Airport Scheduling and Operational Performance: A Clustering Analysis of Airport Response to COVID-19

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In early 2020, the Coronavirus disease 2019 (COVID-19) pandemic started and forced air travel demand to decrease sharply in most parts of the world due to travel restrictions that were put in place to limit the spread of the virus. The pandemic also impacted capacity due to reasons such as workforce social distancing, days when Air Traffic Control (ATC) facilities were shut down due to COVID cases, and financial challenges due to the decreased demand. The reduced demand created a unique challenge in the system since capacity exceeded demand by very large margins in the NAS, however, delays in the system did not fall to zero despite the sharp drop in demand. This study analyzed operations at 77 United States (US) airports to compare and contrast their responses to the COVID-19 pandemic in terms of capacity, throughput, and the resulting operational performance. We evaluate the response of airports to the initial shock event during 2020 in addition to the recovery period that followed in 2021. The data showed a 67% decline in total operations at the lowest point during the pandemic. The impact during the shock time period varied greatly across the airports, ranging from a reduction of 14.8% at MEM to 81.5% at LGA. We performed a clustering analysis to study airports' response to the COVID-19 pandemic. There was a number of airport characteristics that were correlated to the changes in airport metrics. For example, the data showed that being located in a multi-airport city was significantly correlated to the decrease in operations during the shock, however, it was not significant in the recovery trends. Our analysis showed that delays in the system did not change proportionately to the change in operations. Similarly, there were only minor improvements in punctuality, on-time flights at the ASPM 77 airports increased by 9.5% while operations declined by 52% during the shock event time period compared to pre-COVID. Part of this phenomenon was a result of schedule peaking which caused delays due to creating busy hours at the airports. This analysis can inform airport management when responding to future disruptive events, it provides insight into airport operational resiliency, response to disruption, and demand recovery patterns based on airport characteristics.

I. Introduction

Passenger air travel has been steadily growing in the past decade, both globally and in the United States [[1]-[3]]. Throughput at airports has been increasing to levels that are getting closer to the declared capacity of airports. During peak hours, some airports are regularly operating close to their capacity, some of these airports are so busy to the point where the FAA need to implement slot control or schedule monitoring to prevent schedules of exceeding capacities [[4]]. There have been trends to help alleviate stress on airports such as the increasing average seats per

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flight in domestic US flights, this helps the National Airspace System (NAS) accommodate more passengers using the same runway capacity available at airports. Also, the FAA implemented strategies to manage demand-capacity imbalances when capacity is reduced due to various reasons. For example, weather events cause airports to reduce capacity which results in time periods where demand is exceeding capacity, here is where the FAA implements strategies to manage the imbalances until the system recovers from the associated delays that occur because of that.

In early 2020, the Coronavirus disease 2019 (COVID-19) pandemic started and forced air travel demand to decrease sharply in most parts of the world due to travel restrictions that were put in place to limit the spread of the virus. The pandemic also impacted capacity due to reasons such as workforce social distancing, days when ATC facilities were shut down due to COVID cases, and financial challenges due to the decreased demand. Although the COVID-19 pandemic impacted both demand and capacity, the reduced demand created a new challenge in the system since capacity exceeded demand by very large margins in the NAS. This scenario is unique because the delays in the system did not fall to zero despite the sharp drop in demand.

The purpose of this study is to evaluate 77 United States (US) airports to compare their responses to the COVID-19 pandemic in terms of capacity, throughput, and the resulting operational performance. We evaluate the response of airports to the initial shock event during 2020 in addition to the recovery period that followed in 2021. The motivation for this study stems from the ability for this shock event to measure the degree to which airport operational performance is driven by the airport versus the airlines operating at the airport. For example, prior to COVID-19, congested airports would have peak times with increased number of scheduled operations. This increased demand on a set amount of resources (capacity) typically results in delays, impacting the airport's Key Performance Indicators (KPIs) for on-time performance and for capacity and throughput efficiency. However, COVID-19's reduced demand can show if airlines continue to peak their schedules resulting in delay even during a low-demand time period. Additionally, the recovery period provides insight on the resilience of the NAS from an operational performance standpoint when managing the increase of demand that followed the shock event caused by the COVID-19 pandemic.

II. Literature Review

Throughput and capacity have been extensively studied in literature because balancing the two variables is an important goal of air traffic management. Throughput at airports is limited by the available capabilities in the system which include existing infrastructure and operational capacity. From a performance standpoint, airports set their objectives to maximize throughput and minimize delays without exceeding capacity. The estimation of airport capacity is a topic of interest since it is important for performance measurement. Di Mascio et al. compare different methods of capacity estimation that range from using tables and charts to sophisticated simulations [[5]]. The use of simulation to estimate airport capacity is demonstrated in a study by Bubalo and Daduna [[6]]. They used the modeling tool SIMMOD to simulate different scenarios at Berlin-Brandenburg International airport to evaluate practical capacity under realistic demand and possible capacity gains.

Over the past few decades, there have been several studies that proposed models to optimize the available capacity at airports. For example, Gilbo discusses the estimation and representation of airport capacity and presents an optimization model to help satisfy the demand and mitigate congestion during busy time periods [[7]]. The objective of that optimization is to minimize the total delay in arrivals and departures by varying the capacity of each operation. Gilbo's model is based on the notion that arrivals and departures are interdependent since both types of operations share the available resources at any airport to varying degrees. Zografos et al. discuss how slot scheduling can be used as a technique to increase the utilization of airport capacity [[8]].

Jacquillat and Odoni discuss the dynamic relationship between airport capacity, demand, and on-time performance [[9]]. They bring insights to the non-linear relationship between flight schedules and delays, this is why peak throughput is one of the key performance indicators and often compared with airport capacity to assess how stressed an airport can be during times of high demand. Odoni et al. compare between Newark International (EWR) and Frankfurt International (FRA) to demonstrate how differences in scheduling practices can lead to dramatic impacts on delays [[10]]. In the case of EWR, peaking of demand during certain hours of the day lead to operating the airport at or above its declared capacity which resulted in significant increases in delays. In addition, research using simulation models showed that there are multiple benefits to capacity optimization, while it is aimed at mitigating delays, it can help in reducing fuel consumption and emissions that harm the environment [[6], [11]].

COVID-19 impacted the operational performance of the NAS significantly, the number of departures in the United States dropped by over 70% in May 2020 compared to May 2019 [[12]]. An analysis by Monmousseau et al. shows that although demand dropped sharply, the portion of passengers who faced interruptions still suffered from high delays [[13]]. Their study analyzed data on how airlines reacted differently to the COVID-19 challenges. Research by Guo et al. provided a qualitative assessment of airport network resilience during the COVID-19 pandemic [[14]].

