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Aircraft Maintenance 4.0 in an era of disruptions

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Abstract

Digital transformation in manufacturing is having a distinct impact on a variety of business models, including aircraft maintenance. Airline operators are revamping their Maintenance, Repair and Overhaul (MRO) activities with the use of integrated digital platforms and data mining to achieve greater operational efficiencies in parts usage, downtime, and service costs. The term Aircraft Maintenance 4.0 captures the leveraging of information to achieve greater operational agility and to reduce costs. Consolidating data obtained via wireless connectivity from diverse sources enables effective performance monitoring that can inform MRO operations. The severe restriction of flights worldwide due to the pandemic has disrupted the progress of Aircraft Maintenance 4.0 by altering flight routes and rendering most of the historical data obsolete. In this paper, certain aspects of the disruption that deal with airline network changes and their evolution during the pandemic are studied by using publicly available data of a commercial airline.

Keywords: Aircraft maintenance; predictive maintenance; airline networks; airline logistics.

1. Introduction

Commercial aviation logistics and maintenance present many research challenges because of the complexity and sophistication of the airline networks. Optimizing flight schedules, maximizing aircraft utilization, and minimizing aircraft maintenance costs and inventory are essential for competitiveness and profitability. Indeed, the need for reduction of operational cost is essential as the sector is characterized by low profit margins [1]. Airlines were at the forefront of firms that embraced a data-driven culture and used early-on digital processes of optimization to develop

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and fine-tune their operational plans. In fact, the Digital Optimization Maturity Model has been devised to assess best practices and to provide optimization benchmarks for 49 airlines worldwide [2].

Airline resource management usually proceeds in several discreet stages resolved sequentially. There are four major optimization problems in the airline industry: flight scheduling; fleet assignment; crew pairing and aircraft maintenance. After the flight scheduling has been decided and the fleet assignment and crew pairing issues are resolved, aircraft rotation must be managed so that each aircraft gets enough maintenance opportunities. These four problems have been widely studied over the past few decades but do remain largely unsolved due to their size and complexity [3].

Naturally, solving optimization problems sequentially leads to globally suboptimal solutions. More recent approaches integrating two stages, such as airline network and aircraft family optimization or maintenance routing informing crew pairing, have met with limited success.

The maintenance problem has attracted special attention because of its direct impact on reducing operational costs. Indeed, Maintenance, Repair and Overhaul (MRO) activities are at the core of an airline's cost structure [4] accounting roughly for 10% of an airline's total operating costs [5].

The basic aircraft maintenance problem addresses the issue of rotating individual aircraft across routes so that each aircraft is routed after a set number of flight segments to a maintenance station for maintenance, repair and overhaul within the prescribed manufacturer recommendations, aviation authority regulations and internal airline guidelines. The problem is complicated by daily issues such as flight delays and more persistent ones like workflow capabilities and available inventory at each maintenance station. At the core of the problem is the fact that spare parts manufacturing for aviation is a high-tech, small-batch production industry that delivers a great variety of custom-ordered products and specifications [7].

With passenger numbers rising over the past decade, and constant challenges around fuel efficiency and reducing CO2 emissions, optimizing aircraft maintenance became a key priority for commercial airlines [1].

Industry 4.0 provided the impetus for the digital transformation of all maintenance operations. Maintenance 4.0 emerged as a distinct subset of Industry 4.0 in the form of self-learning digital systems that can make diagnoses, predict failures, and establish maintenance plans [8]. Deep Digital Maintenance (DDM) and Predictive Maintenance (PdM) are two alternative terms that have been put forward to signal the use of digital systems to optimize maintenance activities [9, 10]. In this general context, the term Aircraft Maintenance 4.0 has been coined to characterize the transformation of aviation MRO activities to digital along the entire value chain [11].

Consolidating data procured from a variety of sources and transmitted wirelessly around the world, and employing advanced analytics and machine learning, has empowered airlines to gain new insights from their own data and to implement PdM.

