This methodology includes network busyness analysis, node impact assessment, and correlation analysis.

The findings highlight the vulnerabilities and resilience within the air travel network, demonstrating how external factors like pandemics impact travel patterns. Furthermore, we offer insights into what effects remain on airports in the network even after network recovery begins. Our work and other reports like it are intended to be a reference of how an external event of worldwide magnitude can affect a domestic air travel network.

This paper details our methodologies, analyses, and conclusions, along with directions for future research in the field of air travel dynamics.

KEYWORDS

Air travel, network analytics, flight networks, temporal analysis, passenger flow, COVID-19, busyness analysis, node importance, impact analysis, correlation analysis

1 INTRODUCTION

Domestically in the United States, air travel is a business that moves hundreds of millions of people and produces trillions of dollars in net income for carriers [3][6]. This intricate web of flight routes forms a complex network, where nodes represent airports and edges signify flights. Analyzing how this travel network changes over different time frames can offer insights into things like economic activity, migration patterns, potential disease spread, and how important events like pandemics drastically affect commercial travel in this trillion-dollar business.

In this project, the goal is to analyze the temporal evolution of the domestic flight network in the United States over periods of months throughout COVID-19. In this project, the state of the air travel network before, during, and after COVID-19 will be analyzed to see both the initial effects of COVID-19 on the domestic flight network and how its influence has changed domestic air travel since the worst effects of the pandemic on the network subsided.

The questions that we aim to answer in this report include things such as how have airports recovered compared to each other after COVID-19, what were the most important airports before, during, and after the pandemic, and how different factors related to the airport and the state it is in affect the airport's recovery after the pandemic.

2 RELATED WORK

The study of flight networks has been a topic of interest in various research domains. One notable work is by Lordan et al. [1], which focuses on the temporal variations in the distribution and connectivity properties of major European airports. Another significant contribution is by Guimerà et al. [2], which delves into the worldwide air transportation network, highlighting anomalous centrality and community structures.

A seminal work in the realm of flight network analysis is by Colizza et al. [5], which employs a complex network approach to study the worldwide airport network. Their study reveals the airport network's scale-free nature, where a few hubs dominate the global air traffic. This work provides a foundational understanding of the structural properties of flight networks.

Another intriguing study by Woolley-Meza et al. [7] delves into the resilience of the global air transport network. They employ a percolation-based approach to understand how the network responds to random failures or targeted attacks akin to the disruptions caused by events like COVID-19. Their findings underscore the importance of hub airports and their role in maintaining global connectivity.

Hagberg et al. [8] have utilized graph algorithms to study the US airport network. Their approach, which involves community detection and shortest-path calculations, offers insights into the most influential airports and potential vulnerabilities in the network. Their methodology can be adapted and extended in our project to understand the US domestic flight network's dynamics.

While these works provide a foundational understanding of flight networks, there's a gap in analyzing how these networks evolve over shorter time frames, such as monthly. Our project aims to bridge this gap by offering a temporal analysis of flight networks, focusing on how they change over different months.

3 PROBLEM DEFINITION

The first problem that will be solved is determining what time periods the flight network is affected by COVID-19. In this instance, the metric that will be used to find these time periods is total monthly busyness. Busyness in this report refers to the total number of incoming and outgoing passengers on all considered flights for the given time period. The time period that we are looking for is a period of time when the air travel network's total monthly busyness is drastically affected.

Given our data set, construct a graph G<m,y> with m representing a month, y representing a year, and G<m,y> representing the flight network for that time interval. We will create such a graph for each month and year of interest.

The analysis problems we will address are as follows.

Given G<M, Y> for each month and year of interest, our first analysis problem to be solved will be to see how the most positively and negatively affected airports in terms of their comparative busyness for given months will recover year-over-year after the pandemic.

Given G<M, Y> for each month and year of interest, our second analysis problem is to determine which airports recover the fastest after the effects of the pandemic become present in the air travel network. This recovery will be measured by the percentage change in both incoming and outgoing passengers between two months. These months will be firstly, when the air travel network is first impacted by COVID-19, and secondly, when the network begins to recover.

Given G<M, Y> for each month and year of interest, our third analysis problem will be to find the 10 most important airports and see whether they change as a result of COVID-19. This analysis will be completed using both the PageRank algorithm and Degree Centrality. This analysis will be completed before, during, and after the effects of COVID-19.

Given the node importance for each airport in G<M, Y> for each month and year of interest, we will look at the airports that either went up by importance or went down in importance during COVID-19 as our fourth analysis problem.

Given G<M, Y> for each month and year of interest, our fifth analysis problem will be to construct a scatter plot comparing the change in activity between two time intervals of interest and the population of the city the airport is in.

The final analysis problem is trying to find any correlation between node importance and the spread of COVID-19.

4 METHODOLOGY

Figure 1 is a high level representation of how our analysis has been conducted.

4.1 Dataset

The primary dataset used in this project was sourced from the Bureau of Transportation Statistics [9], which provides comprehensive flight data from 1990 to 2023 for individual months, quarters, or years. Included in this data are details on departure and arrival airports, carriers, and the passenger counts on these flights, as well as the year and month that these flights took place. A second source of data used for this project is also from the Bureau of Transportation Statistics, which provides information on airport longitude and latitude data used for creating the visualization of the network [4].

Our raw data from the primary dataset is in the form of a CSV file that was retrieved from the "Bureau of Transportation Statistics." This data displays the air travel data in the form detailed in **Table 1**.

We also used a COVID-19 dataset to gather information about COVID-19 spread for every State. This dataset was sourced from a NY Times GitHub repository [11]. Additionally, we used population data from the United States Census Bureau [10].

