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RESEARCH ARTICLE

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Tracing the spatial-temporal evolution dynamics of air traffic systems using graph theories

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Abstract

Air traffic systems are of great significance to our society. However, air traffic systems are extremely complicated since an air traffic system encompasses many components which could evolve over time. It is therefore challenging to analyze the evolution dynamics of air traffic systems. In this paper we propose a graph perspective to trace the spatial-temporal evolutions of air traffic systems. Different to existing studies which are model-driven and only focus on certain properties of an air traffic system, in this paper we propose a data-driven perspective and analyze a couple of properties of an air traffic system. Specifically, we model air traffic systems with both unweighted and weighted graphs with respect to real-world traffic data. We then analyze the evolution dynamics of the constructed graphs in terms of nodal degrees, degree distributions, traffic delays, causality between graph structures and traffic delays, and system resilience under airport failures. To validate the effectiveness of the proposed approach, a case study on the American air traffic systems with respect to 12-month traffic data is carried out. It is found that the structures and traffic mobilities of the American air traffic systems do not evolve significantly over time, which leads to the stable distributions of the traffic delays as evidenced by a causality analysis. It is further found that the American air traffic systems are quite robust to random airport failures while, respectively, 20% and 10% failures of the hub airports will lead to the collapse of the entire system with respect to the two proposed cascading failure models.

KEYWORDS
air traffic system, airport networks, evolution dynamics, graph theory, spatial-temporal networks

1 | INTRODUCTION

Traveling is part of daily lives. Everyday people travel from one place to another, either for work or for leisure. Among all travel means, air transport plays an important role in transportation.[1–3] Air transport services are provided by the air transport systems which are very complicated as they encompass many components such as airports, airways, airspaces, etc. Note that the components of an air traffic system usually interact with each other and they can evolve over time.[4] As a consequence, an air traffic system is spatially and temporally evolving. It is of great significance to trace the spatial-temporal evolutions of air traffic systems as such tracing can provide scientific supports to traffic managers for their decision makings.[5–7]

Since air traffic systems are extremely complicated, it is therefore challenging to build a holistic view toward their evolution dynamics.[4,8] Scientists have made tremendous efforts to achieve this goal. In the literature, the most efficient and effective way for tracing the evolution dynamics of air traffic systems is based on graph theories.[9] A graph, also known as a network, is composed of a set of nodes and edges. By modeling a complex system as a network is every straightforward as the nodes and edges of the network can depict the structural properties of the studied system.[10,11] The most important thing is that modeling a complex system as a network can provide a systemic view toward the understanding of the focal complex system.[12–14]

To trace the spatial-temporal evolution dynamics of air traffic systems, scientists normally model the air traffic systems as spatial-temporal networks and then apply network theories to probe the evolution dynamics of the modeled air traffic systems. In Ref. [8], the authors reviewed studies on complex networks for air traffic system modeling and analysis. However, studies as surveyed in Ref. [8] only deal with static networks. Meanwhile, only basic network properties such as nodal degrees, betweenness, shortest path, etc., are discussed. The authors in Ref. [15] investigated the evolution dynamics of air traffic systems by applying network theories and evaluated traffic complexity using clustering methods. The research in Ref. [16] provided a systemic view of the dynamics of air transport networks with a focus on traffic delay. The authors in Ref. [17] investigated the evolution of air traffic systems long time ago. But they focused on the evolution of nodal degrees over time. The very recent work in Ref. [18] proposed highly effective spatial-temporal network models for air traffic systems. But the authors only paid attention to the propagation dynamics of the traffic delays. Another recent work in Ref. [19] investigated network theories with applications to air traffic systems. However, the focus of that work is also on traffic delays. Apart from delays, the work in Ref. [20] investigated the reliability of air traffic systems from the viewpoint of complex networks, while the work in Ref. [21] applied dynamic weighted network models to measure the air traffic complexity. An earlier work dealing with network topologies with air traffic system evolution can be found in Ref. [22].

