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Vulnerability of the worldwide air transportation network to global catastrophes such as COVID-19

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ABSTRACT

This paper studies the vulnerability of the worldwide air transportation network (WATN) during a global catastrophe such as COVID-19. Considering the WATN as a weighted network, many airport connections could be completely or partially disrupted during such extreme events. However, it is found that existing weighted metrics cannot reflect the impact of connection capacity reduction on network connectivity. Therein, this work proposes a novel network efficiency metric termed as layered weighted network efficiency (LWNE) metric to measure the connectivity of the air transportation networks (ATNs) and study their vulnerability in response to different levels of disruptions, including airport level, country level, and global level. The most critical airport connections and their impact on network connectivity are identified. It is found that the critical connections are mostly between so-called bridge airports but not core airports in the WATN. By examining the impact of partial link disruptions, it is found that some connections mainly serve local travel demand and are very robust to partial disruptions, while the others connecting global hubs are sensitive to partial disruptions. Further, the WATN is robust to the individual disconnection of most countries; however, it is vulnerable to the simultaneous disconnection of countries that serve international transfers. Interestingly, the WATN is insensitive to the disconnection between any two countries, even those with sizeable domestic ATNs. Concerning global disconnections, as long as all the international connections hold 10% of their original flights, the WATN can still expect 40% of its pre-disruption performance. This paper deepens the understanding of ATNs under extreme events and provides a method for studying transportation networks’ vulnerability facing global disruptions.

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1. Introduction

1.1. Background and motivation

The air transport network (ATN) is a complex infrastructure system consisting of various nodes (airports) and links (airport connections). With rapid globalization, the ATN is becoming an important infrastructure contributing to the domestic and global economy. In 2019, the worldwide ATN (WATN) handled nearly 4.54 billion scheduled passengers (Statista, 2020). Notwithstanding, the WATN is fragile, and the system’s performance can be affected by many forms of disruptions. In 2020, the world witnessed global economic damage caused by the Coronavirus Disease 2019 (COVID-19). The COVID-19 pandemic has heavily impacted international trade, transport, and tourism. As far as international passenger transport and tourism are concerned, the ATN has been affected the most. The airports worldwide have witnessed a sharp decline in air traffic due to worldwide policy restrictions, international flight cancellations, travel restrictions, and quarantine measures (IATA, 2020) for containing the spread of COVID-19. The decline in the pre-COVID and post-COVID air traffic can be observed in Fig. 1. Hence, it is critical to study and explore the behavior of ATNs in response to such global catastrophe-induced disruptions.

In recent years, a growing number of research works have been conducted to investigate the performance of ATNs in response to disruptions based on robustness (Lordan et al., 2014b; Pien et al., 2015; Yang et al., 2019; Zhou et al., 2019a), vulnerability (Klophaus and Lordan, 2018; Voltes-dorta et al., 2017; Wilkinson et al., 2012), resilience (Dunn and Wilkinson, 2016; Thompson and Tran, 2020; Zhou et al., 2019b), and connectivity (Allroggen et al., 2015; Cheung et al., 2020; Du et al., 2016; Zhou et al., 2021). Further, studies inform that ATNs are usually scale-free (Bombelli et al., 2020; Wandelt and Sun, 2015; Wang et al., 2011), which means that a few airports, acting as hubs, have more connections while most airports, usually connected to the hubs, have fewer connections. This structural property determines that the ATN is mostly robust to the random failures of the airports, albeit vulnerable to intentional attacks on the hubs. However, the COVID-19 pandemic has highlighted new challenges in the design and management of ATNs. Note that previous studies on ATNs were mostly focused on the disruption of nodes (airports) (Zhou et al., 2019a). However, the COVID-19 pandemic has disrupted the links (airport connections). Besides, unlike previous studies based on small-scale disruption (few links got disconnected) (Voltes-dorta et al., 2017), the number of links (worldwide airport connections) being disrupted due to COVID-19 is very large, accounting for over half of the entire set of air travel connections. Further, it is also worth noticing that the connections (links) between different airports (nodes) also vary, highlighting that the number of flights is critical while understanding the vulnerability of ATNs disrupted by the COVID-19 pandemic.

Motivated by the above problem background on COVID-19-induced ATN disruption, this paper aims to answer the following specific questions:

1. How to quantify the impact of the disruption of airport connections (partial and complete) on the connectivity of the weighted ATNs?
2. What is the impact of different levels such as airport level, country level, and global level of link (airport connections) disruptions on the connectivity of the WATN?

1.2. Contributions and paper’s organization

The contributions of this paper are twofold. First, the proposed model introduces and incorporates the concept of layered weighted efficiency metric into the connectivity evaluation of ATNs. It permits for characterizing the impact of partial and complete disconnection1 of airports on the entire network’s connectivity. Second, the vulnerability of the WATN to different levels of airport disconnections are evaluated, including airport level, country level, and global level. To the best of our knowledge, this is one of the first studies that explore the effect of international airport disconnections (partial and complete) using a novel layered weighted efficiency metric, thus enhancing the scientific rigor of this study.

The rest of this paper is organized as follows. Section 2 outlines the relevant literature. Section 3 elucidates the proposed model. Section 4 supports the application of the proposed model using specific case illustrations by considering partial and complete disconnections at different levels. Section 5 draws conclusions of this study, offers managerial insights, and proposes future research directions.

2. Literature review

This section gives an overview of the literature on assessing the performance of ATNs under normal and disrupted scenarios. We categorize the scenarios according to the metrics used and discuss their limitations for studying global disruption-induced ATNs, including connectivity, vulnerability, robustness, and resilience.