Their research assessed resilience in the aviation system from a network perspective in China and Europe. They included networks of 232 airports in China and 82 airports in Europe, their conclusions show that the two networks recovered differently due to implementing different policies in each region. While their assessment is qualitative, it shows the importance of policy and airport characteristics in the ability to recover when responding to disruptive events such as natural disasters, technological failures, or pandemics. In our research we investigate how airports in the US reacted to the COVID-19 pandemic, we identify the significant factors driving their behavior including airlines variables and other factors such as airport size and multi-airport city status.

III. Data

In this analysis we study the 77 airports of the Aviation System Performance Metrics (ASPM) database [[15]]. These airports include the core 30 airports in the U.S. To analyze the responses of airports to the COVID-19 shock event, we use three sets of airport metrics. Pre-COVID metrics span May 1, 2019-September 30, 2019 and the two post-COVID metrics include the same dates, May through September, of 2020 and 2021 to account for "shock" and "recovery", respectively. Throughout our study, pre-COVID refers to the time period prior to COVID-19 and the term post-COVID refers to time periods affected by COVID-19. The same months of each year were used to account for any seasonality changes in schedules, where certain airports have high demand for certain months of the years. These months were chosen with respect to regulations in the Coronavirus Aid, Relief, and Economic Security (CARES) Act [[16]] and the Coronavirus Response and Relief Supplemental Appropriation (CRRSA) Act [[17]]. The study time periods are shown in Fig. 1 along with the evolution of air traffic at the ASPM 77 airports. The data showed that the number of arrivals declined by 67% during April 2020, the lowest point in the curve, compared to April 2019.

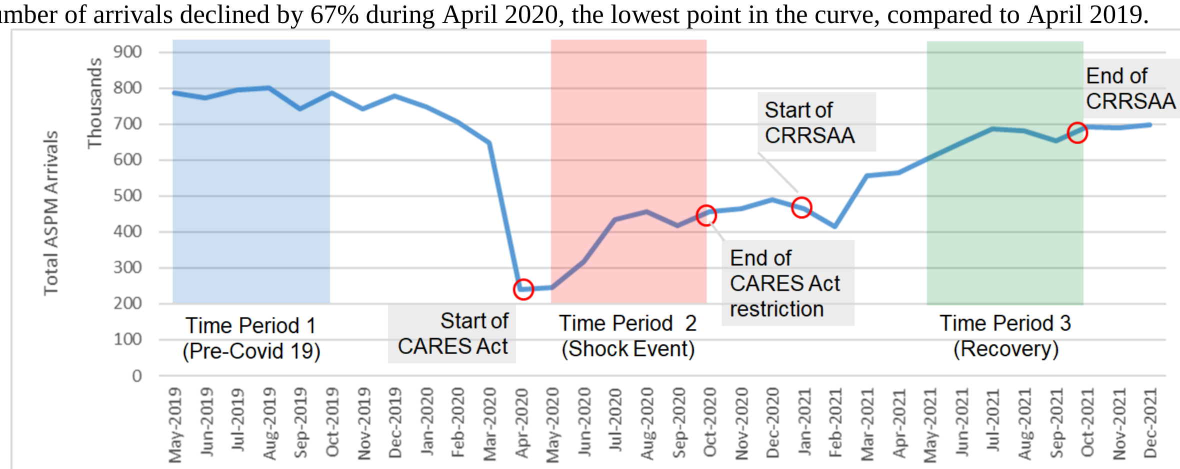

Fig. 1 Evolution of air traffic over the study timeline (ASPM 77 airports)

The CARES Act provided stimulus funds to airlines in exchange for following imposed minimum service requirements along with restrictions of staffing or pay cuts. It was signed into law on March 27, 2020 and airline restrictions ended on September 30, 2020 [[18]]. The choice of our study months gave a one-month buffer before the beginning of government financial assistance as it took time for airlines to stabilize their schedules and the logistics to follow the service regulations. Minimum Service Obligations (MSOs) required air carriers that accepted financial assistance to maintain minimum levels of scheduled air transportation service to points served by that air carrier before March 1, 2020, with some exceptions. Under the CARES Act, MSO levels depended on the size of the carrier and the level of service at those points in the air carrier's network. Carriers were allowed to consolidate service at a single airport in multi-airport metropolitan areas.

The CRRSA Act was signed into law on December 27, 2020 [[19]] providing extensions to the payroll assistance for air carriers. The CRRSA Act re-implemented the MSOs from the CARES Act from January 15, 2021 through March 31, 2021, and then a final order was issued on April 29, 2021 to extend the financial assistance regulations through September 30, 2021[[20]]. Since air travel demand was recovering during 2021, airports covered under the CRRSA Act were able to meet and exceed the required MSOs. Specifically, the U.S. Department of Transportation recognized that during the effective time period of CRRSA Act "virtually all Covered Points continued to receive service in excess of minimum levels required by the [CRRSAA]" [[21]].

Time period 1 in our study timeline was used as a reference for airport characteristics for pre-COVID-19 conditions. Time period 2 was meant to represent the reaction period to the shock event that the aviation system went through. During this time period, travel restrictions were still in place and operations were influenced by the CARES

Act requirements. Time period 3 was meant to represent the system's reaction while travel restrictions were loosened and the CRRSA Act was in effect.

A. Datasets Summary

The first set of variables provide the *"Pre-COVID-19 Airport Characteristics"* that could impact their response and outcomes to the shock event. This includes information about carrier service (i.e. major, low-cost carrier, cargo), multi-airport city status, airport hub size (i.e. small, medium, large [[24]]), and the ratio of arriving passengers that use the airport for a connection flight to those who use it as a final destination. In our data, flights by Delta, United, and American airlines accounted for major carriers. Low Cost Carrier (LCC) flights were flights by Southwest, Spirit, JetBlue, and Frontier. Cargo flights were flights by UPS and FedEx.

The second set indicates *"Airport Metrics Changes"*. The operational metrics include, peak capacity, peak throughput, and total operations count. Throughput is the number of actual operations that took place at the airport. Capacity is represented by the number of arrivals and departures that the airport can accept during a time period, this is also known as the called rate. Called rates are usually estimated values reported by the air traffic control (ATC) personnel managing air traffic at the airport based on weather conditions, separation requirements, and active runway configuration [[23]].

