Fifteenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2023)

Studying structural change in the European Aviation Network

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***Abstract*— Drastic loss of flight connections due to the COVID-19 pandemic has called for new approaches to accurately study structural change in the European Aviation Network. This study highlights the limitations of traditional centrality-based network approaches and proposes a diffusion-based graph embedding approach using the GraphWave algorithm. This new approach was validated using domain knowledge and tested in its ability to capture known events that occurred during and after the COVID-19 pandemic. The network is modelled based on all flights departing from and arriving to European airports in the period of 2019 through 2022. Flight connections were aggregated on a weekly basis to analyze structural embeddings and the structural role of airports. The temporal analysis supported the identification and assessment of changes to the role of airports and structural changes of the network. This study shows the potential of the approach by applying the model to uncover global, regional, and local change dynamics, and highlighting its potential as a valuable tool for researchers and practitioners studying the evolution of complex networks.**

Keywords-component; network analysis, graph representation learning, change dynamics

I. INTRODUCTION

The COVID-19 pandemic had a significant impact on the European Aviation Network, resulting in an unprecedented loss of flight connections. The travel restrictions imposed by governments to curb the spread of the virus severely limited the demand for air travel, leading to a dramatic decline in passenger traffic. Following the drop in 2020, traffic in the EUROCONTROL (ECTL) area recovered to 6.2 million flights in 2021. This corresponds to roughly half of the traffic in 2019 [1].

Differences in policies implemented by different countries to address the pandemic, such as the timing and severity of travel restrictions, as well as the effectiveness of their response to the crisis, made the effect of the pandemic on the aviation network highly variable [2,3,4]. Both within and between countries airports differ in the extent to which they lost flights and connections to other airports. This raises the question whether the network still functions the same way as it did before the pandemic, or whether the network underwent fundamental structural changes.

Modeling the European Aviation Network as a network where airports are denoted as the nodes of the network, the flight routes between airports as the edges, and the number of flown flights as the edge weights, we find that answering this question may not be straightforward. Traditional centrality based network analysis techniques are ill equipped to deal with both: (i) the strong changes in network activity and (ii), the accurate capture of structural changes in the network. First, to detect meaningful structural changes over the course of the pandemic, we need to be able to compare the network at any given time to a reference network (i.e., pre-covid network). This poses challenges, as traditional centrality measures used for weighted networks such as weighted betweenness and weighted degree centrality are directly linked to the amount of activity (i.e., number of flights) present in the network. In other words, the centrality measures that are calculated in the network during the pandemic will be on a different scale compared to those of the pre-covid network, as the weights along the edges dropped significantly. Traditional centrality measures such as PageRank return scaled centrality measures, but may give a biased representation of structural changes, as the centrality measure of a node is directly dependent on the centrality of all the other nodes in the network. This is problematic when looking at local structural changes in a network, as the local structural role of a node should not be dependent on changes in distant parts of the network. In general, traditional centrality measures do not match with our conception of structural roles, as they represent the importance of a node with respect to the entire network, while we are interested in the importance of a node in its local network neighborhood. To determine changes in the functioning of the network with regard to the pre-covid network, we need an approach that is able to accurately capture the role of each airport in its local network neighborhood, while also being able to accurately compare this structural role with a baseline in the pre-covid network.

To help fill this gap, we propose to study changes in the structure of the network by identifying its structural roles. Specifically, using a combination of a state-of-the-art unsupervised graph representation learning algorithm (i.e., GraphWave [5] and k-means clustering, we derive a structural embedding for each airport in the network and find clusters of airports that have a similar structural role within their local network topology. By identifying roles in the network, we show how airports and regions switch between roles over the course of the pandemic, and how their current roles relate to the roles in the pre-covid network. Moreover, we show how studying the difference in these change patterns may help to uncover interesting global and regional dynamics.

This paper makes three contributions. First, we create a model that captures the temporal structure of the European Aviation Network from 2019 to 2022. Second, we show initial findings and applications of the model that showcases structural changes over the course of the pandemic. Lastly, we provide researchers with a guide on how to implement the study of structural changes to their own research.

II. BACKGROUND

The GraphWave algorithm is a diffusion-based node embedding algorithm from the field of graph representation learning. Graph representation learning is a field of machine learning that focuses on learning meaningful and compact representations of graph-structured data. The goal is to map the nodes and edges of a graph to a low-dimensional vector space, such that the properties of the graph are preserved in the embedding, allowing for downstream tasks such as link prediction and node classification.

While most network embedding techniques tend to model the proximity between nodes in a network, there has been increasing attention towards structural embeddings which focus on identifying node equivalences. Such equivalences are collections of nodes that share a similar role in the network (e.g. a hub, or a bridge between parts of the network), irrespective of their location in the network [6]. In contrast to traditional proximity based approaches—which consider nodes in close proximity to one another to be more similar than nodes that are more distant—structure based approaches draw on the intuition that nodes that share a similar role in the network also perform a similar function in the network [5].

A clear example of such equivalences with regard to the European Aviation Network can for instance be seen when looking at airports such as Heathrow, Schiphol, and Istanbul Airport. While these airports are located in different regions of the network, they share a similar role in the network. All three airports serve as hubs, connecting large parts of the network both within, as well as outside of Europe.

GraphWave uses spectral graph wavelets to analyze the diffusion patterns of a heat kernel centered at each node. These patterns consist of wavelet coefficients, which are the amount of energy that is passed from the target node to each other node in the network before the signal has decayed. These wavelet coefficients are then treated as a probability distribution by sampling the empirical characteristic function for each coefficient. Intuitively, the algorithm passes a heat signal through each airport and detects how far it can reach in the network before cooling off. The more connections an airport has, the more places the signal can spread to. Likewise, the more flights on a given connection, the more energy can be passed along the route and the further the signal can reach before decaying. Notice that strong heat propagation is not only dependent on the number of flights and flight routes departing from the starting airport, but also on the amount of flights and connections of its neighbors. This means that airports with a similar number of flights and flight routes can have a vastly different role in the network depending on which airports they are connected to. Think for instance of the hypothetical case of two airports who only have one flight connecting them to another airport. The first airport is connected to an airport with connections to two other airports, while the second airport is connected to an airport which has connections to sixty other airports. While both starting airports are identical, the propagation of heat will be vastly different. Moreover, this also means that the role of an airport is not only dependent on changes in the number of flights and flight routes it has with its direct neighbors, but also on changes in airports that are connected to its neighbors.