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1 Disconnection in this work refers to the disconnection of flights operating between airport pairs unless otherwise specified.
2.1. Connectivity

Connectivity measures the number of connections between the node pairs in a network. Malighetti et al. (2008) studied the connectivity of the European airport network based on the minimum travel time between airport pairs and made comparisons between airline alliances. Similarly, Hsu and Shih (2008) investigated the effects of an alliance on network connectivity. Arvis and Shepherd (2011) proposed a gravity-like model to capture the full range of interactions among all network nodes, even when no direct flight connections between them exist. Allroggen et al. (2015) applied the Global Connectivity Index to assess the quality and quantity of all connections and computed yearly scores for the WATN from 1990 to 2012. Paleari et al. (2010) and Zhu et al. (2019) compared the connectivity of various domestic ATNs. Zhang et al. (2017) studied airport connectivity trends in China over the period 2005–2016 and found that low-cost carriers are conducive for airport connectivity. Wei et al. (2014a) and Wei et al. (2014b) investigated maximizing the algebraic connectivity of ATNs by adding edges and choosing the edge weights. Redondi et al. (2011) applied module identification techniques to assess the effect of new routes on a network’s connectivity. Note that most of the above studies either compared the connectivity of different ATNs or studied the structural evolution of an ATN. Besides, one limitation is that connection capacity was rarely considered in the utilized and proposed methods. Further, in the existing studies, ATNs were considered undamaged networks, and the impact of disruptions on the networks’ connectivity has not been investigated.

2.2. Vulnerability

Vulnerability captures the susceptibility of a system to incidents or disasters (Zhou et al., 2019b). In other words, it measures how easily a network can be disconnected. Wilkinson et al. (2012) investigated the vulnerability of the European air transport network to spatial hazards such as the ash cloud caused by a volcano eruption in Iceland, in which a group of spatially connected airports is disrupted simultaneously. Voltes-dorta et al. (2017) assessed the vulnerability of the European air transport network to major airport closures based on the delays of the disrupted airline passengers. The closures of the 25 busiest European airports are simulated, and the affected passengers are relocated to minimum-delay alternatives. Klophaus and Lordan (2018) studied the vulnerability of global airline alliances to alliance members exiting based on the relative difference of the normalized average edge betweenness. Li et al. (2019) found that the vulnerability and critical areas of the high-speed rail and air transport coupling system are different from those in individual subsystems. The most significant difference between this stream of research and our study is the type of disruptions that have been considered. In the previous studies, disruptions are modeled as the removal of an airport or a group of airports. While in our study, disruptions are modeled as the complete or partial removal of airport connections, as in the case of COVID-19-induced airport disconnections.

2.3. Robustness and resilience

Robustness measures the ability of a system to maintain its initial state when perturbed (Cacchiani et al., 2012; Zhou et al., 2019a). Lordan et al. (2014b) studied the robustness of ATNs by evaluating the effect of airport disconnection on the size of the giant components of the network graph and detected critical airports in the network. Lordan et al. (2014a) applied a complex network approach to the robustness of airline route networks from several perspectives: global route networks, airline alliances, airlines, and airports. Pien et al. (2015) proposed the Relative Area Index to quantify the effect of a node’s disruption on the system’s performance. This index is used to study the robustness of the European air traffic network. Wandelt et al. (2015) developed a computationally efficient model for the robustness analysis of ATNs. Zhou et al. (2019b) proposed a weighted efficiency metric to assess the robustness of air networks considering the link capacities.

Resilience assesses the ability of a system to maintain functionality under disruptions and to restore the previous performance level after a disruption (Alderson et al., 2018; Chen and Miller-Hooks, 2012; Zhou et al., 2019b). Cardillo et al. (2013) analyzed the
resilience of the European air transport network to random flight failures by computing the number of re-scheduled passengers. Janić (2015) assessed the resilience of the air transport network for three layers: physical, service, and cognitive. Dunn and Wilkinson (2016) compared two strategies for increasing the resilience of air traffic networks: an adaptive reconfiguration strategy and a permanent re-routing strategy. Clark et al. (2018) examined the resilience of the U.S. National Airport Network using recovery strategies based on airport network topology. Thompson and Tran (2020) provided a defender-attacker-defender model to investigate the impact of intentional attacks and worst-case disruptions on the U.S. ATN, together with possible mitigations to minimize the negative outcomes of such disruptions. Janić (2019) studied the resilience of an airline cargo transport network affected by a large-scale disruptive event using indicators such as flights, airline profit, and inventory cost. More recently, Zhou and Chen (2020) measured the performance of airport resilience to severe weather events.

Most of the above-mentioned studies investigated airport disruptions rather than connection disruptions, with only a few exceptions, such as Cardillo et al. (2013). However, the ATN was treated as an unweighted network in their model. More importantly, all of the studies considered a complete disruption of airports or flights in the network, while partial disruption of airport connections, as happened during COVID-19, is not investigated yet.

2.4. Research gap

Comparing the ATN affected by a global catastrophe such as COVID-19, we find three limitations in the literature. First, most disruptive scenarios are developed by assuming the closure of airports, i.e., network nodes, but not the disruption of airport connections, i.e., network links. In reality, the closure of an airport is much more infrequent than the closure of certain flights or routes. Even during the COVID-19 pandemic, most airports still operate, while some routes were canceled, and other routes significantly reduced in capacity. The impact of the disruption of airport connections on the performance of the entire ATN is much more complicated than that of airport closures. That is because the number of airport connections is much larger than that of airports, and the combinations of different airport disconnections may have very complex effects on the network.

Second, the number of affected airports and connections during a global catastrophe such as COVID-19 is higher than those in the existing studies. In the literature, only a few airports are assumed to be disrupted. The performance of the overall network is mainly left unaffected. In the COVID-19 pandemic, many airport connections were severely affected, which raises the likelihood that the WATN may be divided into several standalone subnetworks, labeled as communities in network science (Girvan and Newman, 2002), and significantly lowering system performance.

Third, in the previous literature, once an airport connection (link) is affected, it is assumed to be completely broken. However, in reality, airport connections are usually only partially disrupted, which means that the airport connection remains, but the number of flights serving that connection is reduced. Therefore, there is a need to develop a method that can comprehend the effect of partial airport disconnections on system performance.