The peak throughput and capacity metrics were estimated consistent with the definitions set by the ICAO GANP KPIs [[22]]. Both peak throughput and capacity were measured as the 95^{th} percentile of data for the study time period using the ASPM data reported at 15-minute intervals. The hourly peak throughput was calculated on a 15-minute rolling hour basis, which means that the one-hour time frame moved at 15-minute intervals instead of every one hour on the clock. Rolling is recommended since demand does not necessarily align with the top of the hour, for example, a busy "hour" at an airport could refer to the time frame of 7:30 - 8:30 AM. On the other hand, hourly peak capacity was calculated without rolling since capacity has less variability compared to throughput.

Under the CARES Act, airlines were required to continue a minimum level of service to "points" or cities in their network. If an airline served two airports in a multi-airport city prior to COVID-19, it only had to continue serving one of these airports during the regulation period. For the purposes of this study, an airport was given a multi-airport city indicator of 1 if there was another large airport in its city, not counting itself. While part of the CARES Act service requirements were based on multi-airport definitions, the data shows that there are other airport characteristics that had significant relationships to the changes in airport metrics (capacity, throughput, and total operations). Fig. 2 shows the correlation between pre-COVID-19 airport characteristics and change in airport metrics during the shock event while Fig. 3**Error! Reference source not found.** shows the correlation with the change in airport metrics during the recovery.

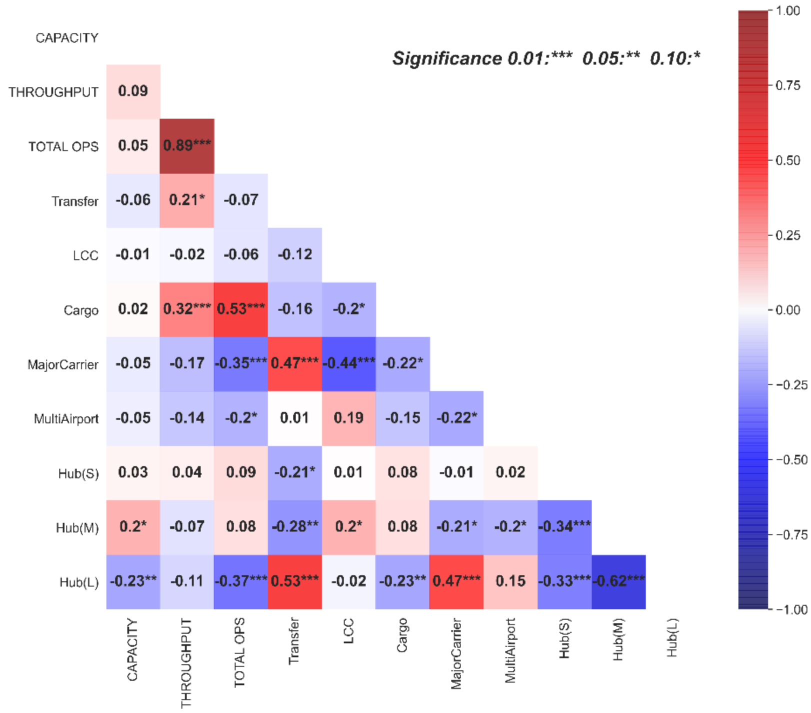

Fig. 2 Correlation matrix of airport characteristics and metrics changes (Time period 2)

The data showed that the percentage of cargo operations at an airport was positively correlated to the change in total operations. As shown in Fig. 2, airports with higher cargo percentage were able to retain more operations during the shock event. Transfer rate was positively correlated to peak throughput, meaning that a higher percentage of transferring passengers could be contributing to airlines peaking their schedules. It is more efficient for airlines to coordinate the arrival of connecting passengers coming from different origins within a short period of time in order to board the same outbound flight. The multi-airport indicator was negatively correlated to the change in total operations as expected due to the minimum service requirement set by the CARES Act.

The data showed that the percentage of major carriers operations was negatively correlated to the change in total operations. Similarly, the large hub airport indicator was negatively correlated to the total operations, this was expected since there is a large percentage of major carriers operations in large hubs. The percentage of Low Cost Carrier (LCC) operations did not have a significant correlation with changes in throughput or total operations. This is most likely due to being correlated with both the major carrier and cargo variables.

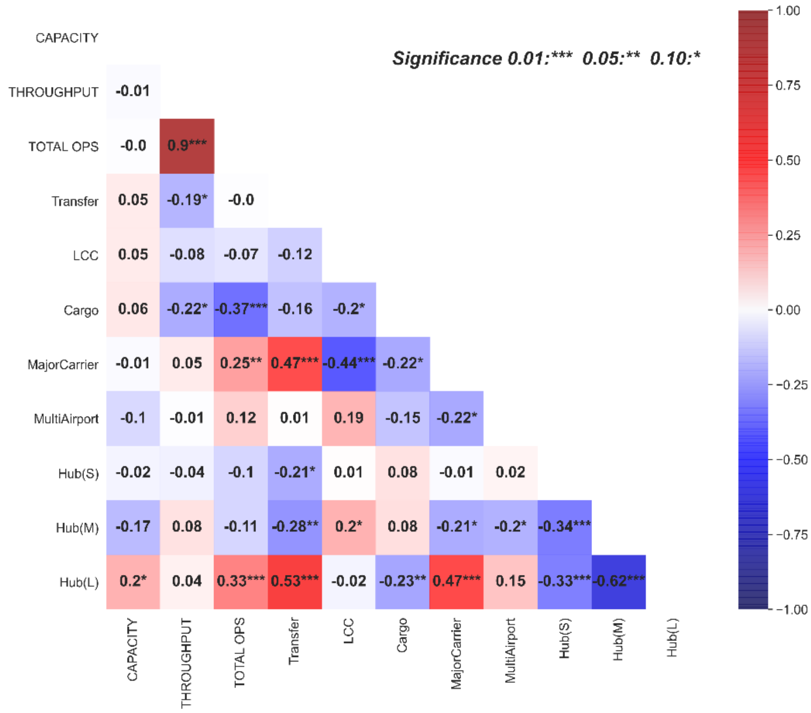

Fig. 3 Correlation matrix of airport characteristics and metrics changes (Time period 3)

As shown in Fig. 3, cargo operations were negatively correlated with total operations and peak throughput during recovery. This could be because cargo was the least impacted segment during the shock event, therefore, it was not expected to have a positive impact on recovering operations that were mostly passenger traffic. Major carrier operations were positively correlated to total operations recovery. Similarly, the large hub indicator was positively correlated to both total operations and throughput peak. Lastly, the multi-airport indicator was not significant during the recovery although it was significant under the CARES Act. This trend indicates that airlines scheduling was the major factor in recovery trends since airports covered under the CRRSA Act were able to meet and exceed the minimum service requirements anyway due to demand improvement in 2021, as previously stated.

