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Connectivity of the European air transport network during the Covid-19 pandemic

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Abstract

The global Covid-19 pandemic has had a great impact on the air transport network (ATN) and on aviation in general. April 2020 saw the largest decline in connectivity, with an average drop of more than 80% compared to 2019. This paper investigates this decline in terms of centrality measures. To capture the first wave of the pandemic, i.e., the largest decline followed by a partial increase, 40 weeks were examined. The selection of the 24 European airports made. This selection was used to describe the European ATN generated by the operations of the selected airports. The methodology of this selection is presented in this work. A methodology based on statistical methods and graph theory was used to evaluate the data. Based on the analysis, 6 airports with a different development of weighted centrality values were found. The development of values of these 6 airports differed from the other airports and these airports also differed from each other. This paper is describing development of the ATN centrality in context with operations and connectivity between airports.

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Keywords: connectivity; air transport network; centrality; Covid-19 pandemics

1. Introduction

The global Covid-19 pandemic has affected air transport in the most significant way to date. In order to slow the spread of the virus, states started to implement various restrictions. Some countries closed airports to commercial air traffic, while others imposed up to a 14-day quarantine for passengers arriving in the country (Airports Council International Europe, 2020). The peak of the crisis occurred in April 2020. According to IATA (2020), the number

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of flights decreased by 80% compared to the values at the beginning of the year. As a result of the restrictions, the number of unique city-pairs decreased by 67% compared to the same period levels in 2019. ICAO (2022) reported that as a result of the pandemics, passenger air transport in 2020 decreased by 60% compared to 2019 levels. To evaluate and analyze this decline, the concept of connectivity may be used.

In the available literature, many authors deal with connectivity. There is no unitary definition for the concept of connectivity, and depending on the point of view, it can be understood very differently. ICAO (2020) defines connectivity as: ‘Movement of passengers, mail and cargo involving the minimum of transit points which makes the trip as short as possible, with optimal user satisfaction and at the minimum price possible.’ According to IATA (2020), connectivity reflects how individual states are connected to the rest of the world and how air connections contribute to the development of the state’s economy. A similar view is offered by Zeigler et al. (2017), who state that connectivity makes it possible to describe the availability of specific regions based on available air connections. In addition to this point of view, IATA (2020) mentions several others. From the passenger point of view, connectivity can be understood as the possibility of traveling from origin to destination as quickly as possible. From the airport's point of view, it can be an important tool for assessing the value of individual air connections. ACI Europe (2019) describes four types of connectivity from the perspective of passengers, namely direct, indirect, airport, and hub connectivity. Together, they describe the connectivity provided by an airport. In general, connectivity reflects how the different parts of the network are connected.

In many resources dealing with connectivity, the abbreviation ATN can be encountered. ATN stands for Air Transport Network. According to Lordan et al. (2014), ATN is one of the most important, the most extensive, but also the most critical networks. According to Paleari et al. (2010), it has a significant impact on local, national, and international economies and social evolution. It enables a better connection of individual parts of the world and significantly increases the possibilities of travel and transport of goods. The impact of air transport on the economy was described by Zhang and Graham (2020), and they divided it into direct and indirect.

Many authors started to deal with impact of Covid-19 on air transport network and connectivity. Among the recent studies, Mueller (2021) investigated changes in connectivity patterns for the air transport network in Europe. The worldwide air transport network was investigated by Bao et al. (2021), using OAG data. Another study focuses on connectivity and ATN in terms of international flights, domestic flights and airports in the United States, Europe and China (Sun et al., 2021).

In order to study air transport network, graph theory is mainly used. This theory is the basis for a considerable number of methodologies and approaches for examining individual aspects of these networks. It is possible to represent the air transport network using a graph consisting of nodes and edges that connect the individual nodes. Air transport is made up of a large number of elements that interact and cooperate with each other, resulting in more possibilities to interpret the network (Zanin and Lillo, 2013). In most studies (Wei, Chen and Sun, 2014), (Song and Yeo, 2017), the nodes represent individual airports. If there is a direct connection between these airports, the graph shows the edge connecting the respective nodes. In their article, Zanin and Lillo (2013) mention, for example, a network in which nodes represent navigation equipment and edges represent flight paths.