To address the research gap, we propose a novel connectivity evaluation method for ATNs, which enables assessing the impact of partial and complete disruption of airport connections (links). Further, this method is used to assess the vulnerability of the WATN to different levels of disruptions incurred by global catastrophes such as COVID-19. In this study, vulnerability is quantified by the connectivity change of the WATN due to disruptions.

3. Methodology

3.1. Methodology background

This paper aims to investigate the vulnerability of ATNs in response to disruptions such as flight disconnections between airport pairs. As already mentioned in Section 1 that ATNs are generally modelled as a complex network, the performance of a complex network can be evaluated using network efficiency metric (Latora and Marchiori, 2001; Zhou et al., 2019a). In previous studies, the network efficiency\(^2\) of an unweighted network has been defined as the average of the reciprocal of the shortest link length between node pairs and is expressed as

\[
NE_{UW} = \frac{1}{N(N-1)} \sum_{i,j \in R} \frac{1}{d_{ij}}
\]

where \(d_{ij}\) is the number of links in the shortest path between node \(i\) and \(j\). In the unweighted ATN, the shortest path is the path with the least number of links between the two nodes (Zhou et al., 2019a). \(N\) is the number of nodes in the considered network \(\mathcal{N}\).

Example 3.1. Consider a simple network \(\mathcal{N}\) (Fig. 2) for exposition.

Let \(N = 3\), \(d_{ab} = 1\), \(d_{bc} = 1\), and \(d_{ac} = d_{ab} + d_{bc} = 2\). Then the unweighted network efficiency of \(\mathcal{N}\) is obtained as \(NE_{UW} = \frac{1}{6} \left( \frac{1}{2} \times 2 + \frac{1}{2} \times 2 \right) = \frac{2}{3}\).

\(^2\) Similar treatments can be seen in the works of (Chen et al., 2012; Zhou et al., 2019a; Zhou and Wang, 2018).
Notice that, in the above expression of network efficiency (Eq. (1)), the efficiency is based on the shortest path length between a node pair. The effect of link capacity on network efficiency is not considered, which is a critical component in ATN. The link capacity in an ATN is represented by the flight frequency between an airport pair. Further, it is generally known that different airport pairs have different flight frequencies. Therefore, to address this gap, Zhou et al. (2019a) proposed a new efficiency metric called weighted efficiency considering the capacity weight of links, i.e., the frequency of flights between an airport node pair in the ATN and is expressed as

$$NE_w = \frac{1}{N(N-1)} \sum_{e \in E} e_{ij} = \frac{1}{N(N-1)} \sum_{e \in E} \frac{1}{n_e L_{ij}}$$  \hspace{1cm} (2)

where $e_{ij}$ is the weighted path efficiency between node pair $i$ and $j$, $n_i$ is the capacity weight of link $i$, and $L_{ij}$ is the set of links along the shortest path between node pair $i$ and $j$.

**Example 3.2.** Consider a simple network $\mathcal{G}$ (Fig. 3) for exposition.

Let $n_{ab} = 2$ (capacity weight of the link connecting node $a$ and $b$), $n_{bc} = 1$ and $\frac{1}{n_{ab}} = \frac{1}{n_{bc}} = \frac{1}{n_{ac}}$. Then the weighted network efficiency of $\mathcal{G}$ is obtained as $NE_w = \frac{1}{6} \left( \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2} \right) = \frac{11}{9}$.

Note that the weighted network efficiency metric considers the impact of link capacity on network efficiency by treating the reciprocal of the link capacity as link length. However, the weighted efficiency metric may not provide appropriate insights on the vulnerability of ATNs in response to catastrophe-induced disruptions such as partial and complete flight disconnections (links disconnections).

**Proposition 3.1.** The removal of links does not necessarily reduce the weighted efficiency of a network, quantified by $NE_w$, and the weighted network efficiency metric cannot accurately reflect the impact of link disruptions.

**Proof.** Let us consider three networks (Fig. 4) for exposition.

It can be observed that the network $G_1$ and $G_2$ are almost similar except that the capacity weight of the link between node $a$ and $c$ of network $G_2$ is one. The situation is analogous to pandemic-induced disruption of ATNs where flights between airports got partially shut down due to demand reduction. The weighted network efficiency of network $G_1$ and $G_2$ obtained using Eq. (2) is 2 and 1.67, respectively. Hence, a link weight reduction in the network results in a decrease in the efficiency. Now, if the entire direct connection between node $a$ and $c$ got disconnected, the resultant network is $G_3$. While comparing network $G_2$ with $G_3$, one can observe that the weighted network efficiency is same, i.e., 1.67. Thus, Proposition 3.1 holds.

However, from a catastrophe-disrupted ATN perspective, $NE_w$ may be an inaccurate metric to measure the vulnerability of ATNs. Taking the COVID-19 pandemic as an example, various travel restrictions are in place by respective countries, restricting transit traveling as in the network $G_3$ (Fig. 4), where one needs to transit at node $b$ before arriving $c$, unlike the situation in network $G_2$, where one can directly travel between node $a$ and $c$. In reality, the network $G_3$ is less efficient than $G_2$, but the difference is not reflected by their weighted efficiency metric. Hence, a new metric is desired to capture the impact of both complete and partial link disruptions on network efficiency and to assess the vulnerability of catastrophe-disrupted ATNs.

### 3.2. Impact of link capacity reduction on network connectivity and efficiency

In this part, we investigate why the weighted efficiency metric fails to capture the impact of link capacity reduction on network efficiency, and what a valid metric should be like. In ATNs, link capacity is quantified by flight frequency, which is determined by traffic demand. Besides, higher traffic demand usually indicates stronger connections between node pairs. Thus, in ATNs, link capacity is strongly correlated to node pair connectivity. Considering that network efficiency is the integrated evaluation of the connectivity between all the node pairs, link capacity is also strongly correlated to network efficiency. The only problem in the weighted network efficiency, as in Eq. (2), is determining the shortest path. After regarding the reciprocal of link capacity as link length, there is a possibility that a path consisting of more links has larger efficiency than that of fewer links for a given node pair if the capacity of the links on the former path is much larger than that of the latter one. Therefore, after the capacity reduction of certain links, the path efficiency of all the node pairs may remain unchanged. The weighted network efficiency, in turn, also remains unchanged.