Table 1: Raw Data

# of passengers	origin airport id	origin airport iata code	dest airport id	dest iata code	month

4.2 Network Construction

For each month over the period of time that will be analyzed, a weighted directed graph will be constructed from the data in the main dataset sourced from the Bureau of Transportation Statistics. Nodes will represent airports, and directed edges will signify flights between the origin and destination airports. The weight of the edges is determined by the total number of passengers that have traveled from the origin to the destination in that time frame (for example, for April 2020).

Our network has the following structure

- **Nodes**: The airports
- **Edges**: The flight paths
- **Weights**: the passenger volume

The construction of a graph for a given month contains the following steps:

(1) Create a node for each airport present in the dataset for the given month
(2) Retrieve all rows from the dataset for a given month where there are more than 0 passengers and the origin and destination are not the same airport (within the US)
(3) Create one edge for each flight path
(4) Add up the passengers flying using different airlines for each flight path for their weights

4.3 Temporal Analysis

To complete the temporal analysis as described in **Section 3**, after the graphs are created from the data as described in **Section 4.2**, the algorithms in **Section 4.4** will be run. To solve the first analysis problem from **Section 3** the Airport Busyness Analysis algorithm and the Node Busyness Ranking algorithm (**Sections 4.4.2 and 4.4.3**) will be run on the graphs of interest as first determined by running the Network Busyness Analysis algorithm (**Section 4.4.1**) on all of the graphs.

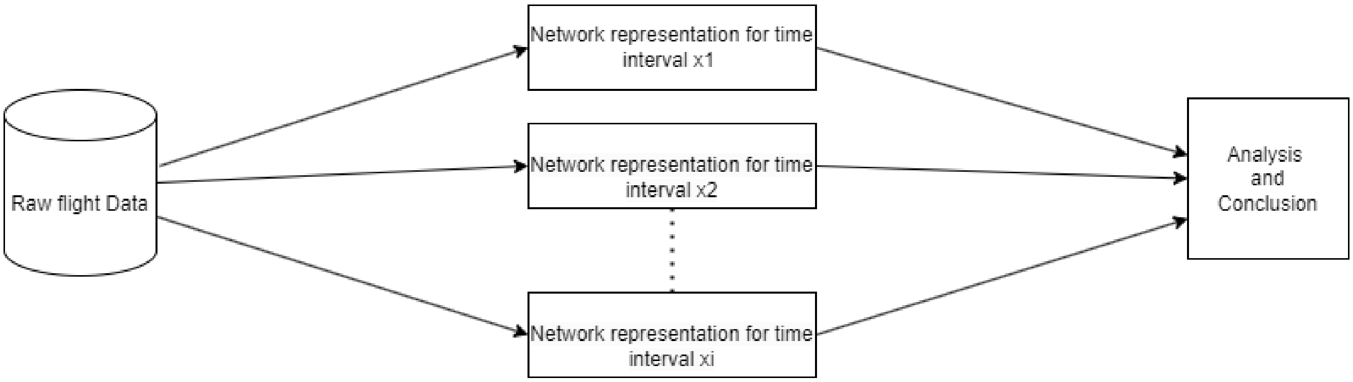

Figure 1: Framework for finding conclusions about COVID-19's impact on the travel network

To complete the second and the fifth problems we will use the Node Impact Analysis algorithm (**Section 4.4.4**). To get the change in busyness for our time intervals of interest.

To complete the third, fourth and sixth analysis problems we will use the airport importance algorithms (**Sections 4.4.5 and 4.4.6**) and the Event Correlation Analysis algorithm (**Section 4.4.7**) to determine the importance of each given airport and analyze how they change over time.

4.4 The Algorithms

4.4.1 Network Busyness Analysis. To calculate the total passenger volume across all flights in the network for a given month, providing a measure of how busy the overall network is.

$$T = \sum_{e \in E} w(e)$$

- Where:
  - T is the total network throughput.
  - E is the set of edges (flights).
  - $w(e)$ is the weight (passenger volume) of edge e.

Algorithm 1 Network Busyness Analysis

Require: A set of edges E representing flights within a month, each with a passenger volume $w(e)$.
Ensure: Total network throughput T for the month.

```
T ← 0
for each flight e in E do
    T ← T + w(e)
end for
output T
```

4.4.2 Airport Busyness Analysis. To calculate the total passenger volume across all flights through an airport for a given month.

$$T = \sum_{e \in E} w(e)$$

- Where:
  - T is the airport throughput.
  - E is the set of edges (flights) for a particular airport.
  - $w(e)$ is the weight (passenger volume) of edge e.

Algorithm 2 Airport Busyness Analysis

Require: A set of edges E representing flights within a month for a particular airport, each with a passenger volume $w(e)$.
Ensure: Total airport throughput T for the month.

```
T ← 0
for each flight e in E do
    T ← T + w(e)
end for
output T
```

4.4.3 Node Busyness Ranking. To rank airports by their busyness, we calculated a nodes throughput and sorted the results in descending order.

Algorithm 3 Node Busyness Ranking

Require: Sorted Throughput T for each node v in descending order where for a position in the list i, $T[i][0]$ is the node id and $T[i][1]$ is its node throughput value, a value s to scale the ranking to

```
R ← []
r ← 1
v ← T[0][1]
R.append([T[0][0], r])
for each element i in T do
    if i[1]! = v then
        r+ = 1
        v = i[1]
    end if
    R.append([i[0], r])
end for
for each element i in R do
    i[1] = round((s − 1) ∗ (i[1] − 1)/(r − 1) + 1, 0)
end for
output R
```

4.4.4 Node Impact Analysis. To calculate the change in passenger volume for a specific airport before and after a significant event, helping identify which airports experienced the most significant drops in activity.

$$\Delta T_v = T_{v,\text{pre}} - T_{v,\text{post}}$$

- Where:
  - ΔT_v is the percentage change in throughput for node v (airport).
  - $T_{v,pre}$ is the throughput of node v before the event (e.g., COVID-19).