An active sub-field of the aircraft maintenance problem deals with the issue of reassigning aircrafts when a disruption occurs. The airline industry encounters disruptions daily due to inclement weather, volcano eruptions, temporary closures of airports or airspaces, unscheduled maintenance, etc. leading to flight delays and cancellations that can affect scheduled aircraft maintenance, crew pairing and passenger itineraries. The process of recovering the schedule after disruptions occur, that is modifying flight and aircraft schedules to compensate for irregular operations is defined as disruption management [12].

The impact of unplanned maintenance events on airline operations is felt directly through increased labor costs and inventory expenses, and indirectly through its ripple effect on network operations. Indeed, unplanned maintenance costs account for approximately 27% of all maintenance expenditures and for approximately half of an airline's delays [4, 5].

The current Covid-19 pandemic has had a singularly distinct and serious impact on the aviation industry due to travel restrictions and a slump in demand resulting in cancelled flights and sever financial stress for the airlines [13]. The pandemic-related severe restriction of flights worldwide has created a problem of historic proportions for Aircraft Maintenance 4.0 by altering flight routes and rendering most of the historical data obsolete [14].

The objective of this paper is to examine network related aspects of the disruption. Indeed, an airline's network structure provides the platform for studying the maintenance problem in the sense that the choice itself of maintenance stations -be they owned or leased facilities- is determined by the structure of the network [15]. Specifically, the objective of this paper is to assess how airline network characteristics have evolved from the pre-pandemic "normal" schedules to the post-pandemic "emergency" and "new-normal" ones. The findings will inform disruption management and in particular aircraft maintenance and spare-part logistics.

The paper is organized as follows. A concise review of airline networks and their characteristics is presented in Section 2. This is followed, in Section 3, by an articulation of the issues involved via publicly available data of a commercial airline. An informed discussion of the results obtained is provided in Section 4. Finally, in Section 5, the conclusions of the paper are summarized along with limitations and suggestions for future research.

2. Airline Network Configurations

Air traffic networks are essential to today's global society because they are the fastest means of transporting physical goods and people. Airline networks are spatial networks that address the subset of air traffic that is covered by a single airline [16].

An airline connection network is defined by the set of arrival or departure airports (nodes) and the flight arcs (edges). Node and edge attributes are defined according to the scheduling problem at hand. Node attributes can be the population of the area that each airport serves (for routing and ticketing) or the presence or absence of a maintenance facility (for inventory purposes). Edge attributes can be the distance covered or the frequency of the connection or the type of plane flown in each flight segment. In most cases, the networks are bidirectional.

The simplest form of an airline network is the point-to-point (PP) configuration in which airports are connected by direct routes. This is the preferred configuration of (typically low-cost) airlines which operate only on routes where demand guarantees a high load factor on aircrafts. The PP configuration allows for substantial cost reduction but makes long-haul routes out of reach for many airlines.

Most full-service airlines do not implement a straight PP configuration and plan their routes from one or more base airports. In the basic hub-and-spoke (HS) configuration all destinations are linked to a main airport called hub. The main advantage of this configuration is that it allows for the connection of many origins and destinations with a low number of routes. In addition, airlines can centralize services such as aircraft maintenance in hubs to gain operational advantages. The key drawbacks of the HS configuration are that it increases the time and cost of travel between non-hub airports and that it can lead to congestion at hub airports.

A variant of the HS configuration is the multi-hub-and-spoke (MHS) configuration, which is like the HS, but with several hubs instead of one. (These individual hubs are not necessarily of the same importance in the network.) The MHS configuration is observed in fragmented markets or when a hub airport reaches its scheduled capacity.

Irrespective of their configuration, airline networks are characterized by a large set of graph theory metrics which help inform and parametrize all the relevant optimization problems. Some of these metrics describe the entire network while others describe individual nodes [17].