A valid network efficiency metric should not only involve the impact of link capacity but also capture the impact of the reduction of link capacity. To achieve this, a feasible way is to treat the ATN as a multilayer network, and the number of layers of each link is determined by its capacity. The new metric, termed as layered weighted network efficiency, is presented in the next section, followed by the proof of validity in Section 3.4.
3.3. Network disintegration model for pandemic-disrupted ATNs

The underlying idea of the proposed approach is to first disintegrate the original capacity-weighted network into definite unweighted subnetworks and then evaluate the network efficiency metric of each subnetwork. Finally, the network efficiency of each subnetwork is added to obtain the layered weighted network efficiency (LWNE) metric of the original network. Fig. 5 illustrates the proposed network disintegration model.

The network disintegration is conducted by removing one unit of a link between all the connected node pairs from the residual network and use these removed links to constitute a subnetwork in each step. The following algorithm helps to determine the LWNE of the network under consideration, and code is available at our project page (https://github.com/YaomingZhou/MultilayerEfficiency-LWNE).

\begin{algorithm}
\caption{Computation of layered weighted network efficiency (LWNE) metric}
\begin{algorithmic}[1]
\State \textbf{Input} original network for disintegration
\State \textbf{While} there are links in the original network
\State \hspace{1em} Remove one weight of the link between all connected node pairs
\State \hspace{1em} Use removed links to form a subnetwork
\State \hspace{1em} \textbf{End while}
\State Compute network efficiency of each unweighted subnetwork
\State Sum network efficiency of each subnetwork to compute LWNE of the original network
\State \textbf{Output} LWNE of the original weighted network
\end{algorithmic}
\end{algorithm}

To justify the applicability and effectiveness of the proposed approach over the existing methodology (as discussed in Section 3.1), recall Proposition 3.1. Fig. 6 demonstrates the proposed network disintegration model to compute LWNE metric of the network $G_1$, $G_2$, and $G_3$.

Comparing Fig. 6 illustration with Fig. 4, it can be observed that the proposed network disintegration model provides a robust approach to investigate the effect of link capacity reduction on overall network efficiency. Unlike existing methodology, the proposed model permits characterizing the effect of any addition or deletion of links and increase or decrease of link capacity on network efficiency, which is critical to understand the vulnerability of catastrophe-disrupted ATNs. The decrease of link capacity here can be interpreted as flight disconnection between airports due to COVID-19 induced inter-country travel restrictions. By disintegrating the original network into different subnetworks, any increase or decrease of link capacity will change the structure, and in turn, the efficiency of one of the subnetworks. This is subsequently reflected in the value of the LWNE of the weighted original network. This new metric overcomes the limitation of the weighted network efficiency approach as described in Section 3.1.

3.4. Proof of validity

Next, we prove the validity of the proposed LWNE metric on capturing the impact of link capacity reduction on network efficiency.

Lemma 3.1. \textit{In an unweighted network, any deletion of links will decrease its network efficiency and vice versa.}

\textbf{Proof.} Consider an unweighted network $G$, its network efficiency is calculated by Eq. (1). Suppose that the link to be deleted is $(a, b)$, connecting node $a$ and $b$. In the original network, the length of the shortest path between node $a$ and $b$ is 1. After the deletion of link $(a, b)$, the length of the shortest path between node $a$ and $b$ will be at least 2, as both nodes need to transit by other nodes to reach each other. Moreover, the deletion of link $(a, b)$ may also increase the shortest path length of other node pairs which previously have link $(a, b)$ on their shortest paths. Thus, the deletion of a link will necessarily result in a decrease in the network’s efficiency. On the other hand, the addition of a link will necessarily result in an increase in the network’s efficiency.

\cite{Jeong2000, Tan2016}

The concept of network disintegration is well established in network science (Jeong et al., 2000; Tan et al., 2016).
hand, suppose that a new link \((c, d)\) is to be added, where node \(c\) and \(d\) are not directly connected in the original network. The length of the shortest path between node \(c\) and \(d\) will decrease from some larger value to 1. In addition, the shortest path length of some other node pairs may also decrease. As a result, according to Equation (1), the network efficiency will increase. This completes the proof of Lemma 3.1.

**Proposition 3.2.** For a given network, any reduction of link capacity will result in the decrease of its LWNE and vice versa.

**Proof.** As presented in Section 3.3, to calculate LWNE, the weighted network is first disintegrated into a group of unweighted subnetworks. The number of subnetworks that a link appears in is determined by its capacity in the previous weighted network. Thus, if the capacity of a link is reduced by one unit in the original weighted network, there will be a subnetwork in which the corresponding link is deleted. According to Lemma 3.1, the unweighted network efficiency of this subnetwork will decrease. Since all the other subnetworks remain unchanged, the LWNE of the weighted network will decrease. The proofs for augment of link capacity are similar. Thus, Proposition 3.2 holds.

In conclusion, by treating the weighted ATNs as multilayer networks, the impact of link capacity on network connectivity can be included. Moreover, as any change in link capacity will be reflected on the structure change of subnetworks, which in turn changes the value of LWNE, the impact of link capacity reduction (including complete and partial link removal) on network connectivity can be captured.

4. Implementation

This section investigates the vulnerability of the WATN to link disruptions at different levels, including airport level, country level,
and global level.