– $T_{v,post}$ is the throughput after the event.

Algorithm 4 Node Impact Analysis

Require: Throughput $T_{v,pre}$, for each node v before an event, and throughput $T_{v,post}$ after the event.
  $T \leftarrow 0$
  for each node v **do**
    $\Delta T_v \leftarrow (T_{v,pre} - T_{v,post})/T_{v,pre}$
    output ΔT_v
  end for

4.4.5 *PageRank.*

To identify important airports, we used a PageRank algorithm.

Algorithm 5 PageRank

Require: Graph G
  $pagerank\_vector \leftarrow \{\}$
  for each node n in G **do**
    $n.pagerank \leftarrow \frac{1}{G.number\_of\_nodes()}$
  end for
  if iteration $<$ max_iter **or not** convergence **then**
    for each node n in G **do**
      $n.pagerank \leftarrow 0$
      for each node i in $n.indegree$ **do**
        $n.pagerank \leftarrow n.pagerank + \frac{i.pagerank}{i.outdegree}$
      end for
      $pagerank\_vector.update(\{\text{n : n.pagerank}\})$
    end for
    $iteration \leftarrow iteration + 1$
  end if
  return $pagerank\_vector$

4.4.6 *Centrality.*

To determine how much traffic an airport compared to other airports, we will be using the following formula for degree centrality

$$C_D(n) = \frac{deg(n)}{|N| - 1}$$

- Where:
  - n is the node
  - |N| is the maximum possible degree of a node

Algorithm 6 Degree Centrality

Require: Graph G.
  if G.number_of_nodes() ¡= 1 **then**
    return n: 1 for n in G
  end if
  $s = 1.0/(G.number\_of\_nodes() - 1.0)$
  $degree \leftarrow \{\}$
  for each node n in G **do**
    degree.update($\{n : n.indegree + n.outdegree\}$)
  end for
  centrality = n: d * s for n, d in degree()
  return centrality

4.4.7 *Event Correlation Analysis.*

To correlate the changes in network busyness and node impact with external events (e.g., COVID-19 restrictions, policy changes).

- Analyse the network and node metrics before, during, and after significant events.
- Look for correlations between the events and changes in network activity or node impact.

By combining these analyses, we can provide a comprehensive view of how the overall network's busyness was affected by the COVID-19 pandemic.

5 EXPERIMENTS AND EVALUATION

5.1 Analysis of Total Network Busyness

Table 2: Busyness values for each month from 2019 to 2022 including yearly totals

Month	2019	2020	2021	2022
January	58,185,242	61,844,883	24,449,690	45,997,746
February	55,819,776	60,065,784	24,588,071	49,231,486
March	70,404,902	34,526,274	39,489,100	64,841,579
April	67,090,219	2,896,307	43,966,250	63,721,190
May	71,515,164	7,887,873	52,891,694	67,155,069
June	72,915,275	16,183,983	60,279,219	67,542,875
July	75,417,132	22,993,286	66,911,806	69,644,145
August	72,893,862	24,518,111	60,810,515	66,722,554
September	64,221,475	23,965,173	54,141,972	63,423,971
October	70,183,366	28,176,731	60,836,225	68,245,284
November	65,095,698	26,427,392	60,034,544	63,961,939
December	69,946,227	27,385,067	59,745,130	62,737,942
Year Total	813,688,338	336,870,864	608,144,216	753,225,780

Our analysis of COVID-19's impact on the air travel network in the United States begins with a high level analysis of busyness - the total number of passengers on all considered flights - for all flights in the network for the months between 2019 and 2022. The results of this analysis can be seen in both **Table 2** and **Figure 2**.

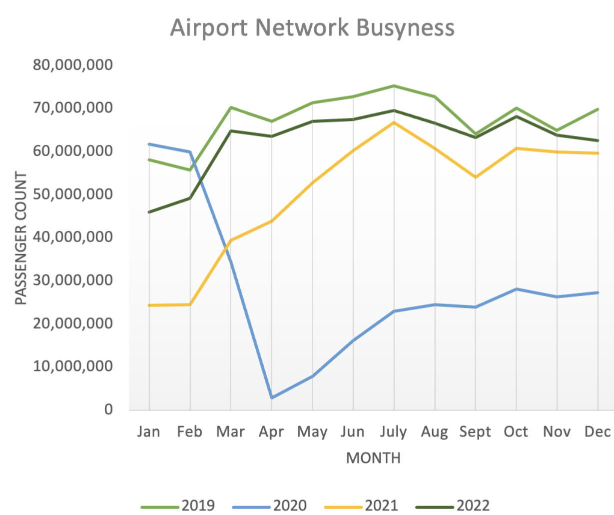

Figure 2: Network Busyness by Year

From **Table 2** it can be seen that throughout 2019 and until February 2020, monthly busyness fluctuated between around 58 and 75 million, indicative that the effects of COVID-19 had not yet hit the network. In March 2020, COVID-19 appeared to begin affecting the air travel network, with a noticeable drop in monthly busyness from both the previous month and March 2019. It was then in April 2020 that COVID-19's effects on the network were the most pronounced, with busyness dropping by 95% from January. Recovery can be seen in 2021, with busyness after May 2021 returning to values close to what was seen in 2019. In 2022, it appears that this recovery continues with increases every month to network busyness as compared to 2021.