For MRO operations, the issue is the optimal placement of maintenance stations and spare parts depots at key nodes of the network. Node centrality, which characterizes the level of connectivity of an airport in the airline network, is of paramount importance for aircraft maintenance because a significant portion of maintenance operations is dependent upon ferrying spare parts.

There are three common measures of node centrality, degree, closeness and betweenness representing distinct perspectives of importance [18]:

- Degree centrality is defined as the number of nodes directly connected to the node in question out of the totality of nodes within the network.
- Closeness centrality indicates how close a node is to all other nodes in the network. It is calculated as the inverse of the average geodesic distance from the node in question to every other node in the network.
- Betweenness centrality measures the importance of a node in a network based upon how many times it occurs in the shortest path between all pairs of nodes. It measures the times a node acts as a bridge along the shortest path between two other nodes.

The degree of an airport in an airline network refers to the number of other airports having direct flights with this airport. The higher the degree of an airport the greater its importance, to some extent, in the network.

The closeness of an airport broadly refers to the accessibility of the airport and is defined through the number of direct and indirect air travel connections available at the airport. An airport with higher closeness is more central in the network, in the sense that all other airports can be reached more easily from this airport.

The betweenness of an airport measures the number of transfer opportunities available via the specific airport. Higher betweenness of an airport indicates a stronger effect of the airport as a bridge, and a more important role in the network.

3. Operational Disruptions

The increasing reliance of the global world economy on air traffic networks requires these networks to have high resilience. While previous events show that air traffic networks can be reasonably resilient to most natural hazards, the current pandemic has created a disruption with colossal effects.

During the several phases of the pandemic, airlines attempted to rebuild, albeit slowly, their networks. The new routing schemes that emerged reflect both local and global conditions and can provide valuable new insights on how re-routing solutions can improve the resilience of air traffic.

This paper is based on the real-world example of Air Astana, the flag carrier of Kazakhstan. Air Astana is a medium-size airline that has been recognized as "Best Airline in Central Asia and India" in the Skytrax World Airline Awards for eight consecutive years.

Air Astana has three major maintenance hubs in Almaty, Nur-Sultan and Atyrau that are certified by the European Aviation Safety Agency (EASA) to perform full maintenance services of its aircraft. Major aircraft maintenance relates to airframes (referred to as the C-check, D-check, and redelivery preparation program) and engines. The C-check is heavy maintenance with approved performance interval. It takes place at the earliest of every 6,000-7,500 flight hours, 3,000-5,000 flight cycles and 18-24 months according to aircraft type. The D-check is heavy maintenance connected with deep aircraft disassembly, structure inspection and anticorrosion prevention program. It takes place with an interval of not more than 72 months. Air Astana additionally engages third-party maintenance and repair organizations in Asia and Europe (typically Hong Kong, Istanbul, and Frankfurt). Maintenance costs account for about 12% of Air Astana's operational expenses for the years preceding 2020.

Table 1 summarizes some key operational figures of Air Astana from 2019 and 2020 culled from its audited financial statements [19]. These include *provisions* (C-check, D-check, engines, auxiliary power units, landing gear), *components* (inventory parts that are consumed or repaired and reused), *spare parts* (inventory to maintain redundancies for uncertain demand in terms of locations and time) as well as the cost of scheduled and unscheduled *inspections* of the aircrafts the airline owns. In addition, the airline is obliged to carry out and pay for maintenance based on its use of leased aircraft and to return such aircraft to the lessors in a satisfactory condition at the end of the lease term. IATA maintenance accounting rules mandate that maintenance of leased aircraft is reported as a total, composite entry in financial statements because the corresponding expenses are amortized differently [20].

Table 1. Air Astana financials 2019 vs 2020.