4.1. Data of the WATN

The WATN is constructed by the data of flights obtained from the aviation data provider Official Airline Guide (OAG) (https://analytics.oag.com/). Since most flights operate at least once weekly, the flights in one specific week at the pre-pandemic stage are used, which includes 720,137 commercial flights linking 3909 operating airports worldwide from November 21 to November 27, 2019. Each record of the 720,137 flights consists of the following information: departure airport IATA code, arrival airport IATA code, airline IATA code, and flight number. The WATN is treated as an undirected network. We categorize the flights according to their origin–destination information and regard the number of weekly flights as the capacity weight of the corresponding link. Finally, a capacity-weighted WATN is obtained (Fig. 7), which contains 3,617 nodes (airports) and 23,163 links (airport connections). The average weight of the links is 15.3. The link connecting Jeju International Airport and Gimpo International Airport has the largest capacity weight, 840, suggesting that 840 scheduled flights are operating in both directions between Jeju and Seoul. About 74% of the links have at most 15 scheduled flights, and 8% of links only have one scheduled flight. Thus, the distribution of capacity weight on the WATN is non-uniform. The LWNE of the WATN is 3.1087. In comparison, the unweighted efficiency of the WATN is 0.2695.

4.2. Vulnerability of the WATN to airport-to-airport disconnection

By calculating the LWNE of the WATN when an individual airport connection is disrupted, the vulnerability of the WATN to airport-to-airport disconnection can be evaluated. In addition, the most vulnerable airport connections and their impact on the connectivity of the WATN can be determined. The top 20 vulnerable airport connections are listed in Table 1. Columns 2 and 3 show the two connected airports and corresponding cities of each connection.

The most vulnerable connection is between ANC (Anchorage) and BET (Bethel), both in Alaska in the U.S. The two airports have 35 and 23 direct connections with other airports, respectively. There are 30 flights between the two airports in both directions each week. The reduction in LWNE when different proportions of flights on this connection are canceled is also presented. Specifically, if all the flights on this connection are shut down, the LWNE of the WATN will decrease by 0.6183%. The location of the two airports in the ATN of Alaska is shown in Fig. 8. ANC (Anchorage) is the largest airport in Alaska, acting as the transit hub for Alaska and the continental United States. BET (Bethel) is a sub-hub in Alaska, which connects the 22 smaller airports around it with ANC (Anchorage). Therefore, the shutdown of the flights between ANC and BET will almost result in the isolation of these 22 smaller airports from the WATN. It explains why this airport connection is the most vulnerable ones in the WATN. It is worth mentioning that there are two alternative connections between the 22 airports and ANC, as indicated in Fig. 8. However, since the capacity of these two connections is relatively small, they cannot undertake the traffic volume which previously using the connection between ANC and BET. From the perspective of network disintegration, after the removal of the connection between ANC and BET, the 22 small airports keep connected with the WATN in a few subnetworks using the two alternatives. However, in the other subnetworks, they are isolated from the other parts of the WATN.
## Table 1
Top 20 vulnerable airport connections in the WATN.

| Rank | Airport 1 (city)     | Airport 2 (city) | Airport 1 degree | Airport 2 degree | Weekly flights | Percentage reduction of LWNE | 25% link capacity reduction | 50% link capacity reduction | 75% link capacity reduction | 100% link capacity reduction | Connection type        |
|------|---------------------|------------------|------------------|------------------|---------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|-------------------------|
| 1    | ANC (Anchorage)     | BET (Bethel)     | 35               | 23               | 30            | 0.0312%                     | 0.1575%                     | 0.4491%                     | 0.6183%                     | Bridge-bridge             |
| 2    | SJU (San Juan)      | CPX (Culebra)    | 46               | 3                | 38            | 0.0098%                     | 0.0273%                     | 0.0797%                     | 0.1713%                     | Bridge-periphery          |
| 3    | JFK (New York)      | LHR (London)     | 173              | 178              | 128           | 0.0113%                     | 0.1077%                     | 0.1670%                     | 0.1690%                     | Core-core                 |
| 4    | THR (Tehran)        | MHD ( Mashhad)   | 40               | 34               | 141           | 0.0002%                     | 0.0005%                     | 0.0009%                     | 0.1504%                     | Bridge-bridge             |
| 5    | CAI (Cairo)         | ASW (Aswan)      | 90               | 2                | 73            | 0.0030%                     | 0.0145%                     | 0.0458%                     | 0.1502%                     | Bridge-periphery          |
| 6    | YXE (Saskatoon)     | YPA (Prince Albert) | 11             | 5                | 21            | 0.0084%                     | 0.0208%                     | 0.0449%                     | 0.1473%                     | Bridge-bridge             |
| 7    | SEA (Seattle)       | ANC (Anchorage)  | 112              | 35               | 111           | 0.0052%                     | 0.0183%                     | 0.0706%                     | 0.1433%                     | Core-bridge               |
| 8    | ANC (Anchorage)     | OTZ (Kotzebue)   | 35               | 13               | 13            | 0.0461%                     | 0.0976%                     | 0.1127%                     | 0.1379%                     | Bridge-bridge             |
| 9    | LLA (Lalea)         | ARN (Stockholm)  | 4                | 117              | 87            | 0.0224%                     | 0.0136%                     | 0.0381%                     | 0.1377%                     | Bridge-core               |
| 10   | CPH (Copenhagen)    | (Kangerlussuaq)  | 139              | 8                | 4             | 0.0234%                     | 0.0565%                     | 0.1295%                     | 0.1344%                     | Core-bridge               |
| 11   | ASB (Ashgabat)      | IST (Istanbul)   | 17               | 280              | 20            | 0.0409%                     | 0.0974%                     | 0.1276%                     | 0.1293%                     | Bridge-core               |
| 12   | MEX (Mexico City)   | BOG (Bogota)     | 110              | 85               | 65            | 0.1136%                     | 0.1169%                     | 0.1222%                     | 0.1283%                     | Bridge-bridge             |
| 13   | ANC (Anchorage)     | ADQ (Kodiak)     | 35               | 3                | 36            | 0.0086%                     | 0.0206%                     | 0.0466%                     | 0.1268%                     | Bridge-bridge             |
| 14   | LIM (Lima)          | BOG (Bogota)     | 67               | 85               | 58            | 0.1145%                     | 0.1179%                     | 0.1202%                     | 0.1229%                     | Bridge-bridge             |
| 15   | CNS (Cairns)        | HID (Horn Island) | 30              | 8                | 14            | 0.0064%                     | 0.0159%                     | 0.0256%                     | 0.1216%                     | Bridge-bridge             |
| 16   | AEP (Buenos Aires)  | (Montevideo)     | 37               | 12               | 39            | 0.0002%                     | 0.0795%                     | 0.0952%                     | 0.1187%                     | Bridge-bridge             |
| 17   | DXB (Dubai)         | LHR (London)     | 225              | 178              | 63            | 0.0721%                     | 0.1105%                     | 0.1174%                     | 0.1177%                     | Core-core                 |
| 18   | ACK (Nantucket)     | BOS (Boston)     | 8                | 127              | 70            | 0.0069%                     | 0.0316%                     | 0.0783%                     | 0.1166%                     | Bridge-core               |
| 19   | DEL (Delhi)         | KTM (Kathmandu)  | 135              | 45               | 51            | 0.0588%                     | 0.1022%                     | 0.1642%                     | 0.1665%                     | Bridge-bridge             |
| 20   | JNB (Johannesburg)  | LHR (London)     | 81               | 178              | 32            | 0.0642%                     | 0.0916%                     | 0.1052%                     | 0.1063%                     | Bridge-core               |
This shows the advantage of our proposed method in capturing the impact of link capacity and link disruption.