The third set of metrics measure the *"Operational Performance"* at airports, particularly related to airport delays. We calculated arrivals delay as the difference between the scheduled gate-in time and the actual gate-in time reported in ASPM data. Additionally, we calculated punctuality as the percent of flights that arrived "on-time". A flight is considered "on-time" as long as the delay is less than 15 minutes, consistent with the FAA definition [[2]]. In this analysis, we used punctuality, delay per delayed flight, and delay per flight as metrics of operational performance. The goal of these metrics is to provide insight into how much airlines drive airport operational performance metrics verses the airports themselves. In other words, how much of the delay is due to airport issues versus airline schedule peaking.

IV. Methodology

A K-means clustering methodology is followed to group airports on the second set of metrics *"Airport Metrics Changes"* to see which airports responded similarly to the shock event and recovery. These K-means clusters are then joined with the first set of metrics to see what pre-COVID-19 characteristics of airports influence airport response and increase/decrease operational resilience to shock events. The clusters are also compared to the third set, the delay and punctuality data, to provide insight on the ability to increase traffic while managing the increase in delays.

The clustering analysis was carried out twice for time periods shown in Fig. 1, the shock event comparing time period 2 to pre-COVID, the recovery event comparing time period 3 to time period 2. The elbow method was used to determine the optimal number of clusters to partition the data in the K-means algorithm. As shown in Fig. 4, the sum of squared errors (SSE) indicated that a seven-cluster solution is appropriate since the reduction in SSE starts to diminish after seven clusters.

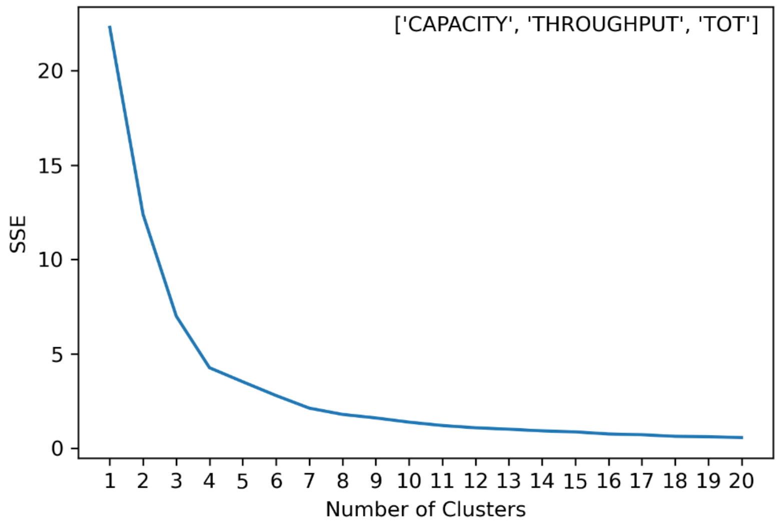

Fig. 4 Number of Clusters vs Resulting SSE

V. Airport Metrics Data Summary

While this study includes the 77 ASPM airports, this section will focus on presenting the Main 34 airports of 2019, which are the airports with the highest number of operations (arrivals plus departures). This section presents a summary of the three variables that were used to group airports in our clustering analysis. Subsection **Error! Reference source not found.** presents how the total operations evolved, which is a metric of demand. Subsection B presents peak throughput which is a measure of how peaky the schedule at the airports was during the busiest hours. Finally, Subsection **Error! Reference source not found.** shows peak capacity as a measure of the highest declared capacity at the airport.

A. Total Operations

The change in number of arrivals plus departures (i.e. total operations) for three time periods covered in this study is shown in Fig. 5. While all airports lost operations in 2020, the impact varied greatly across the airports, ranging from a reduction of 14.8% at MEM to 81.5% at LGA. Some airports were more resilient than others in retaining flight demand, in particular, Anchorage International Airport (ANC) and Memphis International Airport (MEM), two major cargo airports in the US, each saw less than a 16% reduction in flights. The airports that lost the most percent operations were large hub and international airports such as Hartsfield-Jackson Atlanta (ATL), Boston Logan (BOS), Ronald Reagan Washington National (DCA), Newark Liberty (EWR), New York John F. Kennedy (JFK), and New York LaGuardia (LGA).

While air travel demand was recovering in time period 3, some airports recovered more than others. LGA and JFK had the highest recovery rates of 160% and 162%, respectively, after being among the airports that were impacted the most during the shock event. Interestingly, there was a group of airports that reached a total number of operations in the recovery period higher than pre-COVID-19 numbers. These airports include ANC, Phoenix Sky Harbor International airport (PHX), and Salt Lake City International airport (SLC).

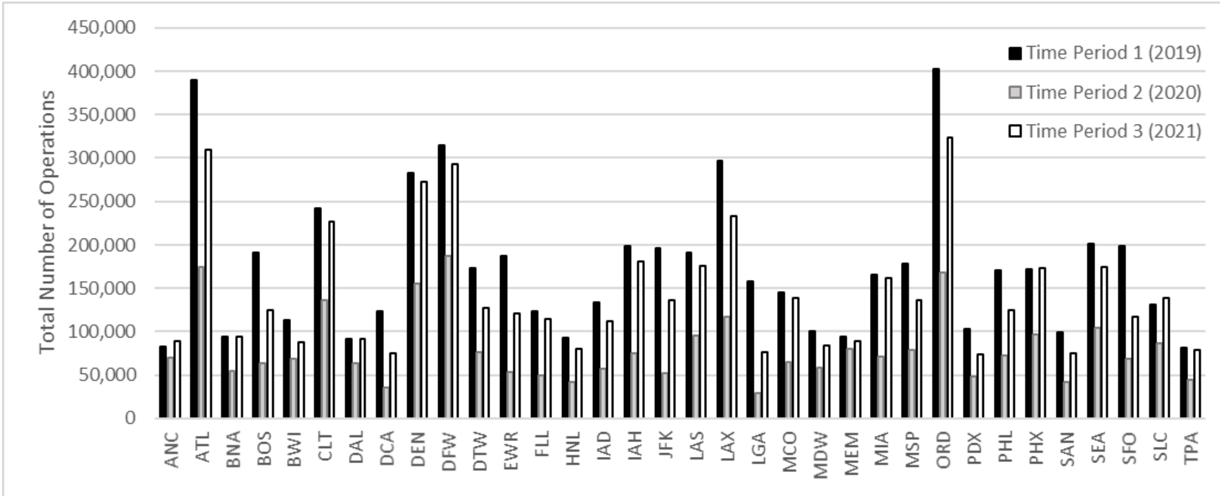

Fig. 5 Change in total operations (Main 34 airports)