’000 USD	2019	2020	CHANGE
Engineering and Maintenance	**94,407**	**43,198**	**-54%**
Maintenance – lease payments	28,154	5,988	-79%
Maintenance – provisions	28,467	20,344	-29%
Maintenance – components	21,418	5,749	-73%
Spare parts	13,875	9,023	-35%
Technical inspection	2,493	2,094	-16%
Passenger revenue	**824,952**	**358,413**	**-57%**
Aircraft crew costs	**35,327**	**14,872**	**-58%**
Total operating expenses	**820,030**	**469,578**	**-43%**
End-of-the-year spare parts inventory	**29,755**	**32,193**	**8%**

The objective of the table is twofold. First, to illuminate the significance of the various types of MRO operations on the bottom line of the airline and, second, to demonstrate the stark effect of the pandemic. Table 1 demonstrates that Air Astana flight operations were severely curtailed in 2020, with passenger revenue and flight personnel costs down by almost 60% compared to 2019. At the same time operating expenses were cut by about 40%, signaling the inflexibility of reducing certain operation costs.

Maintenance costs appear to have been reduced by about 55% accounting for 9% of the total operating expenses in 2020 compared to 12% in 2019. This figure however is deceptive as the bulk of the maintenance savings had to do with leased aircraft that were mostly returned to their owners. If one excludes maintenance lease payments, engineering and maintenance costs were only reduced by about 40% from 2019 to 2020, following the overall trend of the total operational expenses. The situation is exasperated by the fact that the airline ended 2020 with 8% more spare parts in its depots than in 2019.

It is apparent that maintenance costs are not amenable to cost reductions equivalent to the reduction of flight operations because maintenance hubs are not easily movable and incur hefty, fixed costs. In this context, the evolution of Air Astana's network during the pandemic and the resultant changes in its connectivity metrics emerges naturally as a critical issue for MRO operations.

4. Network Evolution and Analytics

The objective was to determine whether the geographical location of the international airports that Air Astana served during the pandemic significantly altered the major metrics of its network. Only publicly available data were used which were obtained from official schedules and dynamically updated repositories (such as routesonline.com).

As the airline continuously adapted to the changing conditions, there were three key dates at which its international network was redrawn with respect to the ebbs and flows of the pandemic: July 12th, August 23rd, and October 18th, 2020. The date of November 1st, 2019 was added as a benchmark of Air Astana's international network before the start of the pandemic.

For the analysis in this paper, the concept of a simplified network was used. That is, only unique flight routes were accounted for without taking into consideration the number of flights operating on each route.

The analysis of the characteristics of the four evolutions of Air Astana's international network was performed using the NodeXL add-in for Excel [21].

Figure 1 displays the initial form of the network, effective from November 1st, 2019 (NOV19). The figure is accompanied by a table detailing the operational nodes of the network and their measures of centrality. In the network graph, the degree of an airport is reflected in the size of the dot representing it.

After a quick ramp down and finally suspension of all international flights (except for evacuation ones) during the first half of 2020, Air Astana unfolded in July (JUL20), August (AUG20) and October (OCT20) three new international schedules to account for allowances and prohibitions on air travel from the relevant countries. Figures 2, 3 and 4 represent the respective forms of the network.

Before the pandemic, Air Astana was operating an international 28-node MHS network with two large hubs, Nur-Sultan and Almaty. Both airports had degree, betweenness and closeness far exceeding those of the other nodes. Frankfurt, Istanbul and Atyrau were in the second tier of importance for the network (Figure 1).

The structure of the network remained mostly intact after reopening in July 2020, with 28-nodes, Nur-Sultan and Almaty the two main hubs and Istanbul, Frankfurt and Atyrau following in terms of importance. The slight increase in average betweenness and the rise of Istanbul to the top of the second tier was primarily due to the cancelation of the direct route from Almaty to Frankfurt.

In August 2020, the start of the second wave of the pandemic resulted in a retrenchment of the network. With only 20 nodes available, there was only one discernible major hub, Almaty, while Nur-Sultan and Istanbul virtually tied at the top of the second tier. Average degree and betweenness were reduced while average closeness increased for the remaining nodes.