III. DATA AND METHODOLOGY

A. Data

This study builds on all flown flights arriving or departing from an airport[1] within one of the EUROCONTROL (ECTL) member states between 01-01-2019 and 31-12-2022. See Table 1 for an overview of the total number of flights and airports connected to the network per year.

Table 1	**Total number of flights and airports per year**				
	Year	*Total # of Flights*	*Total # of airports*		
			Intra ECTL	*Non-ECTL*	*Total*
	2019	10.846.405	2295	1232	3527
	2020	4.861.490	2242	1141	3383
	2021	6.034.669	2311	1178	3489
	2022	9.052.301	2327	1227	3554

The data are aggregated on a weekly level to ease computation, while still being able to capture seasonal variability [7]. Specifically, we create a directed network for each week where the airports serve as the nodes of the network, the flight routes as the edges, and the number of flights as the edge weights.

To ensure reproducibility of the results, the script to run the analysis (including sample data) can be found on the following GitHub repository: https://github.com/euctrl-pru/aviation-network-structure-model

B. Analysis Plan

Create structural embeddings. We first create adjacency matrices for each week in our dataset, where rows and columns consist of the airports that were active in a relevant week, and the values denote the number of flights between each pair of airports.

[1] Land airports with scheduled regional airline service, or regular general aviation or military traffic classified by the OurAirports database as "medium sized". This naming convention also labels major airports as "midsized".

These adjacency matrices are used to create structural embeddings for each week, using the Python implementation of the GraphWave algorithm by the Stanford Network Analysis Project (SNAP)[2]. Specifically, for the embeddings of the baseline weeks, we use the default settings [5] and let the algorithm find the optimal scale values for the network. The scale of the signal determines the radius of the network neighborhood around each node. Intuitively, smaller scale values allow the signal little time to propagate across the network. Conversely, large scale values cause the heat to become equally spread across all the nodes of the network. The algorithm calculates an interval bounded by a minimum and a maximum scale value based on the analysis of variance of heat diffusion wavelets. For our analysis this means that we accommodate for the fact that networks may have different ideal scale values depending on the seasonal activity. For the during- and post-covid weeks, we use the corresponding optimal scale values as the input for the range of the signal, which ensures that the embedding for each week is created using the same signal as the corresponding baseline week.

Create and assess classification model. Next, we train a k-means clustering model for each of the baseline weeks and use the centroids to classify the embeddings of the networks of the corresponding weeks in 2020, 2021, and 2022. This allows for the evaluation of each airport's heat signature as if it had occurred in the corresponding pre-covid week. To evaluate the model validity, we first evaluate different values of k for the k-means algorithm to determine the ideal number of clusters using the Calinski-Harabasz (CH) Index. The clustering for each of the weeks in the baseline year are compared to determine the consistency of the classification of our model. The centroids of the baseline models are then used to classify the corresponding weeks in 2020, 2021, and 2022.

Validate predictions using domain knowledge. Next, we use domain knowledge to cross-reference known events in the period of 2020-2022 to assess the validity of our predictions using the model. Specifically, we focus on four known events that have occurred in this period: (i) the grounding of unused aircrafts during the pandemic, (ii) the stability (and slight increase) of cargo flights during the pandemic, (iii) the large-scale airline strikes in Belgium and Germany in 2022, and (iv) the closure of the Ukrainian Airspace to all civil traffic on the 24th of February 2022. Our analysis focusses on the airports of EUROCONTROL member states. The reason for this is the fact that we do not have complete data for non-EUROCONTROL member states (only flights that depart/arrive from/in airports in member states), making the classification biased and therefore unusable for further analysis.

Analyze global, regional and local change dynamics. Lastly, to demonstrate the possibilities of the structural role based approach, we show how the model can be used as a guided approach to uncover interesting change dynamics that might have been difficult to find using traditional approaches. Specifically, we use the distribution of the cluster membership for each airport —the number of times an airport was classified in a certain cluster over the course of the year[3]— to get an average cluster value for each airport. We compute change scores by subtracting the average cluster values of the pre-covid year from the averages of the subsequent years, to determine which airports have remained stable in their role, and which airports have undergone a change in role.

On a global level, we use this distribution of average cluster values to give insight into the overall change in class distribution of the pre-covid network with the subsequent years.

On a regional level, we add up all the increases and decreases of role membership to detect regions which have undergone the greatest increase/decrease in connectivity. Additionally, we add up the absolute values of change to detect regions with the highest overall cluster mobility.

Finally, we zoom in on a region that has the undergone the most change in connectivity (i.e., the United Kingdom), and use local level change statistics to detect and investigate opposite change trajectories of two London aerodromes; Luton Airport and London City Airport.

IV. Results

A. Network descriptive statistics

Table 2 shows an overview of the average and the standard deviation (SD) of the weekly number of connected airports, flight routes and flights for each of the four years in our dataset. The mean of the number of airports connected and respective flight routes reflect the well-documented decrease and rebound pattern of air traffic.

B. Model Validation

Plotting the CH index for all 53 weeks shows that, on average, there is a peak around 5 centers, but that there is a considerable amount of variability around the 9 centers region (c.f. Figure 1). Ranking the performance of each choice of centers based on their CH-index and calculating the mean rank score for the 53 models, shows that on average the models with 5 centers rank the highest, followed by 6 centers, 7 centers and 10 centers.

This means that the difference between the signals varies in intricacy across the weeks of the year. There is a trade-off between choosing the number of centers that either overfits or underfits the data. Having too many centers runs the risk of finding patterns that are only stochastic noise, while having too few centers may cause distinct patterns to be lumped together, causing them to be obscured from our analysis. This analysis is based on the model using 6 centers as it allows for a more expressive model than the overall best solution (5 centers), while still ranking as the second best number of clusters.

[2] https://github.com/snap-stanford/graphwave

[3] Airports that are not present in a given week are designated to the 0 cluster.