B. Peak Throughput

Peak throughput for arrivals and departures followed similar patterns. Therefore, total peak throughput (departures + arrivals) was used in this study. Fig. 6 shows total peak throughput at the Main 34 airports for the study time periods. During the shock event period, airports with minimal changes to total operations, ANC and MEM, did not change their schedule peaks as much as other airports. Similarly, some of the airports with large reduction in operations had a proportional reduction in their peak throughput, examples include LGA, JFK, and ATL. On the other hand, some airports with significant reductions in their total operations did not see a similar drop in peak throughput. For example, the peak throughput operations at Charlotte Douglas International (CLT) was reduced by 10% during the shock event although the total number of operations dropped by 43% in the same time period. The different trends in reaction to the shock event are mostly driven by airlines operating at the airport and how they schedule flights to support their hub-and-spoke network and allow for passenger connections.

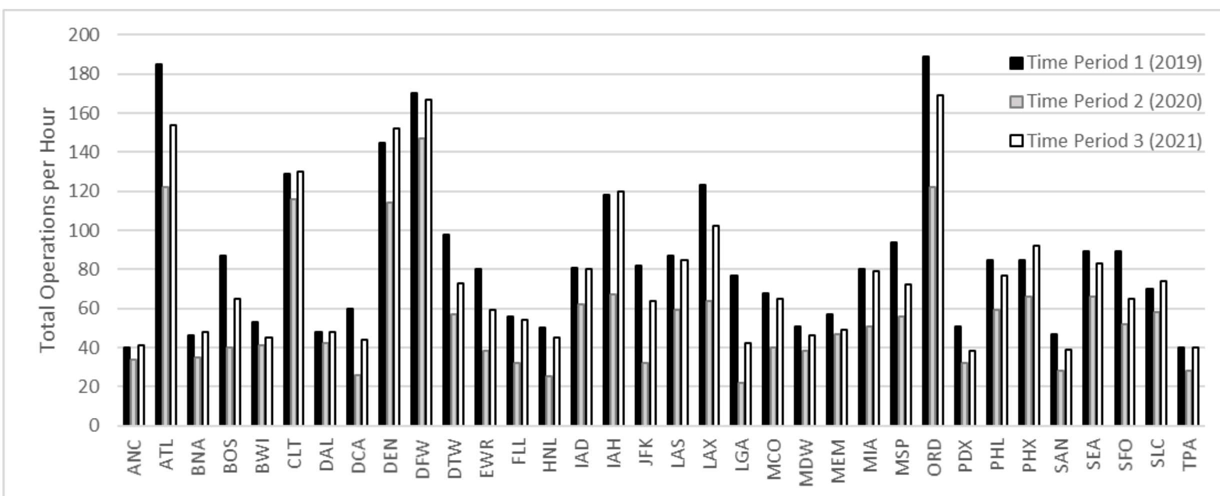

Fig. 6 Change in total peak throughput (Main 34 airports)

The data showed that airports which recovered to higher then pre-COVID total operations also increased their peak throughput. These airports include ANC, SLC, and PHX as shown in **Error! Reference source not found.**. However, there were airports like CLT, Denver International (DEN), and George Bush Houston Intercontinental (IAH) that peaked their schedules higher during the recovery period although their total operations did not recover proportionately. This can be linked to the demand characteristics at the airports which are impacted by factors such as the type of airlines (major or low cost carrier) and the passenger transfer rate. Section 6 discusses the common factors between airports that showed similar trends in change in their KPIs.

C. Peak Capacity

The changes in peak total capacity (arrivals + departures) at the Main 34 airports are shown in. Peak capacity tends to have less variability than throughput since capacity is not driven by demand at the airport. Declared capacity at an airport is impacted by various factors including weather, air traffic control staffing, gate capacity, and runway capacity. Weather conditions impact the airport's capacity when aircraft separation rules change during bad weather for safety. The effect of weather conditions in our analysis wan not major because our data was for the same time periods across the three years which eliminated seasonality differences.

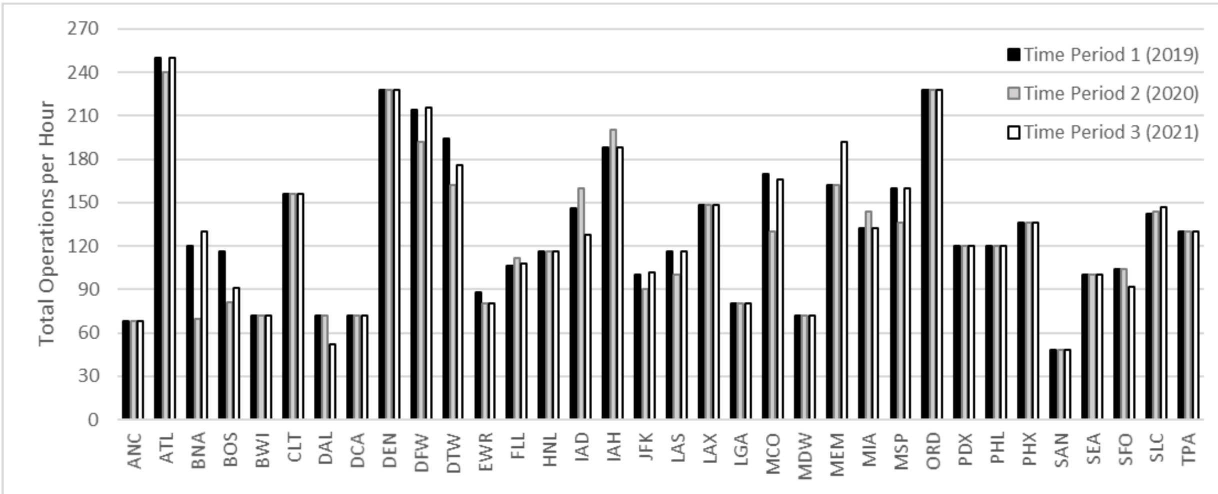

Fig. 7 Change in peak total capacity (Main 34 airports)

Construction projects often have significant impacts on capacity, it can be a negative impact due to temporary closures during construction and positive when the construction is complete and new infrastructure becomes available. Some airports had ongoing construction projects during our study time periods that could explain significant changes in their peak capacity shown in Fig. 7. For example, a new terminal is under construction at Orlando International Airport (MCO) which is expected to add 15 gates to the airport's capacity ([25]). Nashville International Airport (BNA) is having a major terminal expansion project that will add gate capacity to the airport, however, the project has been temporarily impacting the flow of passengers and capacity while construction is taking place ([26]). Additionally, various construction projects were taking place during our study time periods at MEM including apron area improvements and a consolidated deicing facility ([27]).