Finally, in October 2020, the network was further reduced to 10 nodes, with no discernible major hub, and Almaty, Nur-Sultan and Istanbul being delegated to the role of minor hubs. Average betweenness was further reduced, average degree was almost unchanged and average closeness was further increased reflecting the closer association of the remaining nodes.

The summary comparison of the international network characteristics provided in Table 2 demonstrates succinctly the changes of the flight schedules with respect to the pandemic. The most dramatic change is seen in the structure of the network which evolved from being a 2-hub MHS to an HS and finally to a form with no major hubs and increasingly resembling a PP network.

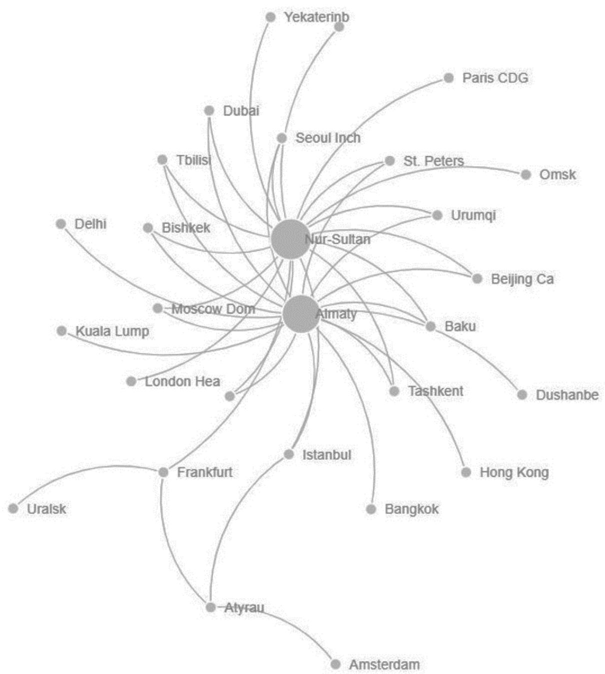
Table 2. International network characteristics over time.

As of:	Nodes	Mean Degree	Mean Betweenness	Mean Closeness	Major/Minor Hubs
NOV19	28	2.786	18.214	0.016	2/3
JUL20	28	2.786	18.286	0.016	2/3
AUG20	20	2.100	14.500	0.022	1/2
OCT20	14	2.143	10.500	0.031	0/3

Within the network the role of the major and minor hubs was restricted to five key cities (Nur-Sultan, Almaty, Istanbul, Frankfurt and Atyrau) with varied importance for each schedule.

While the airline managed to maintain a minimum number of nodes to stay connected and to operate during the pandemic, government restrictions on flights worldwide had a significant and measurable impact on the parameters of the network.

The key question remains of course how these parameter changes were reflected in the operational parameters and maintenance costs of the airline.