Table 2	**Network descriptive statistics: Mean and Standard Deviation in weekly number of connected airports, flight routes, and flights for the European Aviation Network from 2019-2022**						
	Year	*Mean # Airports Connected*	*SD # Airports Connected*	*Mean # Flight routes*	*SD # Flight routes*	*Mean # Flights*	*SD # Flights*
	2019	1851	163	132152	24292	204649	34934
	2020	1663	184	67136	30921	91726	50307
	2021	1783	183	85947	31135	113862	44080
	2022	1840	171	119134	26105	170798	38277

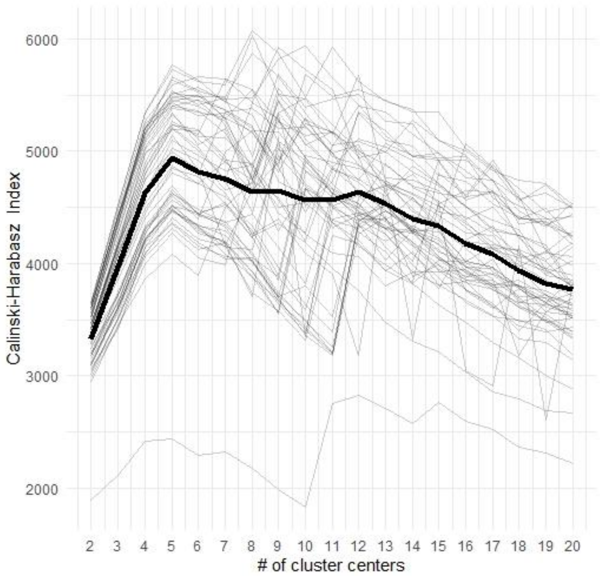

Figure 1. Calinski-Harabasz index scores for models ranging from 2 to 20 cluster centers for each week in 2019

C. Cluster descriptive statistics

To get a feel for the structural roles within the network, we provide the average and the standard deviation of the number of connected airports, flight routes and flights for each cluster, as well as the amount of times an airport is classified as being in the respective cluster across the weeks of 2019 (see Table 3).

During 2019, the majority of the roles within the European Aviation Network falls within cluster 2 (N = 13422), followed by cluster 3 (N = 9876) and cluster 1 (N = 9006). This means that over 50% of the airports in the network are on average connected to less than 12 airports, with less than 16 flight routes and less than 44 flights in a week.

Both the overall number, as well as the variability in the number of airports connected, flight routes, and flights increases for each increase in cluster. This denotes that airports are more similar in the lower clusters compared to the higher clusters. Moreover, this indicates that for higher clusters more emphasis is placed on the number of connected airports and flight routes, rather than the absolute number of flights, indicating that it is not only the amount of flights that is the driving factor for a high structural role, but also the level of connectivity of the connected airports.

D. Classification consistency

To verify the consistency of our model, we compute a Pearson correlation coefficient for each pair of weekly classifications. We find a high overall correlation[4] between the weeks (average r = .92), with high correlations between consecutive weeks (average r = .96), and lower correlations between holiday-season and off-season week pairs (smallest r = .82).

Airports that show the highest variability in their role in the network are airports that handle mostly seasonal traffic. Figure 2 shows the overlap between the increase in flight activity and the increase structural role for Burgas Airport in Bulgaria, Mykonos Airport, Rhodes International Airport, and Zakynthos International Airport in Greece, Samedan Airport in Switzerland, and Kittilä Airport in Finland. Note that while Kittilä Airport only has an average of 66 flights per week (with a max of 216 flights during its peak season), it shows a relatively strong leap in connectivity during its busiest season. This is a perfect example to illustrate the effect of being connected to well-connected neighbors, as during its seasonal peaks Kittilä becomes connected to some of the most connected airports in the European Aviation Network, such as Schiphol, Paris-Charles de Gaulle, London-Gatwick to name a few.

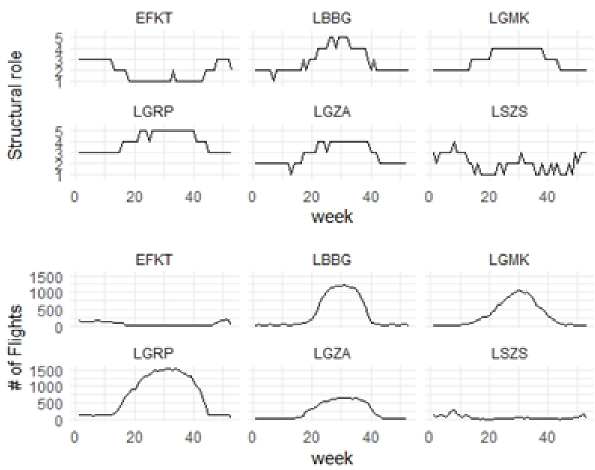

Figure 2. Six Airports with highest variability in strucutral role in 2019.
Note EFKT = Kittilä Airport; LBBG = Burgas Airport; LGMK = Mykonos Airport; LGRP = Rhodos Internationl Airport; LGZA = Zakynthos International Airport; LSZS= Samedan Airport.

[4] Average correlations are computed by averaging the Fisher-Z transformed [8]

Table 3	Cluster descriptive statistics: Mean and Standard Deviation in weekly number of connected airports, flight routes, and flights for each cluster in 2019						
	Cluster	*# of Airports in cluster*	*Mean # Airports Connected*	*SD # Airports Connected*	*Mean # Flight routes*	*SD # Flight routes*	*Mean # Flights*	*SD # Flights*
	1	9006	4	2	4	3	7	6
	2	13422	12	8	16	12	44	31
	3	9876	31	18	46	28	155	86
	4	5070	76	33	126	53	583	278
	5	3029	140	49	245	79	1740	630
	6	1536	227	58	416	105	5634	2152