VI. Results and Discussion

The K-means clustering algorithm was applied to the *Airport Metrics Changes* variables, namely the percent change in each of the throughput peak, capacity peak, and total operations for the ASPM 77 airports. Clustering was done twice to analyze the reaction to each of the shock event and the recovery time periods as described in Fig. 1**Error! Reference source not found.**. The first clustering run was for the changes from time period 1 to time period 2. The second run was for changes from time period 2 to time period 3. Characteristics of the resulting groups are discussed in detail in Sections A and B below.

A. Shock Event Results (Time period 2 compared to time period 1)

The seven clusters were created based on the *Airport Metrics Changes* variables as percent change of time period 2 compared to time period 1. This section of the analysis looks into patterns and factors that influenced reactions by airports to the COVID-19 shock event. The resulting groups and their average airport characteristics are shown in **Error! Reference source not found.**, the highest number in each column is highlighted. While the overall decline in operations was 52% during the COVID-19 shock time period, it can be seen that airports had different responses when comparing across the groups. For example, Clusters 1 and 4 had similar reductions in the number of operations (-56% and -57%), however Cluster 4 airports reported an average 18% reduction in peak capacity. Cluster 1 was the largest cluster with 25 airports, they had the highest percentage of major carriers and were mostly medium and large hubs.

Cluster 3 had 24 airports, mainly single-airport cities with the highest average transfer rate. These airports tended to keep their schedules peaked which was indicated by the relatively smaller reduction in peak throughput compared to the reduction in total operations. This trend might be due to airlines having to coordinate flight schedules to accommodate transferring passengers which create busy time periods, i.e. peaks, to make the transfer process more efficient. Cluster 0 had the most resilient flight demand of all clusters, it was made up of airports that on average had a higher cargo or general aviation flight share. The cargo segment was the least impacted by the COVID-19 pandemic since demand on shipping increased due to most people working from home and businesses shifting to online shopping for safety purposes.

Table 1 Airport Characteristics of Clusters (Shock Event)

	Cluster Size	Average Airport Metrics Changes			Average Airport Characteristics						
		Capacity	Throughput	Total Ops	Transfer Rate	LCC	Cargo	Major Carriers	Multi-Airport	Hub (M)	Hub (L)
0	11	0%	-13%	-19%	1.06	17%	19%	18%	36%	55%	0%
1	25	3%	-39%	-56%	1.21	25%	2%	48%	48%	36%	44%
2	1	93%	-31%	-50%	1.05	50%	1%	29%	0%	100%	0%
3	24	1%	-26%	-41%	1.32	30%	3%	43%	33%	33%	38%
4	8	-18%	-43%	-57%	1.22	35%	2%	46%	25%	38%	63%
5	2	-36%	-30%	-44%	1.11	39%	3%	40%	0%	50%	50%
6	6	-3%	-61%	-72%	1.10	12%	1%	37%	67%	33%	50%

There were two clusters that had a small sample size in each. Cluster 2 included only Sacramento International Airport (SMF) which had a large increase in capacity. The capacity at SMF was originally reduced during time period 1 due a renovation project of runway17R/35L from April to October 2019. This means that the 93% increase shown in Table 1 is capacity gained back after the runway was reopened. Another small cluster was Cluster 5 which contained only two airports, Nashville International Airport (BNA) and San Antonio International Airport (SAT). These two airports had a capacity peak reduction of 36% on average, the largest drop in capacity among all groups. This was caused by major terminal construction works at BNA ([26]) and various taxiway and apron projects at SAT ([28]).

Table 2 shows the operational performance data along with the same clusters from Table 1. Cluster 0 did not see the operational improvements that other clusters experienced, given the smaller decrease in total and peak operations. This was expected since this cluster was the highest in cargo operations and cargo demand was increasing during the COVID-19 pandemic. Cluster 0 was the only group of airports that had a decrease in punctuality on average, however it saw minor improvement in flight delays.

Table 2 Operational Performance of Clusters (Shock Event)

	Cluster Size	Average Airport Metrics Changes			Average Airport Characteristics		
		Capacity	Throughput	Total Ops	Punctuality	Delay/delayed flight	Delay/flight
0	11	0%	-13%	-19%	-1%	-9%	-7%
1	25	3%	-39%	-56%	11%	-22%	-47%
2	1	93%	-31%	-50%	4%	16%	-18%
3	24	1%	-26%	-41%	8%	-25%	-41%
4	8	-18%	-43%	-57%	13%	-33%	-58%
5	2	-36%	-30%	-44%	10%	-32%	-48%
6	6	-3%	-61%	-72%	24%	-31%	-63%

The largest improvement in punctuality and delay per delayed flight were found in Cluster 6, 24% and 63%, respectively. This group of airports had the most reductions in their total operations as well as peak throughput with minor changes in peak capacity. Cluster 6 included airports from multi-airport cities such as JFK, EWR, and LGA which could be related to the reduced stress levels at these airports compared to cargo or single airport cities with high transfer rates. Cluster 3 improved their punctuality by 8% on average, which is small compared to the 41% average reduction in total operations. This could be related to the high transfer rates in this group that can cause schedules to peak during busy hours. The data showed that the average improvement in punctuality was 9.5% for all airports which is considered a small improvement when compared to the percent decrease in total operations shown in Table 2.

B. Recovery Results (Time Period 3 compared to time period 2)

The seven clusters were created based on the Airport Metrics Changes variables as percent change of time period 3 compared to time period 2 to analyze patterns of recovery among airports. The resulting groups and their average airport characteristics are shown in **Error! Reference source not found.**, the highest number in each column is highlighted.