From the point of view of graph theory, Burghouwt and Redondi (2013) define connectivity as: ‘the degree to which nodes in a network are connected to each other.’ The network that represents airports and the connection between them is, in most cases, a directed graph. It means that there may be both connections from A to B and flights from B to A between airports A and B (Zanin and Lillo, 2013). The other significant feature of the graph is the weight of the edges. Networks can be divided into weighted and unweighted. According to Zanin a Lillo (2013), in unweighted network, only topology matters. In case of weighted networks, edges have weight, for example, the number of flights, the number of passengers carried, or the number of seats offered. In this paper, the network is represented by a weighted directed graph, where the edge rating represents the weekly frequency of flights.

The main objective of the research described in this paper is to evaluate how the connectivity of the European air transport network has been ensured during the Covid-19 pandemics. More specifically, the aim is to reveal how connectivity values changed, which airports remained active and what connections were offered from these airports. Research is conducted to better understand the impact of the pandemic on the ATN and air travel in general.

The paper focuses on the connectivity of the 24 most important European airports, which were selected based on the number of passengers carried. The examined period is 40 weeks, starting on 6 January 2020. Part 2 introduces the methodology, specifically the centrality method. In section 2.1, selection of the examined airports is described.
The data source, Flightera, is described in part 2.2. Part 2.3 introduces methods used for data analysis. The results are presented in chapter 3 and discussed in chapter 4.

2. Methodology

To achieve the objective, that is, to evaluate how the connectivity of the European ATN has been ensured during pandemics and understand its impact on the ATN, connectivity values were examined. The methodology used is the centrality method. One reason is the form of the data that were processed. These are freely available data and these data are described in more detail in chapter 2.2. Only direct connectivity is examined (i.e., direct connections from the airports studied) and more complex data would be needed to capture indirect connections. In the available literature, centrality measures were used by Bao et al. (2021), Song and Yeo (2017) or Lordan et al. (2014).

The centrality method allows to determine the importance of each node in the graph, depending on their impact on the network (Bhasin, 2019). The importance of individual nodes can be evaluated from different perspectives, on the basis of which individual types of centrality are defined:

- Degree centrality
- Weighted centrality
- Betweenness centrality
- Closeness centrality

**Degree centrality** reflects the degree of the individual nodes and is the simplest kind of centrality. The degree of a node defines the number of edges connected to the node. In the directed graph, the indegree and outdegree is defined. Indegree is the number of connections from other nodes to the examined one, while outdegree defines the number of edges to another nodes (Bhasin, 2019). **Weighted centrality**, as opposed to direct centrality, takes into account the weight of edges (Opsahl, Agneessens, Skvoretz, 2010). Each edge is assigned a specific number, and thus the network is weighted. As already mentioned, the edges can be evaluated, for example, by the number of flights, passengers carried, or the capacity offered. **Betweenness centrality** evaluates the importance of a node based on how many times the node occurs on the shortest path between two other nodes (Bhasin, 2019). **Closeness centrality** is defined by the distance between the node being examined and other nodes on the network (Sapre and Parekh, 2011). In this paper, degree and weighted centrality are evaluated.

In the context of ATN, degree centrality determines the number of airports to which there is a direct connection from the airport examined. Mathematically, degree centrality \( k_i \) can be defined as:

\[
k_i = \sum_j a_{ij}
\]  

(1)

where \( a_{ij} \) corresponds to the elements of adjacency matrix A. For each pair of airports (i – origin, j – destination), the element equals 1, when there is at least one direct connection between the airports and 0 otherwise (Lordan, Sallan, Simo and Gonzalez-Prieto, 2014). Weighted centrality can be defined by the equation:

\[
s_i = \sum_j w_{ij}
\]  

(2)

where \( w_{ij} \) corresponds to the elements of the weighted adjacency matrix W. The element \( w_{ij} \) equals 0, when there is no connection between examined airports (i – origin, j – destination). Otherwise, the element equals to the weight of the edge between these airports (Opsahl, Agneessens, Skvoretz, 2010).