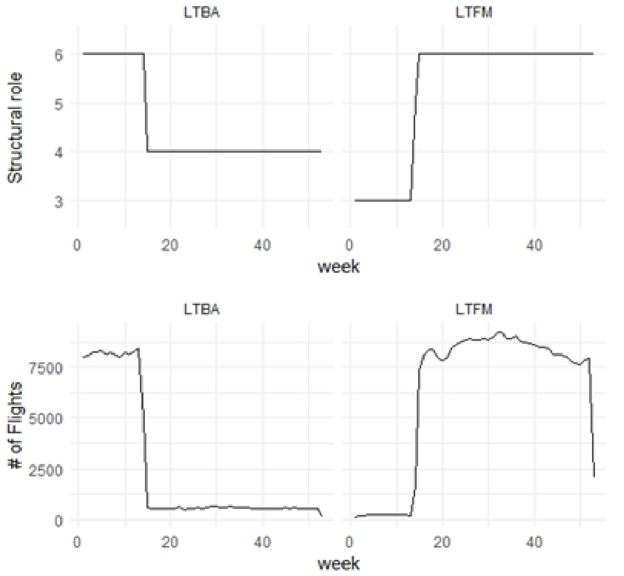

Figure 3. Evolution of structural role of Atatürk Airport (LTBA) and Istanbul Airport (LFTM) in 2019.

Interestingly, within-year role variability also picks up important local changes. For instance, Figure 3 shows the model output for the transfer of all scheduled commercial passenger flights from Atatürk Airport to Istanbul Airport on 6 April 2019. This is present in the structural embedding, as Istanbul Airport's cluster membership varied between three, four, and five for the first 14 weeks of 2019, but as of week 15 (April-8 – April-14) has risen to cluster six, at which it has stayed for the remainder of 2019. Conversely, Atatürk Airport is classified as cluster six for the first 14 weeks of 2019, after which it consistently dropped to cluster four, with three times a rise to cluster five in week 31, 45, and 50.

E. Validating predictions using domain knowledge

Given that we have no ground truth labels to test our model predictions, we make use of domain knowledge to assess the validity of the predictions. Starting with the events during the pandemic, we first look at the grounding of aircraft by airline operators due to the drastic reduction in (air) traffic demand. The idea is that the grounding of aircraft creates new "artificial" connections between airports that would otherwise not be connected. This causes the local networks of the origin airport and the destination to become weakly connected. This weak connection causes the signal to propagate too much more places across the network, causing airports connected by this link to get an increase in their structural role.

Based on the analysis of the Performance Review Unit (PRU) of EUROCONTROL[5], we plot the evolution of the structural role of the six airports with the largest amount of inactive aircrafts (see Figure 4). Looking at the time period when the majority of groundings took place, we see that all the airports experienced an increase in their structural role. A noteworthy exception is Adolfo Suárez Madrid–Barajas Airport which is consistently in the highest structural role.

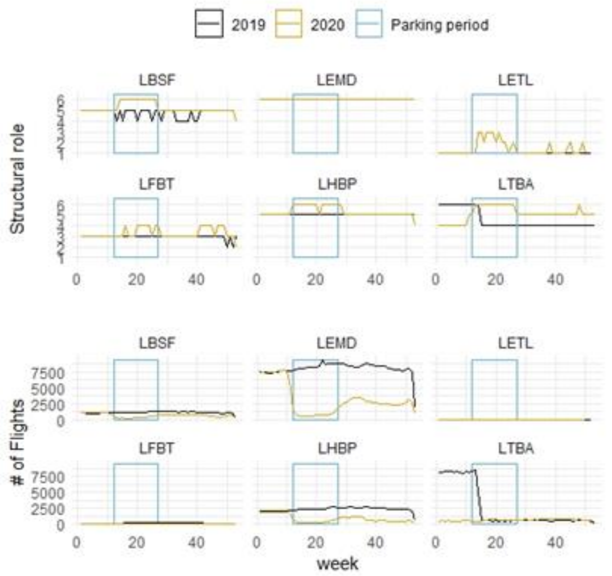

Figure 4. Evolution of structural role and total number of flights of the six airports that stored the largest amount of inactive aircrafts in 2020.

Aside from an increase of inactive aircrafts, the pandemic resulted in an increase in the number of cargo flights operated within the European network. Looking at the six airports with the highest number of cargo flights, and whose market segment consist primarily of cargo flights (i.e., greater than 60%)[6], we see that this increase is reflected in their structural role in the network. All six airports see an increase in their structural role over the course of the pandemic (c.f. Figure 5).

[5] See https://ansperformance.eu/covid/acft_ground/.

[6] This is done to exclude large hub airports such as Paris-Charles de Gaulle, Düsseldorf and Schiphol who already have high connectivity.

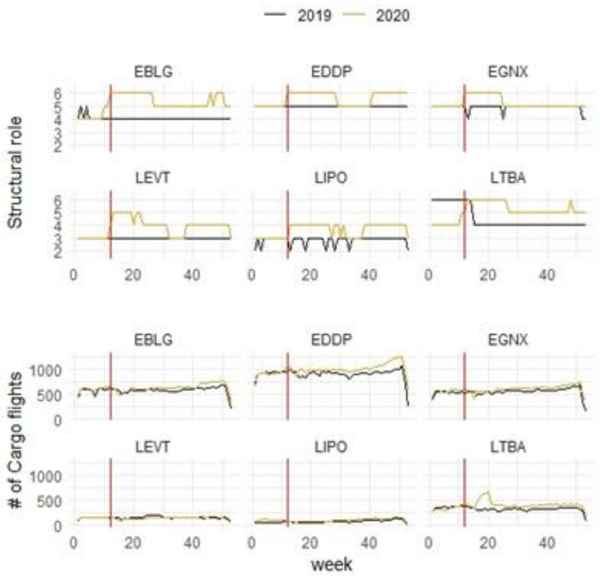

Figure 5. Evolution of structural role and total number of cargo flights of six airports that served the largest amount of cargo flights in 2020.

Specifically, we see a strong increase for Liège Airport and Atatürk Airport[7] resulting in a cluster change from cluster 4 to cluster 6. Vitoria Airport in Spain makes a similar jump, jumping from cluster 3 to cluster 5.