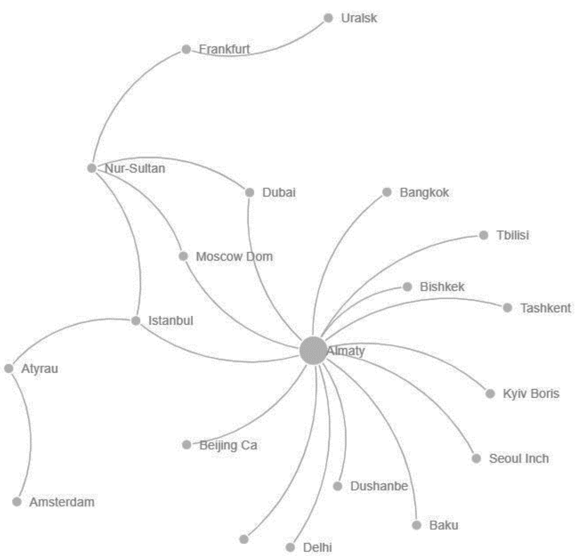


AIRPORT	Degree	Betweenness	Closeness
Nur-Sultan	18	201.744	0.024
Almaty	17	160.333	0.022
Frankfurt	3	39.333	0.014
Istanbul	3	37.513	0.016
Atyrau	3	27.923	0.019
Baku	2	3.923	0.018
Beijing Capital	2	3.923	0.018
Bishkek	2	3.923	0.018
Dubai	2	3.923	0.018
Kyiv Borispil	2	3.923	0.018
Moscow Domodedovo	2	3.923	0.018
Seoul Incheon	2	3.923	0.018
St. Petersburg	2	3.923	0.018
Tashkent	2	3.923	0.018
Tbilisi	2	3.923	0.018
Urumqi	2	3.923	0.018
London Heathrow	1	0.000	0.015
Novosibirsk	1	0.000	0.015
Omsk	1	0.000	0.015
Paris CDG	1	0.000	0.015
Yekaterinburg	1	0.000	0.015
Bangkok	1	0.000	0.014
Delhi	1	0.000	0.014
Dushanbe	1	0.000	0.014
Hong Kong	1	0.000	0.014
Kuala Lumpur	1	0.000	0.014
Uralsk	1	0.000	0.011
Amsterdam	1	0.000	0.010

Fig. 1. Network representation and analytics effective NOV19.

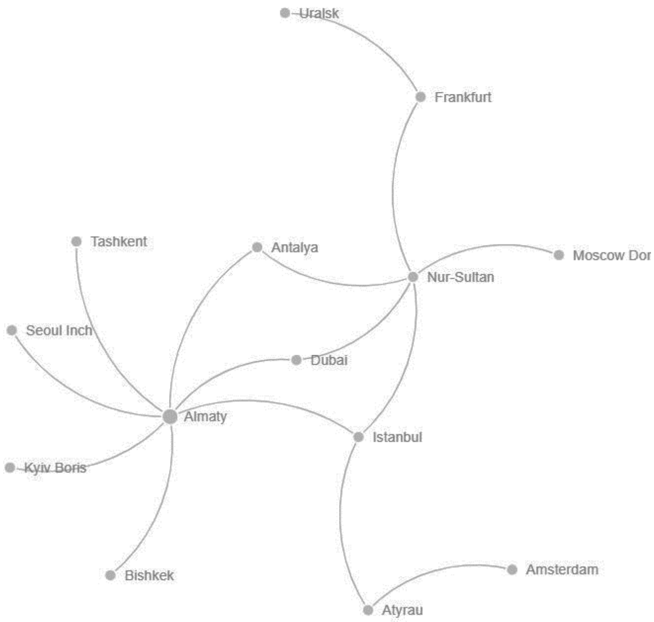
AIRPORT	Degree	Betweenness	Closeness
Almaty	18	181.333	0.023
Nur-Sultan	17	181.590	0.023
Istanbul	3	38.737	0.019
Frankfurt	3	38.333	0.016
Atyrau	3	28.077	0.014
Baku	2	3.994	0.018
Beijing Capital	2	3.994	0.018
Bishkek	2	3.994	0.018
Dubai	2	3.994	0.018
Kyiv Borispil	2	3.994	0.018
Moscow Domodedovo	2	3.994	0.018
St. Petersburg	2	3.994	0.018
Seoul Incheon	2	3.994	0.018
Tashkent	2	3.994	0.018
Tbilisi	2	3.994	0.018
Urumqi	2	3.994	0.018
Bangkok	1	0.000	0.014
Delhi	1	0.000	0.014
Dushanbe	1	0.000	0.014
Hong Kong	1	0.000	0.014
Kuala Lumpur	1	0.000	0.014
Paris CDG	1	0.000	0.014
London Heathrow	1	0.000	0.014
Novosibirsk	1	0.000	0.014
Omsk	1	0.000	0.014
Yekaterinburg	1	0.000	0.014
Uralsk	1	0.000	0.011
Amsterdam	1	0.000	0.010

Fig. 2. Network representation and analytics effective JUL20.