Table 3 Airport Characteristics of Clusters (Recovery)

	Cluster Size	Average Airport Metrics Changes			Average Airport Characteristics						
		Capacity	Throughput	Total Ops	Transfer Rate	LCC	Cargo	Major Carriers	Multi-Airport	Hub (M)	Hub (L)
0	18	-1%	21%	44%	1.34	32%	6%	34%	44%	56%	22%
1	5	1%	89%	145%	1.20	22%	1%	44%	80%	0%	80%
2	11	0%	64%	106%	1.08	21%	2%	43%	55%	27%	55%
3	1	0%	267%	257%	1.00	7%	1%	29%	0%	100%	0%
4	36	-1%	39%	72%	1.22	28%	3%	47%	28%	42%	39%
5	5	4%	-4%	7%	1.01	8%	28%	12%	40%	20%	0%
6	1	86%	37%	71%	1.18	44%	1%	39%	0%	0%	100%

During the recovery time period there was more variation in the changes in airport metrics compared to the shock event time period. Air travel demand recovered during this time period after some travel related COVID-19 restrictions were loosened. The data shows that the total operations at the ASPM 77 airports increased by 75% during the recovery time period. Table 3 shows that total operations recovery ranged from 7% to 257% among clusters.

The largest group of airports with similar recovery metrics formed Cluster 4 which contained 36 out of the 77 airports. Cluster 4 was made up of medium and large hubs with the highest percentage of operations by major carriers. This group had a 72% increase in their total operations while managing to increase their peak throughput by only 39% on average. The second largest group was airports with high transfer rates and LCC operations, they were in Cluster 0 which increased total operations by 44% while keeping throughput peak at 21% increase on average. In contrast, Cluster 5 contained cargo airports that had only minor changes in airport metrics. That was expected since cargo flights were the least impacted segment of commercial air transportation during the shock event. The airport with the least changes in both directions was MEM, the largest cargo airport in our study, operations were reduced by 14.8% in the shock and increased by 12% in recovery.

There were two airports with unique changes during the recovery time period that put each of them in their own single-airport cluster. Kahului airport in Hawaii (OGG) was in Cluster 3, there was a 257% increase in demand during the recovery time period. OGG is located on the island of Maui, a tourist destination, which put it in a unique position to receive high demand after the loosening of COVID-19 travel restrictions. Cluster 6 contained BNA which was unique in its 86% increase in peak capacity. This increase in capacity can be attributed to construction projects at the airport. With the exception of capacity, BNA was similar in other metrics to Cluster 4, the largest group of the recovery time period.

Table 4 shows the operational performance data along with the same clusters from Table 3. Delay increased across all groups ranging from 12% to 195%, punctuality decreased in all groups except Cluster 5 which was the cargo airports. One observation from Table 4 is that the increase in delays per flight was disproportionate to the increase in total operations. This trend is a major difference between the shock and the recovery time periods. It can be an indicator to the resiliency of the aviation system and its ability to manage delays in a unique environment of increased air traffic after disruption in demand. The changes in punctuality were smaller compared to changes in delays per flight, this gives insight that the majority of delays causing the high percentages in delays per flight were due to delays under 15 minutes keeping those flights “on time” according to the FAA definition.

Table 4 Operational Performance of Clusters (Recovery)

	Cluster Size	Average Airport Metrics Changes			Average Airport Characteristics		
		Capacity	Throughput	Total Ops	Punctuality	Delay/delayed flight	Delay/flight
0	18	-1%	21%	44%	-12%	27%	96%
1	5	1%	89%	145%	-18%	38%	157%
2	11	0%	64%	106%	-10%	29%	119%
3	1	0%	267%	257%	-11%	26%	195%
4	36	-1%	39%	72%	-11%	29%	101%
5	5	4%	-4%	7%	3%	5%	12%
6	1	86%	37%	71%	-17%	45%	169%

The highest increase in delay per flight was in Cluster 3, the single-airport cluster that contained OGG. The second highest increase in delay per flight was in Cluster 5, the other single-airport cluster that contained BNA. Cluster 1 had the most negative impacts on operational performance. This cluster consisted of large hub airports located in multi-airport cities, they had 18% decrease in punctuality and 38% increase in delays per delayed flight. Punctuality on average decreased by 10.7% for all airports which brought it back to levels similar to pre-COVID even though air traffic was not fully recovered.

C. Clustering Results Summary

This section presents a side-by-side summary of the clustering results from the previous two sections. Fig. 8 shows a visualization of the flow of airports between clusters from the shock event to the recovery. Each cluster is labeled by its number and size, the thickness of each line is proportional to the number of airports in that flow between clusters. It can be seen that Cluster 4 of the recovery time period, the largest cluster, consolidated multiple airports from clusters 1,3, and 4 from the shock time period.

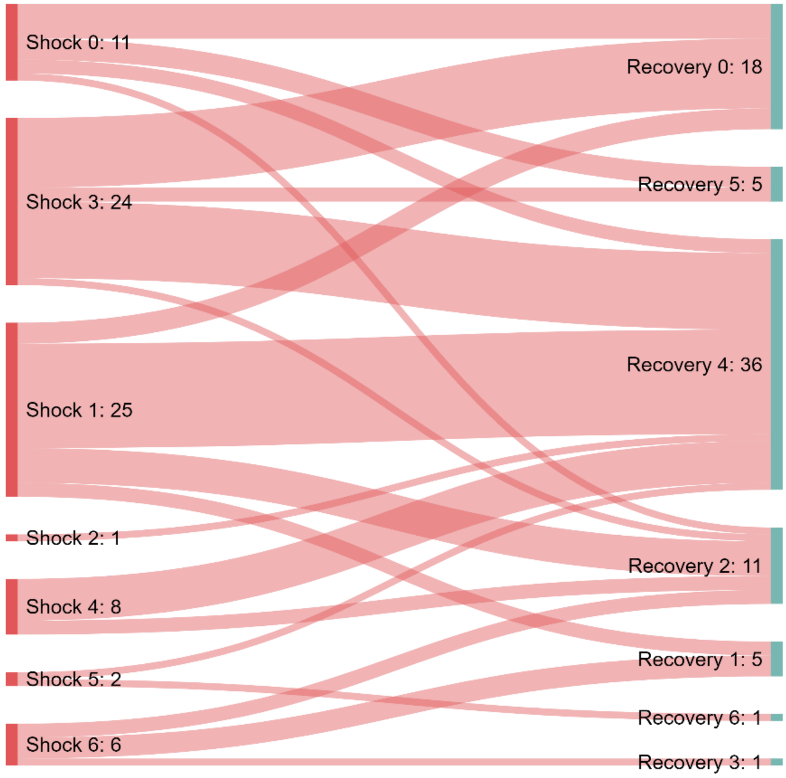

Fig. 8 Flow of airports between clusters from shock to recovery

Fig. 8 shows how Cluster 2 in the recovery was made up of airports from five clusters in the shock event, these airports increased their peak throughput causing them to cluster together away from their previous groups. For example, Los Angeles International (LAX) split from Cluster 1 to join Cluster 2 of the recovery. Although LAX clustered previously with other major airports in California such as San Francisco (SFO) and San Diego (SAN), it moved to Cluster 2 of the recovery which increased its throughput more aggressively compared to Cluster 4 where SFO and SAN clustered.