Looking beyond 2020 to the aftermath of the pandemic, we see an increase in strikes among airline employees as the industry continues to struggle financially. The decrease in travel demand caused by the pandemic led to significant financial losses for airlines, and as a result, companies were forced to make cutbacks such as reducing routes and laying off employees. These cutbacks triggered tensions between the airlines and their employees resulting in strike actions to protest reduced pay and benefits. For example, strikes of Lufthansa's ground staff at Frankfurt Airport in Germany in July of 2022 prompted more than 600 flights to be canceled. Likewise, a national strike in Belgium in November of 2022 caused Brussel-Zaventem to cancel up to half of its flights, while Brussels Charleroi cancelled all Ryanair flights.

While having a profound impact on the daily traffic flow, none of the strikes appear to have shocked the network severely enough to result in a change in its structural role. One main reason for this is that our model is trained on weekly data. Accordingly, the effect of the loss of momentary connectivity is absorbed by the remaining days in the week. In other words, only prolonged events will be picked up by the model.

One such event is the closure of the Ukrainian airspace to all civil traffic on the 24th of February in 2022. Figure 6 shows the change in structural roles for the airports in the Ukraine region. Unsurprisingly, all airports in Ukraine have drastically reduced in their structural role with the exception of one airport close to the border with Hungary. In terms of the structural role of the airports in the neighboring regions, we only find a decrease for airports in Moldova. Rather counter-intuitively, we find an increase in the structural role for the majority of the smaller airports in Romania, Hungary, Poland, Serbia, and Slovakia. The structural role of larger airports such as Henri Coandă International Airport, Belgrade Nikola Tesla Airport, and Bratislava Airport appears to have remained largely unchanged[8], except for Warsaw Chopin Airport, which has slightly decreased in structural role.

F. Change in role dynamics

In the following section, we will show how the model can guide us to uncover interesting change dynamics that might have been difficult to find using traditional approaches. This paper demonstrates how the approach can be used to study the structure of the network on multiple levels of analyses

On a global level, looking at the different distributions of average cluster membership for the pre-, during-, and post-covid years, Figure 7 shows an interesting pattern. The pandemic seems to have caused a shift in the connectivity of the airports where we no longer see the strong equilibria around consistent classification (i.e. peaks around 1, 2, 3, 4, 5, 6), but rather a pattern of diffusion filling the gaps between the peaks. This indicates that airports that had consistent roles in the pre-covid network experienced a shift in connectivity due to changes in the network. There is an increase in connectivity for airports in the lower connected roles, and a slight decrease in the airports that were strongly connected in 2020, with a gradual recovery to the equilibria of the pre-covid network in 2022. Moreover, it seems that the overall connectiveness in the network in 2022 (M = 2.30, SD = 1.49) has slightly increased compared to 2019 (M = 2.27, SD = 1.47), $t(925) = 2.99$, p = .003.

Next, filtering by region, we find that, compared to 2019, the Ukraine is the region with both the highest overall cluster mobility, as well as the highest decrease in cluster membership. Looking at the United Kingdom—the region with the second greatest overall decrease in connectivity (and third in the region with the highest overall cluster mobility behind Ukraine and France)—we see a mixed impact of the pandemic on the connectivity of the UK airports (see Figure 8). Especially in the London area, a notable difference can be seen, both during and after the pandemic. For instance, the central role of Heathrow in the European network has remained unchanged throughout the pandemic, while Gatwick and Manchester airport both dropped a cluster over the course of the pandemic and recovered in 2022 (i.e. returned to their previous cluster). However, among the London airports: Heathrow, Gatwick, London Stansted, Luton, and London City, two stand out; Luton and London City. Luton is the only airport among the five that went up in connectivity during the pandemic and still has higher connectivity compared to 2019. Conversely, London City is the only airport that has not recovered from the pandemic.

[7] Note that Atatürk is also one of the airports that was used to store inactive airports.

[8] Note that our model only looks at origin-destination flights between airports and not air traffic above this region.