We can find that only two of the top 20 vulnerable connections are between those widely known busy international airports, including the connection between JFK (New York) and LHR (London), and that between DXB (Dubai) and LHR (London). Most of the top 20 vulnerable connections are between moderate-sized local hubs and (or) small airports. The results are consistent with the findings reported by Verma et al. (2014) when studying the structure of the world airline network. They found that the world airline network is resilient for long-distance air travel but breaks down by removing short and apparently insignificant connections. The airports are classified into three types: core airports, bridge airports, and periphery airports (Verma et al., 2014). We refer to their classification and find out the types of the connected airports of the top 20 vulnerable connections, as presented in the last column of Table 1. It is shown that most connections are between bridge airports, which connect core airports and periphery airports and are, therefore, very important to the connectivity of the whole network. Although core airports construct the backbone of the WATN, the

Fig. 8. Airport ANC (Anchorage) and BET (Bethel) in the ATN of Alaska State, the U.S. (The width of the lines is proportional to the number of weekly scheduled flights).

Fig. 9. Airport THR (Tehran) and MHD (Mashhad) in the ATN of Iran (The width of the lines is proportional to the number of weekly scheduled flights).
connections among them are highly redundant, and the removal of core-core connections would not damage the whole network significantly.

We also examined the impact of partial connection disruption on network connectivity. As shown in Table 1, the reduction of LWNE when the top 20 connections are individually disrupted at four different levels is listed. It is found that the relationship between LWNE reduction and the level of link capacity reduction is rather complex. The relationship is approximately linear for some airport connections, such as that between ANC (Anchorage) and OTZ (Kotzebue). The relationship is convex for some airport connections, such as THR (Tehran) and MHD ( Mashhad ). When the number of flights between THR and MHD is reduced by 25%, 50%, and 75%, the LWNE of the network will merely decrease by 0.0002%, 0.0005%, and 0.0009%, respectively. However, if all the flights between the two airports are shut down, the decrease of LWNE will be 0.1504%. For the other airport connections, such as that between MEX (Mexico City) and BOG ( Bogota ), the relationship between LWNE reduction and the level of link capacity reduction is concave. If only 25% of the flights are shut down between MEX and BOG, the reduction of LWNE will be 0.1136%, which is very close to the LWNE reduction caused by complete link disruption, i.e., 0.1283%.

By investigating the position of the airports and their connections with other airports in the WATN, we found that the relationship between LWNE reduction and the level of link capacity reduction is determined by the ratio of the number of flights between the two airports to that of their total flights. Taking the airport connection between THR and MHD as an example, the total number of weekly flights of Airport MHD is 322, and 141 are between MHD and THR. It means that the flights between MHD and THR essentially serve the travelers whose origin or destination is MHD, and, therefore, the partial disruption of the connection THR-MHD almost only impacts the travelers from/to MHD, but not those using MHD as stepover. However, if the connection between MHD and THR is completely disrupted, those small airports using MHD as transit hub will have to detour, and the network connectivity will be significantly damaged. Another example is the connection between MEX (Mexico City) and BOG (Bogota), for which LWNE reduction has a concave relationship with the level of link capacity reduction. MEX is the busiest international airport in Mexico, and BOG is the second busiest airport in South America. The total number of weekly flights of Airport MEX and BOG are 4157 and 2815, respectively, while only 65 of them are between these two airports. It indicates that both airports are important hubs for travelers from/to different other airports, and any partial disruption between them will impact the connectivity of the WATN significantly (Fig. 9).

4.3. Vulnerability of the WATN to individual country disconnection

During a pandemic, there is a possibility that a country cancels all the international flights from or to it, especially when this country is the origin of the outbreak. We assume that during a quarantine, a country unilaterally ceases all its international flights, and we compute the LWNE of the residual WATN. The results corresponding to the 20 countries with the largest reduction in LWNE is listed in Table 2. The disconnection of the United States will incur a 30% decline in the performance of the WATN, which is much larger than that caused by the disconnection of the other countries. Fig. 10 shows that the LWNE of the residual WATN is a decreasing function of the number of countries being disconnected, as shown in Table 2. It is worth mentioning that after a country is disconnected from the WATN by removing all its international connections, the domestic flights within the country can still operate. Furthermore, when the top 10 countries are simultaneously disconnected from the WATN, the performance measured by LWNE of the residual network decreases to less than 30% of its original level. This would suggest that the connection of the WATN relies heavily on the flights from and to the top air travel countries.