5.2 Year-Over-Year Airport Busyness Rankings

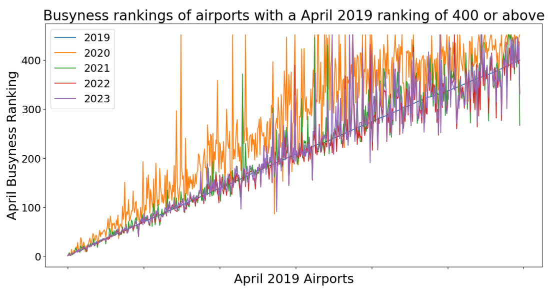

Figure 3: Year-Over-Year busyness rankings for airports with a April 2019 busyness ranking of 400 or above

The airports in the network were ranked by total busyness for the given month and year. Airports with the same total busyness received the same ranking, and thus multiple airports could have the same ranking. The next part was to scale the rankings such that they were all out of the same value. The value selected was 452, as this was the number of individual ranks present in the April 2020 ranking data. All the other years' ranking values were thus scaled to a value between 1 and 452 and then rounded to the nearest whole value.

The rankings were first determined for airports in the April 2019 network and then the scores for these airports in April 2020 were found. From here, the only airports that were considered further were those that had data for both April 2019 and April 2020 and which had a scaled April 2019 busyness ranking of 400 or above. At this point, the airports were sorted by which were most affected in their ranking from April 2019 to April 2020 and a subset was used for further analysis. Finally, the rankings for this subset were determined for April 2017, 2018, 2021, 2022, and 2023 to see how these rankings changed year-over-year before and after the month where COVID-19 most affected airport activity. The results of this experiment can be seen in **Figure 3**.

From **Figure 3**, it appears that the airports with an April 2019 busyness ranking of approximately 50 or below retain a comparatively stable busyness ranking year-over-year as opposed to airports with an April 2019 ranking above 50. The airports with an April 2019 ranking of above 50 appear to have their busyness ranking fluctuate more after April 2019, particularly in April 2020. Though some of the fluctuations in the graph are unrelated to the 2020 ranking change (as these changes occur only in April 2021 and beyond), these changes will not be analyzed further in this section.

From **Figure 3**, the airports that were selected for further analysis were the 22 airports that had their April 2019 busyness ranking drop by the greatest percentage in April 2020. These airports and their change in ranking can be found in **Table 4**. The other set of airports that were selected were the mirroring 22 airports that had their April 2019 busyness ranking increase by the greatest percentage in April 2020. These airports and their change in ranking can be found in **Table 5**.

5.2.1 COVID-19 Year-Over-Year Recovery Analysis For Most Negatively Impacted Airports. In this subsection, the goal is to analyze how the most negatively impacted airports by busyness ranking recovered in their April ranking year-over-year after April 2020.

Beginning with the most negatively affected airports in **Table 4**, it can be seen that most of the airports recover by April 2021, April 2022, or April 2023. By 2023, all airports but three have recovered to above 80% of their busyness ranking from April 2019. These three airports are Kapula Airport, Los Angeles International, and Cincinnati Municipal Lunken Field.

All three airports seem to have recovered somewhat, but their scores fluctuate between 2021 and 2023.

The airport that had an increase of over 20% in their busyness ranking between April 2019 and April 2023, despite the decrease in April 2020, is Newark Liberty International.

This means that out of the twenty-two airports that had their April busyness score most negatively affected, three have not recovered by April 2023 to their April 2019 busyness ranking. This means that approximately 13.6% of airports out of the twenty-two most impacted in their April busyness rankings by COVID-19 never recovered by 2023 and despite the decrease in ranking in April 2020, 4.54% of airports had an increased ranking in April 2023 compared to April 2020 by more than 20%.

5.2.2 COVID-19 Year-Over-Year Recovery Analysis For Least Negatively Impacted Airports. Some airports had an increase in their April busyness ranking in 2020. This is due to these airports being less negatively impacted by COVID-19 when compared to other airports in the United States' flight network. In this sub-section, the goal is to review whether these increases in comparative busyness remain year-over-year as the airports in the flight network undergo recovery.

For most of the airports in **Table 5**, by April 2023, their busyness score had returned to within 20% of the values present in April 2019. The airports that had retained gains that left them with a busyness score around 20% higher than their score in April 2019 were Dallas/Fort Worth International and Waynesville-St. Robert Regional Forney Field.

One airport that had a drop of over 20% in its busyness ranking between April 2019 and April 2023, despite the increase in April 2020, is Charlotte Douglas International. Despite this, its April 2022 and April 2023 values are very similar to those for April 2017, April 2018, and April 2019. There is also Detroit Metro Wayne County.

Overall, while there are some changes, most of the airports that had their busyness score positively affected by COVID-19 in April 2020 returned to similar relative busyness when compared to other airports by April 2023. Out of the twenty-two airports, two, or approximately 9%, retained some positive gains to their busyness score, and two airports, or approximately 9%, had a lower ranking by the margin specified.

5.2.3 Result Comparison. From the most positively and negatively affected airports based on April 2019 and April 2020 busyness scores, it can be concluded that the majority of airports within these two extremes returned to their busyness score from before April 2020 within a margin of 20%, which helps account for general trends taking place irrespective of the pandemic's influence. From both sets of twenty-two airports, which make up forty-four of the top 500 nodes considered in this analysis, an average of around 82% (approximately 81.9% and 82%) returned to their April 2019 rank within the margin specified above.

This means that while COVID-19 did affect airports significantly and some far more than others, overall, approximately 82% of airports that make up the most impacted 44 airports considered in total did return to around the same relative level of busyness in April 2023 as before the pandemic's major impact on the flight network in April 2020.

5.3 Node Impact Analysis

In this section, the Node Impact Analysis algorithm was conducted on the graphs. In **Table 6** are the 20 most impacted nodes from April 2020 to June 2020 and their node impact from April to June 2018 and 2019.

5.4 Year-Over-Year Airport Importance

In this section, we take a closer look at the 10 most important airports in the United States flight network in April before, during, and after COVID-19.