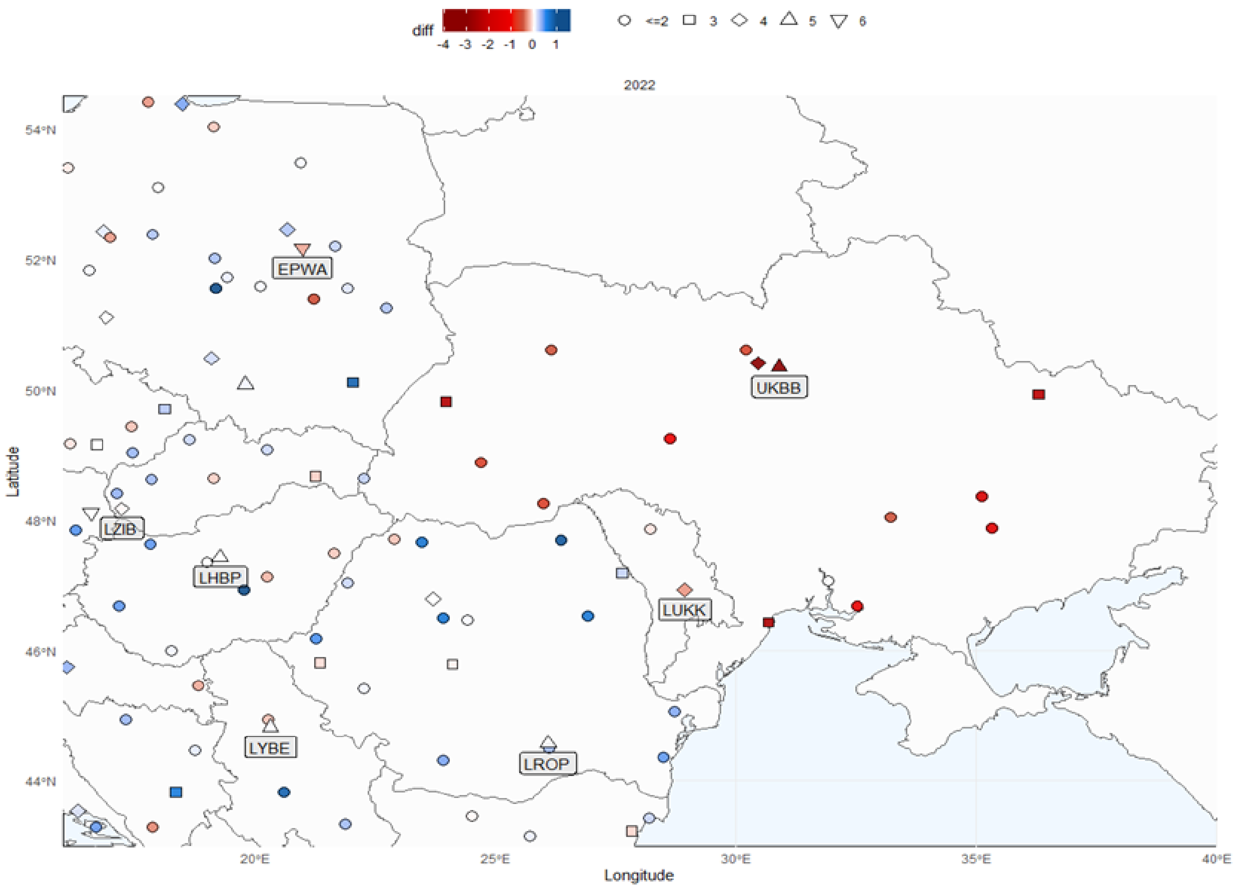

Figure 6. Change in structural role of airports in the Ukraine region in 2022.
Note: Shape denotes structural role in 2019. Color denotes difference of current compared to 2019. EPWA = Warswaw Chopin Aiport; LROP = Henri Coandă International Airport; LYBE = Belgrade Nikola Tesla Airport; LZIB = Bratislava Airport; LUKK = Chișinău International Airport; UKBB = Boryspil International Airport; LHBP = Budapest Ferenc Liszt International Airport.

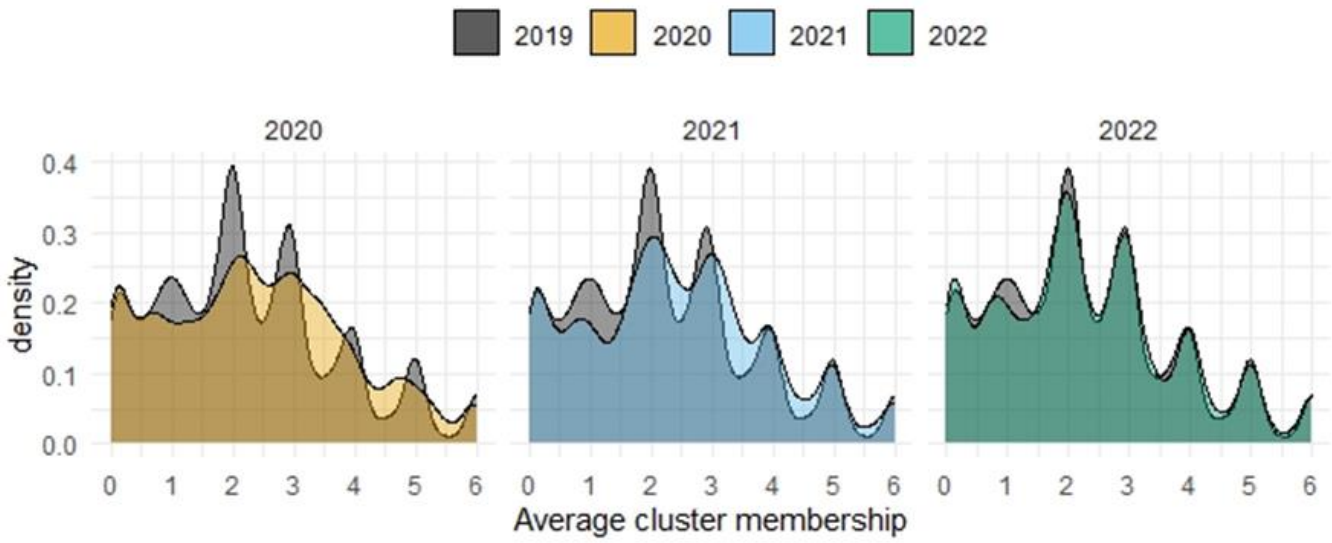

Figure 7. Distribution of average cluster membership from 2019-2022.