2.1. Airport selection

The airports analyzed in this paper were selected based on the number of passengers carried in 2019. The selection threshold was established at 25 million passengers. Data from Eurostat (2022) were used, namely the "Air passenger transport by main airports in each reporting country" (AVIA_PAOA) dataset. Eurostat processes and consolidates data collected by statistical offices of countries that are members of the European Union (EU), the European Free Trade Association (EFTA), and several other countries. For this reason, Eurostat statistics do not contain data on European
2.1. The connection between examined airports is established in the ATN, which is part of the EU in 2019. The selected airports and their number of passengers carried are shown in Table 1. The IATA codes contained in the table are used later in the text instead of the airport names.

| Airport                  | IATA code | Passengers carried |
|--------------------------|-----------|--------------------|
| London Heathrow          | LHR       | 80 886 588         |
| Paris Charles de Gaulle  | CDG       | 76 136 816         |
| Amsterdam Schiphol       | AMS       | 71 689 636         |
| Frankfurt                | FRA       | 70 435 867         |
| Madrid Barajas           | MAD       | 59 747 242         |
| Barcelona El Prat        | BCN       | 51 734 144         |
| Munich                   | MUC       | 47 891 776         |
| London Gatwick           | LGW       | 46 560 536         |
| Rome Fiumicino           | FCO       | 43 397 751         |
| Dublin                   | DUB       | 32 653 249         |
| Paris Orly               | ORY       | 31 853 675         |
| Vienna                   | VIE       | 31 634 898         |

2.2. Data sources

The main data source is Flightera (2021). Flightera provides data and information on arrivals and departures from the selected airport. The available data include, among other information, the date and time of departure/arrival, origin, destination, airline, flight number, and flight status.

Flightera (2021) uses freely available data on the basis of which available information is generated. Sources of such data include, for example, airlines, airports, and data obtained from aircraft tracking. Flightera also uses machine learning algorithms to generate information.

Based on the available data, the period examined in this work is 6 January 2020 – 11 October 2020, that is, 40 weeks. The period was chosen to capture the situation before the outbreak of the pandemic, the greatest culmination in April 2020 and the subsequent anticipated improvement of the situation. A unit of one week was chosen to capture changes during each month. For simplicity, the numbering of individual weeks in the work does not correspond to the numbering of weeks according to the calendar. The weeks are numbered from one and the first week examined, 6 January – 12 January 2020, corresponds to the second calendar week.

2.3. Data analysis

For evaluating the centrality measures, Gephi software was used. Gephi is used for visualization and analysis of graphs and networks. In this work, it was used for calculation of centrality values. All statistical analyzes were performed with Matlab. The data were standardized using the z-score. For comparison of centrality values for individual airports, correlation analysis was used. Specifically, the Pearson correlation coefficient was used to evaluate the relationship.

3. Results

For direct and weighted centrality values, a correlation matrix was created (see Table 2). Based on this matrix, the airports were divided into several groups. Results for weighted centrality are presented in this section.

In terms of weighted centrality, two groups were created. The first group consists of airports, which values of the correlation coefficient did not fall below 0.95, when compared. These are the airports AMS, BCN, BRU, CDG, DPH,
DUB, DUS, FRA, LGW, LIS, MAD, MAN, MUC, ORY, OSL, STN, VIE and ZRH. The higher correlation signifies a similar development of the weighted centrality values. The second group consists of the ARN, ATH, FCO, LHR, MXP and PMI airports. For these airports, the correlation coefficients have fallen below 0.95. The lower correlation coefficient means that the development of the weighted centrality values was different for these airports. These airports are discussed in Section 4.

For an easier description of each airport, the time period can be divided into three parts: before the decline (weeks 1-11), the period of the greatest decline (weeks 12-25), and the period after the decline (weeks 26-40). These periods were set only for the description of the behavior of individual airports and were not used for analysis.

The blue-marked airport group showed significantly lower weighted centrality values after the decline than before the decline. Airports marked in red are shown in a separate figure for clarity (see Fig. 2). This group cannot be described as a whole, as these are airports with a different development of weighted centrality values. These airports are discussed in Section 4.
Discussion