PageRank: The first method used to calculate node importance for the flight network at different time intervals was PageRank. The PageRank scores for the network were calculated in April 2019, April 2020, May 2020, April 2021, and April 2022, and the top 10 airports at each time are presented in **Table 7**.

Degree Centrality: The second method used to calculate node importance for the flight network at different time intervals was degree centrality. For this network, degree centrality represents the fraction of airports a given airport has flights to or from. The degree centrality scores for the network were calculated in April 2019, April 2020, May 2020, April 2021, and April 2022, and the top 10 airports at each time are presented in **Table 8**.

The rankings fluctuate a little bit, but overall, there are no drastic changes. Despite using different methods of analysis, several airports show up on both tables. This indicates that the importance of an airport does not change that much when it comes to the top 10.

5.5 Analysis of Individual Airport Dynamics

We explored the dynamics of individual airports that exhibited significant changes in degree centrality during the study period. While our focus is on a few notable examples, it's important to recognize that similar jumps in centrality were observed across a range of airports, often attributable to comparable causes. These changes are crucial for understanding the resilience and adaptability of the flight network in response to various external factors, including infrastructure developments, policy changes, and specific events like the COVID-19 pandemic (**Table 3**).

After presenting the significant changes in airport degree centrality, it's imperative to analyze the underlying factors contributing to these shifts. Infrastructure development, often a primary driver, not only enhances an airport's capacity but also its appeal to airlines and passengers, leading to increased traffic and connectivity. The case of Kelly Field, for instance, illustrates how a simple name change, potentially signaling broader developments, can significantly impact centrality. Similarly, events like the MCAS Miramar Airshow demonstrate the influence of specific, localized activities on airport traffic.

These examples underscore the dynamic nature of air travel networks, where changes in one node can have ripple effects throughout the system. Furthermore, the resilience and adaptability of these airports in the face of challenges, be they infrastructural or policy-driven, highlight the evolving landscape of global air travel. As we move forward, understanding these dynamics will be crucial for stakeholders in planning and managing efficient, responsive air travel networks.

Airport	Year	Change	Possible Cause
Kelly Field	2019-2020	76.44%	Official name change
Miramar MCAS	2019-2020	82.07%	Renovation project
Miramar MCAS	2022-2023	82.07%	MCAS Miramar Airshow
Tunica Municipal	2019-2020	84.29%	Infrastructure developments
Hudson Valley Regional	2019-2020	84.37%	$2 Million of Improvements
Teton Peaks	2019-2020	84.45%	Operational changes
Dallas Executive	2019-2020	90.31%	Aviation developments
McGuire Field	2019-2020	90.37%	Regional infrastructure projects
Westsound	2019-2020	91.14%	Regional developments
Sedona	2019-2020	101.64%	Runway opens after construction
Grant County	2019-2022	104.95%	Runway reconstruction
Daniel K Inouye	2019-2022	104.95%	Infrastructure improvements
Arkansas	2019-2023	104.95%	Expansion and renovation
New River Valley	2019-2020	105.84%	NRV Airport-Commerce Park development

Table 3: Significant Changes in Airport Degree Centrality

5.6 Comparing impact of COVID-19 to population

To understand the impact COVID-19 had on the top cities, we have prepared a scatter plot that compares the impact with the population for all cities with over 50 000 people. We will compare the busyness of March 2020 to both April 2020 (**Figure 4**) and March 2021 (**Figure 5**).

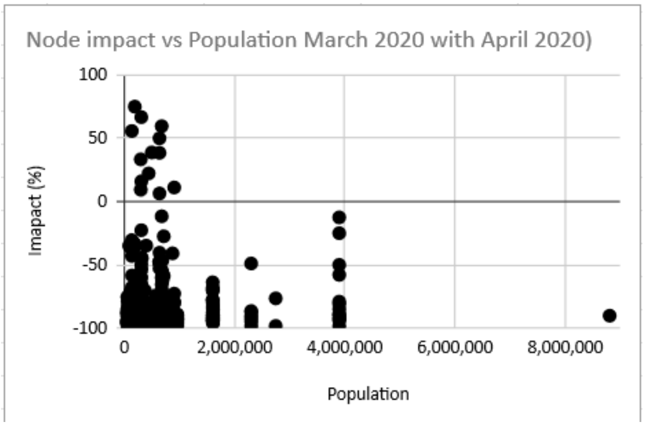

Figure 4

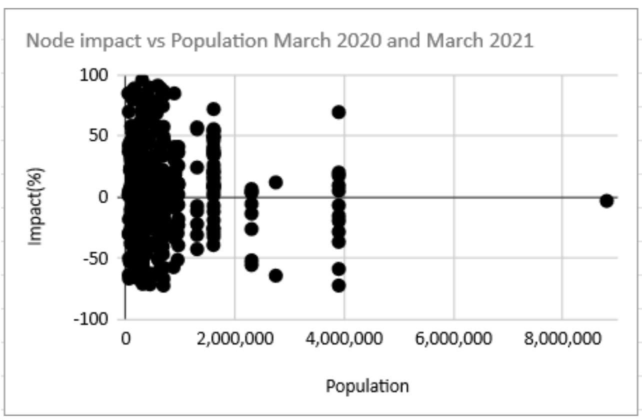

Figure 5

Cities that had a lower population were more likely to be affected by COVID-19 during the first month. This is to be expected because cities with a higher population would be more dangerous during a Pandemic. Looking at **Figure 5**, it seems that population no longer has a huge effect on the Node impact. This might be because people did not fear COVID-19 as much during March 2021.