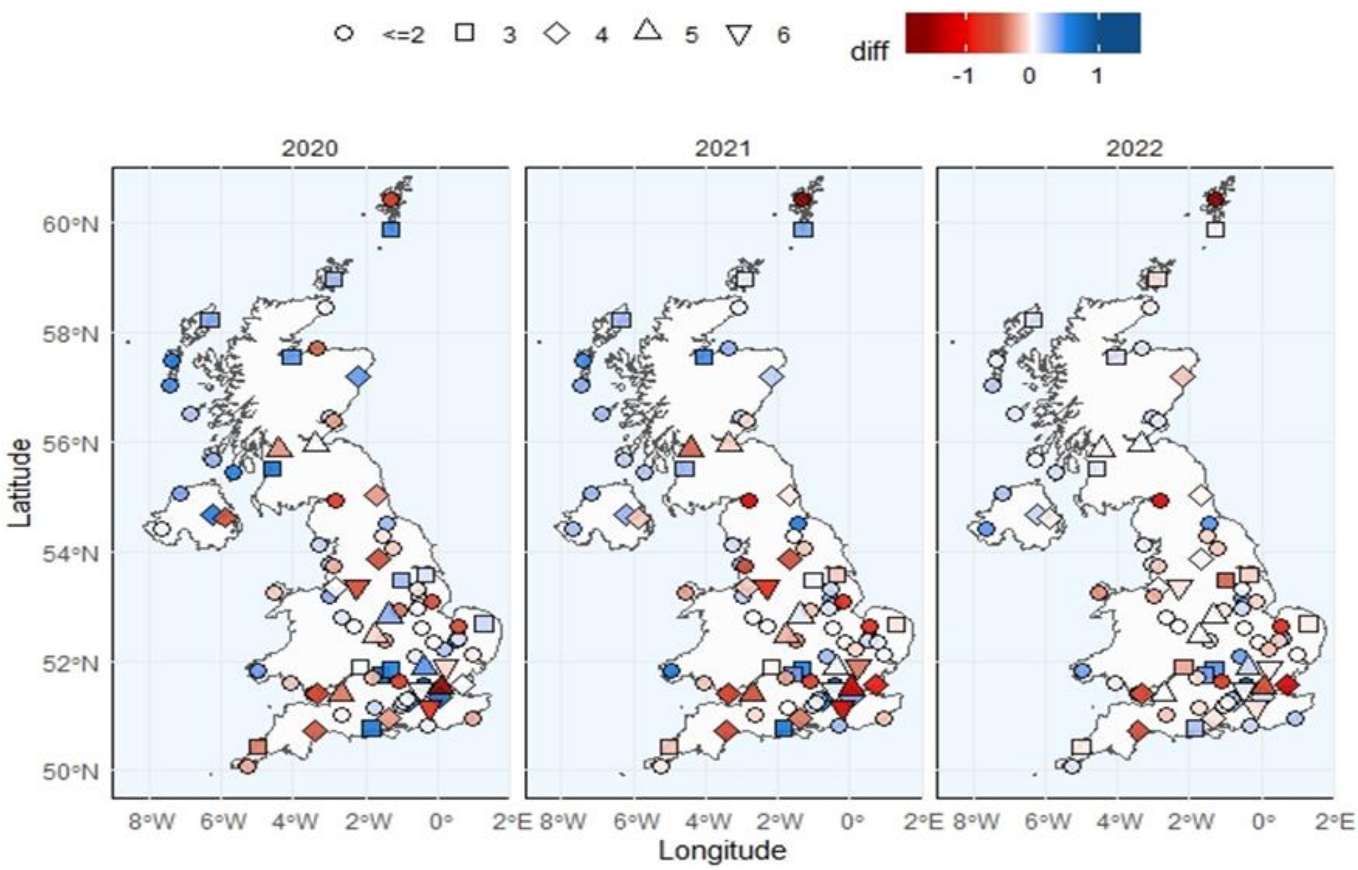

Figure 8. Evolution of structural roles of airports in the United Kingdom with respect to 2019.
Note: Shape denotes structural role in 2019. Color denotes difference of current compared to 2019.

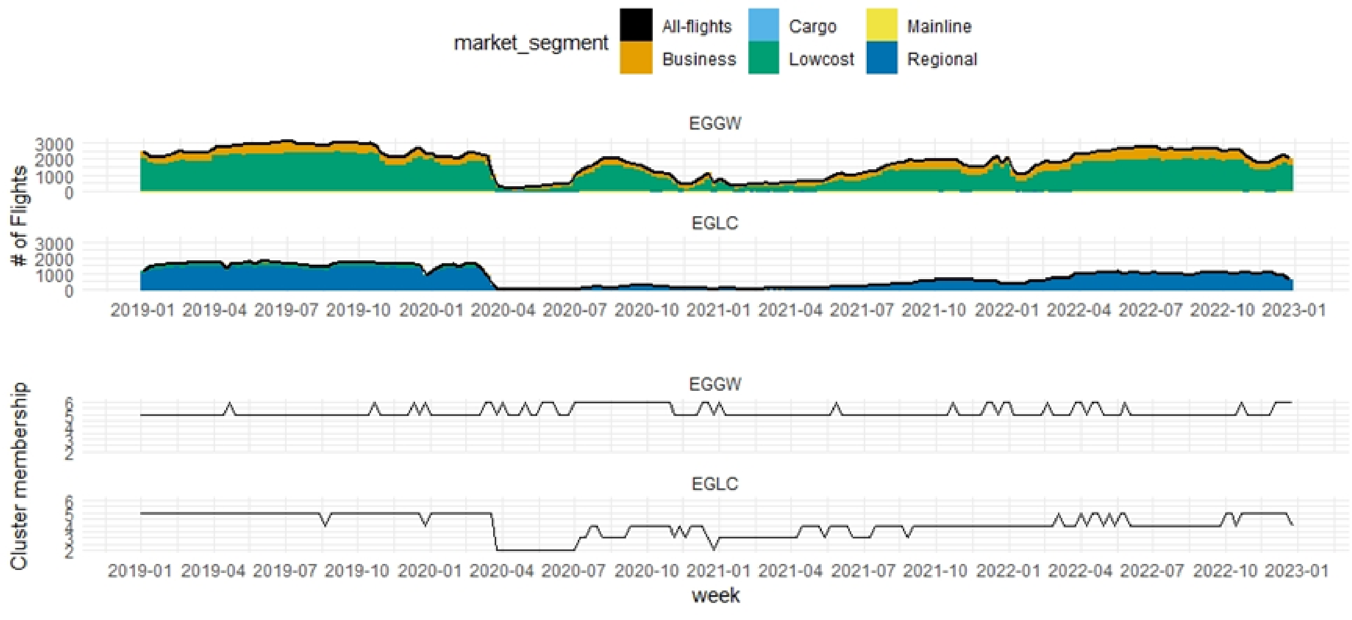

Figure 9. Evolution of market segment coverage and cluster membership for London Luton (EGGW) and London City (EGLC).

Zooming in on the types of flights that depart and arrive at both airports (c.f. Figure 9), we immediately see a significant difference between them: the core market of Luton are low-cost and business flights, while London City primarily provides regional flights. Moreover, it appears that London City lost its share of low-cost flights that it was servicing before the pandemic. Interestingly, while both airports lost significant amounts of flights at the start of the pandemic (London City at a greater rate than Luton), the connectivity of Luton increased, whereas the connectivity of London City decreased.

V. DISCUSSION

The results of this study showcase the potential of using GraphWave to analyse and assess the evolution of the European Aviation Network by studying the changes in the structure of the network.

A. Model Validity

In terms of model validity, the classification model consisting of node embeddings computed using the GraphWave algorithm and k-means clustering agrees with domain knowledge. The model confirms an overall high correlation between consecutive weeks in the year, and a slightly lower correlation between weeks differing in season. Specifically, we find that role mobility of an airport strongly relates to seasonal activity for the airports with the highest variability in structural role.

The model also accurately picks up local changes as seen with (i) the transfer of commercial flight from Atatürk Airport to Istanbul Airport, (ii) the increase of connectivity of airports that stored inactive aircrafts, (iii) and the increase of connectivity of majority cargo oriented airports in 2020.