For airports with a different development of weighted centrality values (see Fig. 2), connections that most affected the weighted centrality values were found. The airport with the most different development was PMI. The period of the greatest decline was mainly due to the restriction of flights to Spain and Germany. The biggest impact was the reduction in the frequency of flights to the Spanish airports BCN, MAD, IBZ (Ibiza), VLC (Valencia) and MAH (Menorca). In the post-decline period, especially in week 31, the airport showed significantly higher weighted centrality values than in the pre-decline period. Flights to Germany had the greatest impact on this increase. These were mainly flights to DUS, STR (Stuttgart), HAM (Hamburg), CGN (Cologne Bonn), MUC and HAJ (Hannover) airports. In the period after the decline, the ATH Airport reached similar values of weighted centrality similar to those before the decline. In the post-decline period, the number of flights to Greek airports PAS (Paros), JMK (Mykonos), JNX (Naxos) or MLO (Milos) increased, and the frequency decreased mainly for flights to IST (Istanbul), SKG (Thessaloniki), TLV (Tel Aviv) or LCA (Larnaca). LHR Airport had values below average in the period after the decline. From week 37, values of weighted centrality began to rise due to increasing frequencies.
of flights to the USA, for example to JFK (J. F. Kennedy New York), ORD (Chicago O'Hare), SFO (San Francisco) or MIA (Miami) airports. In the period after decline, the airport ARN showed below average weighted centrality values. It was mainly caused by the reduction in the frequency of flights, for example to the airports OSL, CPH and HEL (Helsinki). In the case of MXP and FCO airports, the decline started a week or two earlier than in the case of the blue group (see Fig. 1).

The analysis identified a high number of domestic flights. As the number of flights decreased, the share of domestic flights increased. Norway had the highest number of domestic flights, more than one third, in week 15. The high number of domestic flights may have been due to the large size of the country and the islands belonging to the country, which needed to be connected. More than 10% were made in Germany, Spain, Greece and Italy. Similar trends have been reported by ICAO (2022). In their work, the monthly passenger numbers were presented. The share of domestic passengers increased as the number of passengers carried decreased. The largest decrease was recorded in April 2020, when the share of domestic passengers was the highest.

Outside the correlation analysis, airports were compared according to when they reached their minimum values of direct and weighted centrality. 14 airports reached their minimum values of direct and weighted centrality in the same week. Of the remaining airports, CPH, MAN, MUC, STN and ZRH airports reached the direct centrality minima earlier. The ARN, BCN, LGW, LHR, and OSL airports reached the weighted centrality minima earlier. The largest difference can be observed at LHR, which reached the minimum weighted centrality values 6 weeks earlier than the minimum direct centrality values. The opposite is the case for MAN airport, where the minimum values of direct centrality were reached 4 weeks earlier than the minimum of weighted centrality.

These results are in line with those obtained by Sun et al. (2021). The largest drop in flights occurred in April 2020, with a subsequent improvement in the summer. After summer 2020, the number of flights started to slightly decrease again. Similar results are presented by Mueller (2021). In his work, he divides the evolution of ATNs into several phases. In the first phase, until March 2020, the network was not significantly affected. The largest decrease occurred in April 2020 and then the increase in connectivity continued until approximately August 2020.

5. Conclusion

This paper identified how connectivity of the European air transport network was ensured during the Covid-19 pandemics. Centrality measures for 24 European airports were examined. To evaluate the results, z-score and correlation analysis were used. The analysis was made for 40 weeks in year 2020.

This paper has described the development of weighted centrality values for examined airports. According to the results, airports can be divided into two groups. The first group consists of airports whose weighted centrality values behaved similarly during the pandemic. The second group consists of six airports with a different development of weighted centrality values. For each of these airports, connections that affected the development the most were found.

The most important limitation is a result of the selection of the analyzed airports based on the highest numbers of passengers carried. The reason of this limitation is the method used for data gathering. Better alternative might be the selection based on connectivity measures of more than 24 airports. Although, these 24 airports are relevant selection and the results are guaranteed, because the number of passengers is a core measure for domain of passenger transport.

These results broaden our understanding of connectivity of the ATN and this study provides the basis for future research. Among other things, there is need to work on the data description and create a better database of data for further investigation. With the broadening of the data, indirect connectivity could be examined. Connectivity can also be evaluated in terms of quality, taking into account, for example, the time needed for transfers between flights. Additional studies could evaluate the impact of the number of destinations or frequency on connectivity. In other words, what influences the connectivity more, less connections with high frequency, or many connections with low frequency. The next step is also to refine the data model and learn how to get more information and results. Exploring other types of connectivity, such as season-based connectivity, is also suggested. This would then allow for exploring the differences between winter and summer connectivity and reveal trends of disappearing winter connectivity. Connectivity can also be examined in more detail, for example in the form of hourly connectivity for selected airports and major hubs.
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