5.7 Effect of Node Importance on COVID-19 Spread

To compare the effect of node importance on COVID-19 spread we performed an analysis using the following steps:

(1) Collect COVID-19 cases per state per month for a period of time
(2) Find the increase in COVID-19 cases for each month for each state by dividing by the number of cases from the previous month
(3) For each state we added together the node importance of each airport in that state for various node importance metrics to find an overall importance for a state
(4) Collected state importance per month for the same period of time as the COVID-19 cases
(5) Find the increase in state importance for each month by dividing by the state importance of the previous month
(6) Plotted the increase in COVID-19 cases vs increase in node importance for each state for each month

The most interesting finding from this analysis is that there is a correlation between in-degree centrality and COVID-19 rates, as seen in **Figure 6** (One outlier removed for visibility). This correlation is represented by the regression line $y = 0.28x + 4.05$ with values between the points $(-6.6, 2.21)$ and $(38.55, 14.8)$. The meaning of this correlation is that when more flights are coming into a state, that state has an increase in the spread of COVID-19. This is significant as many factors contribute to the spread of COVID-19, so even a slight correlation is meaningful.

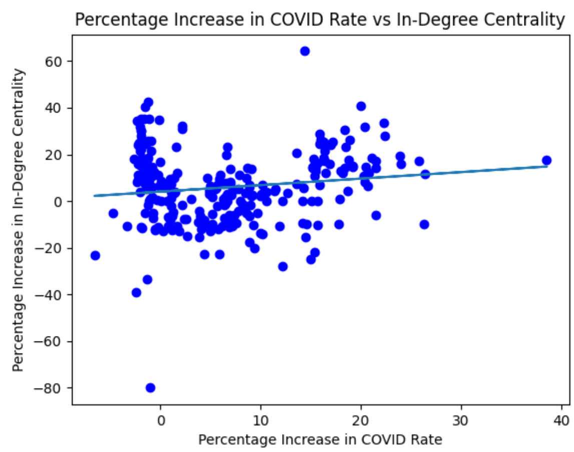

Figure 6: In-Degree Centrality vs COVID-19 Spread February to July 2021

6 CONCLUSION

We have provided a comprehensive temporal analysis study on the United States domestic flight network during the COVID-19 pandemic that offers valuable insights into the resilience and vulnerabilities within the air travel industry. The research methodically analyzed the effects of the pandemic using temporal analysis and weighted directed graphs, focusing on metrics such as passenger flow and airport importance.

Key findings include the substantial impact of COVID-19 on the air travel network, evidenced by a sharp decline in passenger flow and disruptions in airport operations. The study also highlights the significant role played by hub airports in maintaining network connectivity, even in times of crisis. The resilience of the network was evident as it demonstrated a gradual recovery after the initial wave of the pandemic, with most airports returning to near pre-pandemic levels of busyness.

The analysis of node importance and busyness rankings before, during, and after the pandemic revealed interesting patterns of recovery and adaptation among airports. The correlation between airport traffic and COVID-19 spread further underscored the critical role of air travel in influencing pandemic dynamics.

This project and others like it can serve as a reference to how an external event of worldwide magnitude can affect a domestic air travel network. Such reports can be helpful for future events that may disrupt air travel, such as pandemics, natural disasters, or geopolitical conflicts. By establishing a framework for temporal analysis of flight networks, it equips policymakers, airport authorities, and airlines with a robust tool set to anticipate and respond to dynamic changes in air travel patterns. The methodologies developed here, particularly in network busyness analysis, node impact assessment, and correlation analysis, can be adapted to monitor real-time data, enabling a proactive approach to managing disruptions. Furthermore, the insights into the resilience of the network and the importance of hub airports can inform infrastructure investment and emergency planning, ensuring that the air travel network is better prepared and more adaptable to future challenges.

7 GITHUB REPOSITORY

Visit https://github.com/gould-sean/eecs4414-project for all of the code used in our project.

8 REFERENCES

[1] A. Lordan, O. Sallan, P. Simo, and D. Gonzalez-Prieto, "Temporal variations in the distribution and connectivity properties of major European airports," Journal of Air Transport Management, 2016.
[2] R. Guimerà, S. Mossa, A. Turtschi, and L. A. N. Amaral, "The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles," Proceedings of the National Academy of Sciences, 2005.
[3] Bureau of Transportation Statistics. “Passengers | All U.S. Carriers - All Airports.” TranStats,
www.transtats.bts.gov/Data_Elements.aspx?Qn6n=E.
[4] Bureau of Transportation Statistics. "Aviation Support Tables : Master Coordinate." TranStats,
https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FLL
[5] V. Colizza, A. Barrat, M. Barthélemy, and A. Vespignani. "The role of the airline transportation network in the prediction and predictability of global epidemics." Proceedings of the National Academy of Sciences, 2006.
[6] Bureau of Transportation Statistics. “Net Income (In Thousands of Dollars $000) | All U.S. Carriers - Domestic.” TranStats, www.transtats.bts.gov/Data_Elements_Financial.aspx?Qn6n=J.
[7] O. Woolley-Meza, D. Grady, C. Thiemann, and D. Brockmann. "Resilience and robustness of the global air transport network." Nature Communications, 2013.
[8] A. Hagberg, D. Schult, and P. Swart. "Exploring network structure, dynamics, and function using NetworkX." Proceedings of the 7th Python in Science Conference, 2008.
[9] Bureau of Transportation Statistics. "Aviation Support Tables : T-100 Domestic Market (U.S. Carriers)" TranStats,
https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FIL
[10] U.S. Census Bureau 2023. "Annual Estimates of the Resident Population for Incorporated Places of 50,000 or More, Ranked by July 1, 2022 Population: April 1, 2020 to July 1, 2022 (SUB-IP-EST2022-ANNRNK)."
[11] NY Times. "Coronavirus (Covid-19) Data in the United States." https://github.com/nytimes/covid-19-data

Table 4: 22 largest negative percentage airport rank changes from April 2019 to April 2020