Table 5 shows all ASPM 77 airports and their clusters from the shock event time period and the recovery time period. The table is ordered by the recovery cluster numbers to give insight on how the groupings changed. Airports are listed as their three-character FAA location identifier, a list of the ASPM 77 airports and their full airport names are found on the ASPM website ([29]).

Table 5 Summary of clustering results

Airport	Time Period		Airport	Time Period		Airport	Time Period	
	Shock	Recovery		Shock	Recovery		Shock	Recovery
ANC	0	0	HPN	1	2	SMF	2	4
DAL	0	0	LAX	1	2	BHM	3	4
GYY	0	0	MIA	1	2	DEN	3	4
ONT	0	0	PSP	3	2	IND	3	4
SDF	0	0	BOS	4	2	ISP	3	4
OAK	1	0	MCO	4	2	OMA	3	4
PDX	1	0	DCA	6	2	PHX	3	4
PIT	1	0	EWR	6	2	SEA	3	4
ABQ	3	0	OGG	6	3	SJU	3	4
BWI	3	0	PBI	0	4	SLC	3	4
CLT	3	0	VNY	0	4	SNA	3	4
CVG	3	0	ATL	1	4	TPA	3	4
DFW	3	0	BUF	1	4	BDL	4	4
HOU	3	0	BUR	1	4	DTW	4	4
MDW	3	0	CLE	1	4	LAS	4	4
MKE	3	0	DAY	1	4	MSP	4	4
STL	3	0	IAD	1	4	MSY	4	4
TUS	3	0	JAX	1	4	SJC	4	4
FLL	1	1	LGB	1	4	SAT	5	4
IAH	1	1	MCI	1	4	MEM	0	5
JFK	6	1	ORD	1	4	OXR	0	5
LGA	6	1	PHL	1	4	RFD	0	5
TEB	6	1	PVD	1	4	MHT	3	5
RSW	0	2	RDU	1	4	SWF	3	5
AUS	1	2	SAN	1	4	BNA	5	6
HNL	1	2	SFO	1	4			

Table 5 provides details on how some airports in multi-airport areas reacted similarly to the shock event but recovered differently. For example, JFK, LGA, and EWR clustered together during the shock event in Cluster 6, however, JFK and LGA increased their peak throughput and operations more than the rest of the group during the recovery leading them to separate to a different cluster. On the other hand, there was a group of 15 airports that remained in the same group, i.e., reacted and recovered similarly. These airports were in Cluster 1 (shock) and stayed together in Cluster 4 (recovery), they include the busiest airports in the US such as ATL, Chicago O'Hare International (ORD), Philadelphia International (PHL), and San Francisco International (SFO).

Cargo airports exhibited interesting grouping, Cluster 0 contained four of the top cargo airports during the shock event, namely, ANC, MEM, Louisville Muhammad Ali International (SDF), and Chicago/Rockford International (RFD). During recovery, ANC and SDF went to Cluster 0 instead of Cluster 5, the cargo cluster that contained MEM and RDF. Both ANC and SDF increased their total operations during recovery to levels exceeding 2019 levels of the same time period. This significant increase made their recovery patterns more aligned with passenger traffic airports such as SFO and Chicago Midway (MDW) from a percent change perspective.

VII. Conclusions

Our analysis of the ASPM 77 airports data showed that the COVID-19 pandemic resulted in a 67% decline in operations at the lowest point during the pandemic. The impact during the shock time period varied greatly across the airports, ranging from a reduction of 14.8% at MEM to 81.5% at LGA. During the recovery period, the increase in total number of operations ranged from 12% at MEM to 257% at OGG. The latter was an example of increasing demand as a result of loosening travel restrictions related to COVID-19.

We performed a clustering analysis to study airports' response to the COVID-19 pandemic, clustering was done for both the response to the shock event (May-September 2020) and the recovery afterwards (May-September 2021). The airport metrics variables that were used to cluster the airports were the change in peak capacity, peak throughput, and total number of operations. There was a number of airport characteristics that were correlated to the changes in airport metrics including cargo operations, operations by major carriers, multi-airport status, hub size, and the rate of transferring passengers. We found that the cargo airports were the most resilient in retaining air traffic demand which was a result of the shift to working from home and businesses moving towards online shopping during the pandemic. Additionally, the percentage of major carriers operations (Delta, United, and American) was significantly correlated to the change in total operations. The data showed that the rate of transferring passengers was a significant variable as it correlated to the change in peak throughput.

The data showed that being located in a multi-airport city was significantly correlated to the decrease in operations during the shock, however, it was not significant in the recovery trends. Although air carriers that received financial assistance were subject to MSOs, the main difference is that they were able to meet and exceed the MSOs during the recovery period due to normal demand improvement. This can be interpreted that being located in a multi-airport city was only significant when air transportation demand levels were lower than the required minimums, i.e. during the shock time period. Airports in multi-airport areas reacted similarly to the shock event but recovered differently. For example, New York airports JFK, LGA, and EWR clustered together during the shock event, however, LGA and JFK increased their peak throughput by 160% and 162% compared to 125% at EWR.

Our analysis showed that delays in the system did not change proportionately to the change in operations. Similarly, there were only minor improvements in punctuality. On-time flights at the ASPM 77 airports increased by 9.5% while operations declined by 52% during the shock event time period compared to pre-COVID. Part of this phenomenon was a result of schedule peaking which caused delays due to creating busy hours at the airports. Additionally, a portion of the delays could be attributed to COVID-19 reasons such as increased safety measures at airports, increased passenger boarding times due to social distancing, and staffing shortages.

VIII. Future Work

Future work could include evaluating a shorter time span, possibly a month, to see if it returns different results. Current results may be capturing a trend for a small amount of time. Since the peak takes a 95th percentile, it would only take an airport to operate in a unique way for a few days during the study period to skew the results. Including other upper percentile alternatives could be beneficial.

Second, including additional airport characteristics that may be impacting the schedule changes and operational performance. One aspect of this analysis could be related to staffing at airports. Staffing was affected due to social distancing and safety, causing many airports to have capacity changes in the initial months of COVID-19.

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