Although a couple of studies have been carried out to analyze the evolution dynamics of air traffic systems based on network theories, existing studies mainly have two drawbacks. First, existing studies mainly pay attention to a certain property of the constructed networks, therefore cannot present a holistic view towards the system dynamics. For example, the work in [18] mainly deals with the delay property of the networks. This drawback limits the real-world applications of existing studies. Second, which is also the key drawback, is that existing studies normally are model-driven. In other words, existing studies mainly apply network models and seldom take into account real-world traffic data. As a result, existing studies normally model air traffic systems using unweighted networks. For example, the work in Ref. [1,3] only deals with unweighted airport and airway networks. Therefore, research findings of existing studies may not capture the real evolution dynamics of air traffic systems.

To overcome the drawbacks of existing studies, in this study we propose to analyze the evolution of air traffic systems by modeling both spatial-temporal unweighted and weighted networks. Unweighted networks help capture the structural properties of the modeled air traffic systems, while weighted networks help capture the traffic properties of the systems.

To trace the evolution dynamics of air traffic systems, we propose to analyze the dynamic properties of the constructed networks in terms of a couple of network key performance indicators including node degrees, degree distributions, traffic delays on the networks, and network resilience under attacks. To validate whether the proposed network-based approach is feasible or not for tracing the evolution of air traffic systems, we carry out a case study on the American air traffic systems. We construct spatial-temporal airport networks with respect to a 12-month real-world traffic data recording the domestic flights of America for the year 2019. We discover that both the degree distributions and the delay distributions do not change to much over the 12 months. We further adopt three typical similarity indices. We calculate the similarities between each pair of the unweighted matrices corresponding to the unweighted airport networks. We do the same to the weighted networks. We discover that the similarities between the unweighted networks and the similarities between the weighted networks are quite high. This indicates that both the American airport network structures and the traffic mobilities are stable over the 12 studied months. This accounts for the phenomenon why the distributions of the nodal degrees and the delays do not change significantly over time. We also investigate the resilience of the airport networks to the failures of airport. We discover that the American airport networks are robust to random failures of airports. However, if 20% of their hub airports are failed, then the entire traffic systems will collapse.

The remainder of the paper is structured as follows. Section 2 presents the related backgrounds for this study. Section 3 describes in detail the investigated research problem and the proposed research methodology. Section 4 demonstrates the experimental studies on the American air traffic systems, and Section 5 concludes the paper.

2 | RELATED BACKGROUNDS

2.1 | Graph representation for networks

A graph is a straightforward way for modeling complex networks and networked systems.[23–27] A graph is composed of nodes or vertices and edges. Generally, a graph is denoted by

$G = \{V, E\}$. The symbols V and E represent the sets of nodes and edges, respectively. Normally, the number of nodes and edges are respectively denoted by $n = |V|$ and $m = |E|$ in which the notation $|\cdot|$ represents the cardinality.

A graph describes the complex relationships between the nodes of a system by the edges. Each edge corresponds to two nodes. The relationships between two nodes such as information transformation can be depicted by the properties of the edge. Very often, the edge properties are represented by the so-called adjacency matrix $A_{n\times n} = \{a_{ij}\}$ of a graph G. The matrix A can be either symmetric or asymmetric, depending on how one models the specific network or a networked system.

2.2 | Air traffic systems and modeling

Air traffic system is very complex.[28,29] An air traffic system involves many components which include the aerodromes, runways, terminal airspaces, en-route airspaces, controllers, aircraft, and so forth. These components interact with each other and the interactions are usually in a nonlinear mode. Changes on particular components and/or the interactions between the components can propagate throughout the entire system, causing great difficulties for tracing and analyzing the systemic dynamics of the air traffic system.

To build a systemic view of the complicated air traffic system, complex network modeling is a promising approach. A complex air traffic system can be modeled by a network.[30] The nodes of the network can be the components of an air traffic system while the edges between the nodes can be the relations between the components. For example, one can take an airport as a node and an edge can be established between two airports if there are flights between those two airports. By modeling a complex air traffic system as a complex network, one can build a systemic view of the entire traffic system.

2.3 | Representation of spatial-temporal networks

For some networks like airport networks, their nodes contain location information and their edges and even their nodes could change over time. In network science domain, such networks are called spatial-temporal networks.[31,32]

Since a spatial-temporal network is changing with the time, to trace its dynamics, one needs first to model it. In the literature, there are two ways to model a spatial-temporal network.[33] The two ways are shown in Figure 1.