AIRPORT	Degree	Betweenness	Closeness
Almaty	14	146.500	0.036
Nur-Sultan	4	37.500	0.022
Istanbul	3	46.000	0.028
Atyrau	2	18.000	0.019
Frankfurt	2	18.000	0.016
Dubai	2	12.000	0.025
Moscow Domodedovo	2	12.000	0.025
Baku	1	0.000	0.022
Bangkok	1	0.000	0.022
Beijing Capital	1	0.000	0.022
Bishkek	1	0.000	0.022
Delhi	1	0.000	0.022
Dushanbe	1	0.000	0.022
Kyiv Borispil	1	0.000	0.022
St. Petersburg	1	0.000	0.022
Seoul Incheon	1	0.000	0.022
Tashkent	1	0.000	0.022
Tbilisi	1	0.000	0.022
Amsterdam	1	0.000	0.014
Uralsk	1	0.000	0.013

Fig. 3. Network representation and analytics effective AUG20.



AIRPORT	Degree	Betweenness	Closeness
Almaty	7	45.500	0.042
Nur-Sultan	5	35.500	0.038
Istanbul	3	28.667	0.042
Atyrau	2	12.000	0.029
Frankfurt	2	12.000	0.028
Dubai	2	6.667	0.036
Antalya	2	6.667	0.036
Bishkek	1	0.000	0.028
Kyiv Borispil	1	0.000	0.028
Seoul Incheon	1	0.000	0.028
Tashkent	1	0.000	0.028
Moscow Domodedovo	1	0.000	0.026
Amsterdam	1	0.000	0.022
Uralsk	1	0.000	0.021

Fig. 4. Network representation and analytics effective OCT20.

By turning to the financial statements of the airline for the four quarters of 2020, one can obtain the relevant data that roughly correspond to the evolutions of its network.

Table 3. Air Astana quarterly financials 2020.

’000 USD	Q1	Q2	Q3	Q4
Engineering and Maintenance	28,196	3,956	10,278	768
Passenger revenue	154,112	30,944	75,179	98,178
Aircraft crew costs	7,965	1,517	2,121	3,269
Total operating expenses	209,703	55,586	99,661	104,628

Figure 5 demonstrates succinctly the evolution of the Air Astana financials during the four quarters of 2020. By comparing the data in Tables 2 and 3, it appears that maintenance costs are correlated positively with degree and betweenness and negatively with closeness. In addition, they are positively correlated with the number of nodes and number of major and minor hubs in the network.

While four data samples are clearly inadequate for long-term projections, it is informative to perform a linear regression on the maintenance costs with regressors the connectivity metrics (degree, betweenness and closeness). The model that emerges has the following form:

$$Maintenance = -15{,}004 - 3{,}515 * Degree + 2{,}239 * Betweenness \tag{1}$$

with closeness not participating at all. Hence, maintenance costs are positively influenced by the average betweenness of Air Astana’s network and negatively affected by the average degree of the network.

Equation (1) is offered simply as an example of how major network disruptions can affect maintenance operations and costs. Additional regressions can be performed to examine the influence of network characteristics on other components of the airline's cost structure and operating expenses. These types of outcomes can then be used to define the weights in parametrizing maintenance algorithms vis a vis network characteristics for employment and testing under different disruptive scenarios.