Notably, there is a large amount of air traffic demand from or to these countries. Moreover, some airports in these top-ranked

| Index | Disconnected country | No. of airports | No. of international airports | No. of weekly international flights (N_{fi}) | Percentage reduction of LWNE (ΔLWNE) | ΔLWNE |
|-------|---------------------|----------------|-------------------------------|--------------------------------------------|-------------------------------------|-------|
| 1     | United States       | 560            | 70                            | 1266                                       | 30.63%                              | 0.0242% |
| 2     | China               | 219            | 75                            | 1144                                       | 12.61%                              | 0.0110% |
| 3     | Canada              | 233            | 19                            | 404                                        | 8.67%                               | 0.0215% |
| 4     | Australia           | 156            | 12                            | 177                                        | 7.06%                               | 0.0400% |
| 5     | India               | 95             | 30                            | 342                                        | 6.32%                               | 0.0185% |
| 6     | Russia              | 144            | 45                            | 658                                        | 6.17%                               | 0.0094% |
| 7     | Japan               | 78             | 31                            | 378                                        | 6.17%                               | 0.0163% |
| 8     | Indonesia           | 100            | 25                            | 157                                        | 5.95%                               | 0.0379% |
| 9     | United Kingdom      | 56             | 32                            | 1224                                       | 5.58%                               | 0.0046% |
| 10    | Brazil              | 123            | 18                            | 140                                        | 5.13%                               | 0.0366% |
| 11    | Mexico              | 61             | 31                            | 316                                        | 4.63%                               | 0.0147% |
| 12    | France              | 48             | 36                            | 860                                        | 3.60%                               | 0.0042% |
| 13    | Turkey              | 51             | 21                            | 481                                        | 3.48%                               | 0.0072% |
| 14    | Spain               | 41             | 30                            | 1035                                       | 3.33%                               | 0.0032% |
| 15    | Thailand            | 32             | 11                            | 366                                        | 2.89%                               | 0.0079% |
| 16    | Norway              | 47             | 12                            | 177                                        | 2.79%                               | 0.0158% |
| 17    | Colombia            | 46             | 10                            | 86                                         | 2.78%                               | 0.0323% |
| 18    | Philippines         | 41             | 8                             | 119                                        | 2.65%                               | 0.0223% |
| 19    | Italy               | 35             | 30                            | 918                                        | 2.65%                               | 0.0029% |
| 20    | Germany             | 28             | 26                            | 1206                                       | 2.52%                               | 0.0021% |
Fig. 10. Percentage LWNE of the WATN when countries are disconnected in descending order.

Vulnerability to international disconnections of different countries

High    Low

| Scale-free network | Near-complete network |
|-------------------|-----------------------|
| Australia         | France                |
| Brazil            | Germany               |
| Indonesia         | UK                    |

Fig. 11. Domestic ATNs of two types of countries (Black nodes and links represent domestic networks, and blue links represent international connections of this country) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
countries are hubs for flights between the airports of other countries. In short, the WATN is robust to the individual disconnection of most countries, but vulnerable to the simultaneous disconnection of the top air travel countries.

The number of airports, international airports, and weekly international flights of the top 20 countries are listed in Table 2. There is no statistical evidence of a correlation between the percentage reduction of the LWNE (ΔLWNE) and the three indices. It is worth noting that the ΔLWNE of the U.K. is large, while its number of airports is small; the ΔLWNE of Australia is large, while its number of international airports is small; and the ΔLWNE of Germany is small, while its number of international flights is large. However, the ΔLWNE of a country is somewhat correlated to the product of the number of airports and the number of international flights afforded by the airport. The number of airports determines how many cities will be disconnected from the rest of the WATN after the removal of the international connections, and the number of international airports measures how well the country is linked to the other countries.

The ratio of the percentage reduction in LWNE and the number of international flights of the countries studied are listed in the last column of Table 2. This ratio can be regarded as the (international) link vulnerability of the countries, as it measures the average percentage reduction in the connectivity of a country if it loses one of its international connections. Furthermore, the link vulnerability of the countries studied varies quite a bit. For Australia, the removal of an international link incurs a 0.0400% drop in performance of the WATN, while for Germany, that value is only 0.0021%. This would suggest that Australia’s domestic air network is more (internationally) link vulnerable than that of Germany’s.

To appreciate the reason for the spectra of link vulnerability among the countries, we select three countries whose link vulnerability is high, namely, Australia, Brazil, and Indonesia, and three countries whose link vulnerability is low, namely, France, Germany, and the U.K., and highlight their domestic ATNs as exhibited in Fig. 11. Note that that the former group is the scale-free networks, which means that in these countries, a small proportion of airports have a large number of domestic connections, and the international connections are concentrated in the hub airports. In contrast, most of the remaining airports have few domestic connections, and they need to rely on the hub airports to connect to the other countries. This feature informs that the number of international connections is small and concentrated in a few hub airports. Their removal, therefore, will mean a significant decline in the connectivity of the WATN. For example, there are in total 156 airports in Australia, but only 12 of them are international airports.

In contrast, the latter group of domestic air networks is near-complete networks, which means that most of the airport pairs in the domestic network have direct flights between them. Furthermore, most of the airports have their own international connections. This feature suggests that the removal of an international connection will mainly affect the airport itself. The connections between the other airports will experience little effect. For example, in Germany, there are 28 airports, and 26 of them have international airports.

### 4.4. Vulnerability of the WATN to country-to-country disconnection

During the COVID-19 pandemic, some countries have stopped all their international flights to and from other countries. We will now investigate the impact of these country-to-country disconnections on the performance of the WATN. We select the top 10 countries in Table 1 and compute the performance reduction caused by the disconnection between the two countries. As shown in Table 3, all the pairwise country performance reduction is less than 1%. Thus, the shutdown of the direct flights between two countries has little effect on the performance of the overall WATN. The reason could be that the WATN is over-connected. So, even if we remove all the direct flights from two countries, the travelers of these countries can still arrive at the intended destinations by routing through third countries. However, if more than a pair of countries shut down all the international flights between them, the performance reduction would be much more significant. The extreme case is when all the countries shut down their international flights to all the other countries, as studied in Section 4.3.