Airport ID	Airport name	April 2017 score	April 2018 score	April 2019 score	April 2020 score	April 2021 score	April 2022 score	April 2023 score
12892	Los Angeles Int	2	2	2	7	7	4	5
12889	Harry Reid Int	4	4	4	14	6	4	4
10721	Logan Int	9	9	9	19	15	9	9
11618	Newark Liberty Int	10	9	10	28	11	8	8
12953	LaGuardia	13	12	13	38	21	11	11
12478	John F. Kennedy Int	12	13	13	33	17	12	12
14761	Orlando Sanford Int	54	56	53	151	57	56	58
13577	Myrtle Beach Int	60	58	60	133	51	54	57
12197	Westchester County	69	70	69	193	73	73	64
12391	Long Island MacArthur	77	68	73	160	77	75	82
10431	Asheville Regional	89	84	74	166	74	71	70
10158	Atlantic City Int	78	79	81	190	77	87	93
11624	Key West Int	82	83	84	179	63	70	75
15356	Trenton Mercer	95	91	99	297	119	92	106
10732	Rafael Hernandez	114	114	104	452	132	112	100
10666	Bellingham Int	90	99	108	241	128	99	112
12544	Concord Padgett Regional	140	139	137	359	134	128	150
10590	Laughlin/ Bullhead Int	136	143	150	452	175	162	156
14254	Mercedita	160	160	162	452	230	142	146
12492	Kapalua Airport	207	189	188	397	303	271	292
10661	Boulder City Municipal	181	203	200	447	263	214	224
13105	Cincinnati Municipal Lunken Field	210	215	208	452	310	390	328

Table 5: 22 Largest positive percentage airport rank changes from April 2019 to April 2020

Airport ID	Airport name	April 2017 score	April 2018 score	April 2019 score	April 2020 score	April 2021 score	April 2022 score	April 2023 score
11298	Dallas/Fort Worth Int	4	4	4	1	2	2	2
11057	Charlotte Douglas Int	6	5	5	3	3	6	7
11433	Detroit Metro Wayne County	11	11	11	10	12	14	14
14869	Salt Lake City Int	18	17	17	9	14	15	17
14893	Sacramento Int	30	28	29	25	28	26	26
10299	Ted Stevens Anchorage Int	44	46	47	36	43	45	51
13795	Albert J Ellis	130	133	132	123	123	134	142
14709	Deadhorse Airport	201	200	189	86	162	170	169
15626	Antonio Rivera Rodriguez	169	209	197	153	182	185	193
14960	Sheppard AFB/ Wichita Falls Municipal	206	206	205	172	199	199	224
12553	Jose Aponte de la Torre	181	228	210	186	194	201	205
11445	Unalaska Airport	199	207	211	195	219	200	220
14819	Isla Grande	213	246	230	217	213	240	231
14485	Red Dog Airport	261	252	250	221	242	249	249
13241	Key Field	217	237	252	240	254	238	238
14109	Hattiesburg-Laurel Regional	255	269	290	281	247	252	262
15051	Grant County	290	288	304	282	302	275	282
15138	Waynesville-St. Robert Regional Forney Field	270	275	320	267	268	283	253
12127	Jack Northrop Field/Hawthorne Municipal	449	452	330	305	331	273	281
13862	L. M. Clayton	324	321	346	334	314	328	327
14943	Show Low Regional	309	332	354	325	300	311	313
10165	Adak	363	358	355	316	344	341	371

Table 6: Node Impact Analysis from April to June for the twenty airports which had the sum of their incoming and outgoing passengers (referred to as pax in the table) change by the greatest percentage from April 2020 to June 2020

Airport ID	# of incoming pax in April 2018	# of outgoing pax in April 2018	% change of incoming pax in June 2018	% change of outgoing pax in June 2018	# of incoming pax in April 2019	# of outgoing pax in April 2019	% change of incoming pax in June 2019	% change of outgoing pax in June 2019	# of incoming pax in April 2020	# of outgoing pax in April 2020	% change of incoming pax in June 2020	% change of outgoing pax in June 2020
12119	1603	1565	74.1	86.5	1974	2007	99.3	114.4	23	9	8934.8	25233.3
12544	12086	11839	21.5	30.2	13261	13417	43.7	49.1	45	60	17548.9	14036.7
15167	392	317	48.5	124.0	271	264	86.3	125.0	16	2	1975.0	22400.0
10661	3137	3170	94.7	100.2	3224	3375	35.0	42.5	2	3	8450.0	14666.7
10676	12791	12456	46.8	52.8	11792	10964	79.7	97.6	126	123	10623.0	11581.3
10245	2135	1193	447.1	295.6	1854	963	525.1	358.7	43	14	14862.8	7335.7
11511	31	7	1967.7	1385.7	22	8	2272.7	1400.0	2	1	13600.0	2500.0
10917	550	673	83.3	10.1	488	573	157.4	50.8	13	14	7330.8	5392.9
10613	899	988	75.8	38.8	886	867	92.1	73.5	21	20	5800.0	5755.0
15855	988	899	38.5	75.6	867	886	72.9	91.4	20	21	5755.0	5757.1
14761	118292	127613	18.4	7.6	132705	142481	18.6	8.4	926	1812	7285.0	3634.9
11027	2485	2418	52.0	68.2	2736	2767	87.1	89.6	52	41	3486.5	4926.8
14062	41	41	770.7	736.6	36	33	791.7	751.5	4	4	4550.0	3600.0
12841	91	148	251.6	-31.8	88	81	127.3	-23.5	8	1	1525.0	6500.0
12223	7081	6856	81.6	98.1	7735	7187	97.0	124.5	258	200	3263.6	4554.0
12917	16826	14933	11.6	32.4	13779	12337	61.4	87.2	359	380	3903.6	3858.2
11503	4307	7275	32.5	-33.1	2599	3854	198.8	74.8	52	41	4069.2	3207.3
15356	35973	34031	5.0	13.8	33277	33399	22.8	24.2	141	124	3044.7	3321.0
13983	1761	1528	6.0	27.6	1527	1351	26.3	52.7	33	39	3372.7	2797.4
15741	337	460	208.0	184.8	408	468	66.9	88.5	5	5	2320.0	3120.0