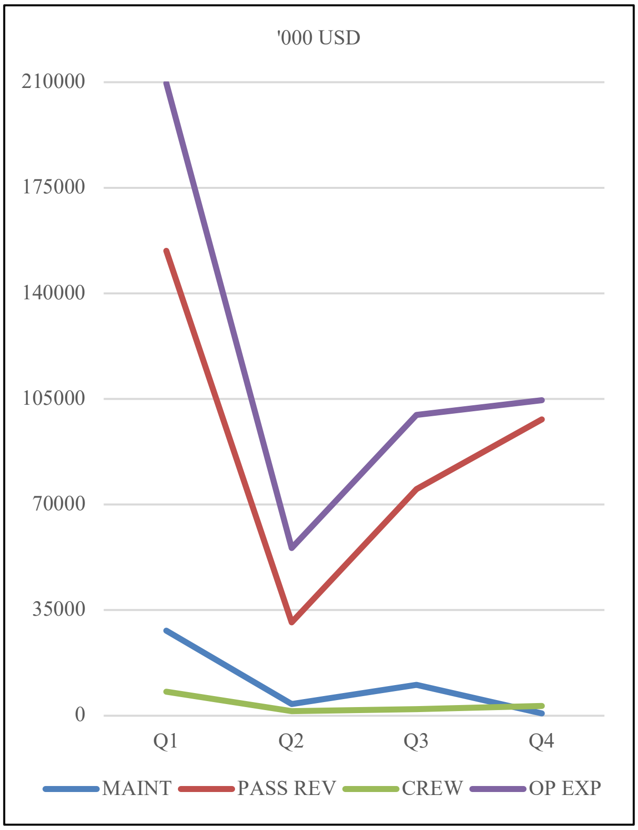


Fig. 5. Quarterly financials in 2020.

5. Conclusions

The aircraft maintenance problem is one of the key logistic problems in the airline industry as thousands of aircrafts undergo maintenance, repair, and overhaul (MRO) operations daily. Maintenance 4.0 emerged as a distinct subset of Industry 4.0 to characterize the digital transformation of aviation maintenance. Predictive Maintenance (PdM) and Deep Digital Maintenance (DDM) systems are emerging to optimize maintenance activities.

Maintenance 4.0 is complicated by the presence of disruptions in airline operations. Past and recent research has focused on how even simple variables such as airline punctuality can have significant effects on maintenance, repair, and overhaul (MRO) costs [24, 25] and that fundamental choices in airline network architectures can impact MRO operations [26, 27]. The digital transformation that is sweeping through airline maintenance operations has allowed for more nuanced analyses that extend beyond the scope of legacy maintenance strategies to provide prescriptive maintenance tools [28] and to assess the risks in air connection dropouts in airline networks [29].

Prescriptive maintenance is still in its infancy. Big data analytics and predictive algorithms have been developed to determine impending failures at individual component, aircraft, and fleet levels, and then to provide for complete repair solutions. While such approaches have succeeded in reducing downtime, they are not yet ready for real-world implementations because they are extremely sensitive to non-trivial network disruptions [30].

The key objective of Maintenance 4.0 is to integrate maintenance activities with design solutions and data gathering within a supportive ecosystem [31]. In aviation maintenance, location is important and location-based solutions are considered the next big step in MRO 4.0 [32]. At a minimum, location is essential for the optimal placement of maintenance stations and spare parts depots at key nodes of the network.

It is thus crucial for air traffic networks to exhibit resilience, that is to have the ability to cope with natural, unforeseen, and intense worldwide disasters. The objective of this paper has been to demonstrate how key network characteristics influence MRO operations. The real-world case examined in this paper demonstrated that the changes due to events like the pandemic are very important and need to be studied further. With airline networks recovering very slowly (if at all) to their pre-pandemic status new data will slowly start to emerge.

It is expected that the insight developed in this paper will be essential to inform and parametrize prescriptive maintenance algorithms and systems within the "supportive ecosystem" called for in [31].

Two immediate issues that need to be examined further are the addition of other metrics of closeness into the mix and the elaboration on the issue of accounting for flight frequencies between any two nodes. Future research should also focus on the taxonomy of disruptive events in air traffic networks so that real-world implementation will proceed across a well-defined continuum of possibilities.

Finally, a similar investigation of another medium-size international airline within a meta-analysis framework [23] might provide adequate support to the thesis of generalizing the results of this paper across bigger segments of the commercial aviation industry.

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