B. Model Application

In terms of model application, we find some interesting patterns regarding of the evolution of the structure of the network.

On a global level, the COVID-19 pandemic has caused a shift in the connectivity of airports. Rather surprisingly, there appears to be a diffusion of connectivity filling the gaps between previously consistent classifications. This indicates that airports that had consistent roles in the pre-COVID-19 network experienced a shift in connectivity during the pandemic due to changes in the network. Specifically, it seems that the lower connected roles gained in connectivity, while airports that were previously strongly connected suffered a decrease in connectivity. Moving past COVID-19 we see a gradual recovery to the equilibria of the pre-COVID-19 network in 2022, with a slight increase in connectivity compared to 2019.

This paints an interesting, but confusing picture, as it feels counter intuitive that connectivity would increase in a time of an unprecedented drop in flight activity. While further research is needed to fully understand this phenomenon, it may be important to rethink what we mean with the concept of connectivity, especially in times with large restrictions on travel. While we normally speak of connectivity in terms of the time it takes for people to reach any destination in the network from a given airport, connectivity during times of travel restrictions can better be viewed as the potential for connectivity. In other words, less connected airports in the pre-covid had a greater potential for connectivity during the pandemic given that there would not have been any travel restrictions.

Future research can focus on the evolution of the flight routes of these lesser connected (i.e., cluster 2 & 3) airports. One possible explanation for instance may be that regional airports may have lost single connections to larger hubs, but in return gained more connections with other regional airports, thereby strengthening their role in a given local structure. Another possible explanation for the increase in connectivity may be due to the grounding of inactive aircrafts. Many planes were stored in regional airports. Transferring aircrafts from larger airports to these smaller regional airports may have caused an increase in the structural role of the airports within their neighborhoods , as they become artificially connected to one another due to the transfer. Future research can therefore test how the connectivity is affected by these artificial connections.

On a regional level, we find that, apart from Ukraine, overall, the airports in the United Kingdom underwent the strongest decrease in their structural role compared to 2019. There are considerable differences in the extent to which airports have endured and recovered from the effects of the pandemic. Specifically, zooming in on two London based airports with opposite change trajectories (i.e., Luton Airport and London City Airport), we find a clear difference in the market segment that both airports operate in. Future research can investigate the effect of market segment on the recovery rate, and if this effect is equal among all sizes of airports.

C. Limitations of the study and potential avenues for future research

One of the main limitations of the model is its' dependency on the available data. The accuracy and reliability of the models' classifications is directly dependent on the airports and flights that are included in the modelled network. For example, during the initial stage of the study, only flights arriving at and departing from airports starting with ICAO code L and E (i.e. Northern Europe, and Southern Europe) where used. The model then classified Manchester Airport in cluster five, despite being the third busiest airport of the United Kingdom in 2019. Adding all flights arriving and departing from EUROCONTROL member states (including Morocco, Ukraine, and Iceland[9]), caused Manchester Airport to be classified as cluster 6. This indicates that airports and flights should not be excluded without a valid reason, and that any

[9] Moroccan, Ukrainian, and Icelandic airports start with ICAO code G, U, and B respectively.

inferences made should be framed within the data that is used.

Another limitation of the approach is that it relies on an unsupervised learning algorithm to extract the structural embeddings and identify the structural roles in the network. While also a strength, given that we can run the analysis on any network without needing pre-classified airports, not having ground truth labels means that it is important to have access to domain knowledge before we can confidently draw inferences from the model. Hence, this approach serves best as a guided exploration tool to uncover change patterns and generate new hypotheses.

Nonetheless, taking heed of these limitations, this model offers potential for future research and application. For instance, applied to the European Aviation Network, the model can be used to detect the regions that were more/less impacted during the pandemic. Impact can then be further analyzed by taking into account the airports within a specific region. Similarly, the model can be used to detect regions/airports with the highest recovery rate.

Expanding the scope of the analysis to include the worldwide air traffic network, the model can be used to provide valuable insights into the global impact of the pandemic on air travel and structural changes of the global air transportation network over time. For example, it can be used to identify the countries and regions that have been most affected by travel restrictions and border closures. It can also be used to track the recovery of air travel in different parts of the world and identify the countries and airports that have seen the fastest recovery. This also offers an avenue to better understand the impact of airspace closures (e.g. conflict areas, volcano activity). Additionally, by analyzing data from a global perspective, it can provide a comprehensive view of the overall impact of such disruptions on the air travel industry and help to inform decisions and strategies for the future. Furthermore, it could be used to detect patterns on how different regions were affected in support of predicting the trajectory of air transportation recovery in those regions.

REFERENCES

[1] EUROCONTROL (2022). Performance Review Report of the European Air Traffic Management System in 2021, https://www.eurocontrol.int/publication/performance-review-report-prr-2021

[2] Bao, X., Ji, P., Lin, W., Perc, M., & Kurths, J. (2021). The impact of COVID-19 on the worldwide air transportation network. Royal Society open science, 8(11), 210682.

[3] Li, S., Zhou, Y., Kundu, T., & Sheu, J. B. (2021). Spatiotemporal variation of the worldwide air transportation network induced by COVID-19 pandemic in 2020. Transport Policy, 111, 168-184. K. Elissa, "Title of paper if known," unpublished.

[4] Sun, X., Wandelt, S., Fricke, H., & Rosenow, J. (2021). The Impact of COVID-19 on Air Transportation Network in the United States, Europe, and China. Sustainability, 13(17), 9656.

[5] Donnat, C., Zitnik, M., Hallac, D., & Leskovec, J. (2018). Learning structural node embeddings via diffusion wavelets. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 1320-1329).

[6] Jin, J., Heimann, M., Jin, D., & Koutra, D. (2021). Toward understanding and evaluating structural node embeddings. ACM Transactions on Knowledge Discovery from Data (TKDD), 16(3), 1-32.

[7] Sun, X., Wandelt, S., & Linke, F. (2014). Topological properties of the air navigation route system using complex network theory. Proceedings of the ICRAT.

[8] Gorsuch, R. L., & Lehmann, C. S. (2010). Correlation coefficients: Mean bias and confidence interval distortions. Journal of Methods and Measurement in the Social Sciences, 1(2), 52-65.