### 4.5. Vulnerability of the WATN to different levels of global disconnections

Examining the origin–destination pairs, we find that among the 23,163 connections, 11,445 of them are international connections. We simultaneously reduce the capacity weight of these international connections to a certain level and examine the LWNE of the residual network. The percentage value of the LWNE of the WATN with respect to the various levels of capacity reduction of the international connections is shown in Fig. 12. We note that the WATN is robust to the capacity reduction of international connections. Even if all the countries cancel half of their international flights, the WATN can maintain 80% of its performance under pre-catastrophe

| LWNE reduction | USA | China | Canada | Australia | India | Russia | Japan | Indonesia | U.K. | Brazil |
|----------------|-----|-------|--------|-----------|-------|--------|-------|-----------|------|--------|
| USA            | /   | 0.21% | 0.84%  | 0.18%     | 0.04% | 0.05%  | 0.24% | 0.03%     | 0.75% | 0.14%  |
| China          | 0.21%| /     | 0.05%  | 0.04%     | 0.02% | 0.06%  | 0.12% | 0.04%     | 0.02% | 0.00%  |
| Canada         | 0.84%| 0.05% | /      | 0.02%     | 0.02% | 0.00%  | 0.01% | 0.00%     | 0.07% | 0.00%  |
| Australia      | 0.18%| 0.04% | 0.02%  | /         | 0.01% | 0.00%  | 0.02% | 0.03%     | 0.01% | 0.00%  |
| India          | 0.04%| 0.02% | 0.02%  | 0.01%     | /     | 0.01%  | 0.01% | 0.00%     | 0.07% | 0.00%  |
| Russia         | 0.05%| 0.06% | 0.00%  | 0.00%     | 0.01% | /      | 0.01% | 0.00%     | 0.05% | 0.00%  |
| Japan          | 0.24%| 0.12% | 0.01%  | 0.02%     | 0.01% | 0.01%  | /     | 0.03%     | 0.02% | 0.00%  |
| Indonesia      | 0.03%| 0.04% | 0.00%  | 0.03%     | 0.00% | 0.00%  | 0.03% | /         | 0.00% | 0.00%  |
| UK             | 0.75%| 0.02% | 0.07%  | 0.01%     | 0.07% | 0.05%  | 0.02% | 0.00%     | 0.01% | /      |
| Brazil         | 0.14%| 0.00% | 0.00%  | 0.00%     | 0.00% | 0.00%  | 0.00% | 0.00%     | 0.01% | /      |
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5. Conclusions

5.1. Concluding remarks and managerial insights

Motivated by the challenges posed by the COVID-19 pandemic and its induced effects on the WATN, this study has presented a novel approach to comprehensively study the complex ATNs vulnerability in response to global catastrophe-induced disruptions. The current work has provided a novel approach and various descriptive findings to address the issues raised in Section 1.

First, from a theoretical perspective, this work conceptualizes a network disintegration model to study the complex ATNs vulnerability in response to global catastrophe-induced disruptions. The multilayer approach helps model the actual scenario where many links (airport connections) got disrupted completely or partially. Therein, the capacity-weighted WATN is disintegrated into multiple layers where each layer is an unweighted subnetwork of the original network. Further, this work develops a novel network efficiency metric termed as layered weighted network efficiency (LWNE) metric to evaluate the performance of the disrupted ATN. It is proven that the LWNE metric can accurately capture the impact of link capacity reduction on network connectivity.

Second, from a practical perspective, this study evaluates the vulnerability of the WATN to different levels of airport disconnections. By evaluating the LWNE reduction due to airport-to-airport disconnections, the most critical airport connections are identified. It is found that the critical connections are mostly between so-called bridge airports but not core airports in the WATN. By examining the impact of partial link disruptions, it is found that some connections mainly serve local travel demand and are very robust to partial disruptions, while the others connecting global hubs are sensitive to partial disruptions. By evaluating the LWNE reduction due to the removal of international connections of individual countries, their impact on network connectivity is evaluated. It is found that the WATN is robust to the individual disconnection of most countries; however, it is vulnerable to the simultaneous disconnection of countries that serve international transfers. By evaluating the LWNE reduction due to disconnection between specific countries, it is found that the WATN is insensitive to the disconnection between any two countries, even those with sizeable domestic ATNs. Finally, by examining the LWNE reduction due to different levels of disruptions of all the international connections, it is found that the WATN is rather robust to international disconnections. As long as all the international connections hold 10% of their original flights, the WATN can still expect 40% of its pre-catastrophe performance. This paper deepens the understanding of ATNs under extreme events and provides a method for studying transportation networks’ vulnerability facing global disruptions to concerned aviation authorities for the safe restoration of the international air travel operations.

5.2. Limitation and future research

Despite the novelty of the proposed network disintegration model and layered weighted network efficiency (LWNE) metric against published models and metrics in related literature, several research limitations may be noteworthy for future research consideration.

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Fig. 12. Percentage LWNE of the WATN under various levels of capacity reduction of international connections.
First, the proposed model provides descriptive knowhow related to the vulnerability of the WATN based only on the past flight data and the associated disruptions (partial or complete shutdowns). Factors associated with the number of COVID-19 cases (in real-time) in a bilateral scenario can be incorporated into the proposed model to characterize the concept of air travel bubble⁴ and air travel pass⁵ for ATN restoration. The above can be gradually extended to a group of countries or regions with fewer COVID-19 cases or with safe immigration protocols and infrastructure. Second, the network metrics can be extended to evaluate the performance of airports by studying the resilience of the airports to large-scale flight disconnections. Moving forward, another possible research focus in the future is to investigate how to reduce the vulnerability and increase the robustness or resilience of the WATN through preparedness and quick response. Further, it is worth studying the integration of multimodal transportation systems and then analyze the effect of the pandemic on its vulnerability.

CRediT authorship contribution statement

Yaoming Zhou: Conceptualization, Methodology, Software, Validation, Writing – original draft. Tanmoy Kundu: Conceptualization, Methodology, Writing – original draft. Wei Qin: Supervision. Mark Goh: Supervision. Jiuh-Biing Sheu: Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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