Table 7: 10 most important airports by PageRank score (rounded to 10 digits) for the indicated month

Rank	April 2019	April 2020	May 2020	April 2021	April 2022
1	Hartsfield-Jackson Atlanta Int 0.0346700217	Dallas/Fort Worth Int 0.0430819847	Dallas/Fort Worth Int 0.0468407547	Denver Int 0.0320912140	Hartsfield-Jackson Atlanta Int 0.0317255198
2	Seattle/Tacoma Int 0.0286006918	Hartsfield-Jackson Atlanta Int 0.0350498783	Seattle/Tacoma Int 0.0357853661	Dallas/Fort Worth Int 0.0303481914	Denver Int 0.0279784304
3	Chicago O'Hare Int 0.0269058999	Seattle/Tacoma Int 0.0349046350	Charlotte Douglas Int 0.0330324033	Seattle/Tacoma Int 0.0300048296	Seattle/Tacoma Int 0.0276323674
4	Denver Int 0.0265397613	Denver Int 0.0307568041	Denver Int 0.0326336464	Hartsfield-Jackson Atlanta Int 0.02927554395	Dallas/Fort Worth Int 0.0269796866
5	Dallas/Fort Worth Int 0.0250771275	Ted Stevens Anchorage Int 0.0289481475	Ted Stevens Anchorage Int 0.0312172324	Ted Stevens Anchorage Int 0.0244817640	Chicago O'Hare Int 0.0247882462
6	Ted Stevens Anchorage Int 0.0248987315	Charlotte Douglas Int 0.0283352205	Hartsfield-Jackson Atlanta Int 0.0258380855	Charlotte Douglas Int 0.0238573856	Ted Stevens Anchorage Int 0.0241650434
7	Los Angeles Int 0.0219749424	Chicago O'Hare Int 0.0275420440	Chicago O'Hare Int 0.0232886500	Chicago O'Hare Int 0.0233290959	Los Angeles Int 0.0192558489
8	Charlotte Douglas Int 0.0169979540	Phoenix Sky Harbor Int 0.0239117434	Phoenix Sky Harbor Int 0.0197994187	Phoenix Sky Harbor Int 0.0209239714	Harry Reid Int 0.0190524411
9	Phoenix Sky Harbor Int 0.0167735533	Los Angeles Int 0.0234083042	Los Angeles Int 0.0176387716	Harry Reid Int 0.0192812354	Phoenix Sky Harbor Int 0.0176665305
10	Harry Reid Int 0.0167066226	Salt Lake City Int 0.0164170435	Bethel Airport 0.0135354109	Orlando Int 0.0191791327	Orlando Int 0.0169242223

Table 8: 10 most important airports by Degree Centrality (rounded to 10 digits) for the indicated month

Rank	April 2019	April 2020	May 2020	April 2021	April 2022
1	Dallas/Fort Worth Int 0.2796027502	Dallas/Fort Worth Int 0.2815768302	Dallas/Fort Worth Int 0.2767497989	Dallas/Fort Worth Int 0.2611781405	Denver Int 0.2763636364
2	Denver Int 0.2689075630	Denver Int 0.2759452936	Denver Int 0.2622687047	Denver Int 0.2569198013	Dallas/Fort Worth Int 0.27345454545
3	Chicago O'Hare Int 0.26508785332	Chicago O'Hare Int 0.24617860016	Chicago O'Hare Int 0.2244569590	Chicago O'Hare Int 0.23988644429	Chicago O'Hare Int 0.25527272727
4	Hartsfield-Jackson Atlanta Int 0.24446142093	Hartsfield-Jackson Atlanta Int 0.23008849558	Charlotte Douglas Int 0.20997586484	Hartsfield-Jackson Atlanta Int 0.2207239177	Hartsfield-Jackson Atlanta Int 0.2298181818
5	Charlotte Douglas Int 0.21161191749	Charlotte Douglas Int 0.2083668544	Hartsfield-Jackson Atlanta Int 0.20193081255	Charlotte Douglas Int 0.2051100071	Harry Reid Int 0.2167272727
6	Minneapolis-St Paul Int 0.2108479756	Philadelphia Int 0.16653258246	Harry Reid Int 0.17216411907	Harry Reid Int 0.1951738822	Charlotte Douglas Int 0.2109090909
7	Harry Reid Int 0.20168067227	Phoenix Sky Harbor Int 0.165728077	George Bush Intercontinental /Houston 0.14320193081	Phoenix Sky Harbor Int 0.1724627395	Phoenix Sky Harbor Int 0.18836363636
8	Detroit Metro Wayne County 0.18105423988	Minneapolis-St Paul Int 0.16251005632	Philadelphia Int 0.1423974256	Minneapolis-St Paul Int 0.16394606104	Minneapolis-St Paul Int 0.1789090909
9	Phoenix Sky Harbor Int 0.1787624141	Detroit Metro Wayne County 0.16090104586	Minneapolis-St Paul Int 0.13917940467	George Bush Intercontinental /Houston 0.16252661462	Austin - Bergstrom Int 0.1650909091
10	Philadelphia Int 0.17494270435	George Bush Intercontinental/Houston 0.1488334674	Phoenix Sky Harbor Int 0.13757039421	Detroit Metro Wayne County 0.1511710433	Fort Lauderdale -Hollywood Int 0.16436363636