In Figure 1A, a spatial-temporal network is modeled as a sequence of networks. Specifically, a spatial-temporal network G_{st}^{t} over a time period $t = [t_a, t_b]$ can be modeled as

$$G_{st}^{t} = \left\{G_{st}^{t_i} | i = 1, 2, \ldots\right\} \tag{1}$$

in which $G_{st}^{t_i}$ is the spatial-temporal network at time $t_i \in t$. Note that t_i can represent a certain time point or a time period.

Representing a spatial-temporal network using the way shown in Figure 1A is very straightforward. However, such a representation does not provide a quick visual clue for the dynamics of the network. In view of this, in the literature there is another way to represent a

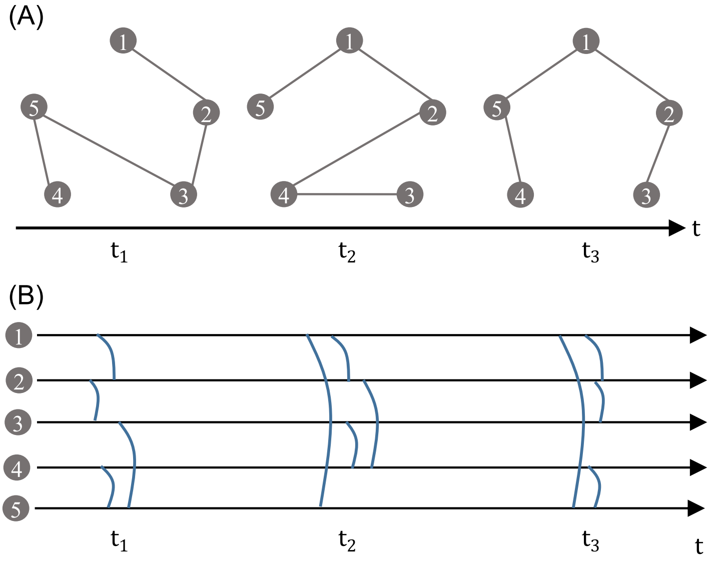

FIGURE 1 Illustrations of the two typical ways for modeling a spatial-temporal network. (A) The network sequence way in which a spatial-temporal network is represented by a sequence of graphs over time. (B) The temporal edge sequence way in which a spatial-temporal network is represented by a sequence of edges over time. [Color figure can be viewed at wileyonlinelibrary.com]

spatial-temporal network. As shown in Figure 1B, a spatial-temporal network is modeled as a sequence of temporal edges. Specifically, a spatial-temporal network G_{st}^t can be modeled as $G_{st}^t = \{E_{st}^{t_i} | i = 1, 2, ...\}$ in which $E_{st}^{t_i}$ is the set of edges at time $t_i \in t$.

3 | RESEARCH PROBLEM AND METHODOLOGY

This study is dedicated to adopting graph theories to trace the spatial-temporal evolution of complex air traffic systems. This study aims to provide a systemic view towards complex air traffic systems such that the corresponding findings can assist aviation decision makers with their decision making process. In what follows, we present the detailed research problem and the corresponding methodology based on graph theories.

3.1 | Research problem description

Given a complex air traffic system which mainly involve airports and the traffic mobility, we aim to answer the following two research questions:

1. How can we analyze the evolution of the air traffic system given the fact that the system is spatially and temporally evolving over time?
2. What quantitative properties could be considered to trace the evolution dynamics of the system?

The first research question actually explores the promising methods for tracing the evolution dynamics of complex air traffic systems. The second research question focuses on the detailed key performance index for quantifying the evolution dynamics of air traffic systems.

3.1.1 | System modeling

To answer the first question raised above, we need to model a complex air traffic system in a scientific way such that its dynamics can be traced and analyzed. In view of this, we propose to represent a complex air traffic system using a spatial-temporal network.

When mapping an air traffic system into a network, we respectively use nodes and edges to denote the components comprising the system and the interactions between the components. More importantly, we construct spatial-temporal networks for an air traffic system. Note that we adopt the first method as shown in Figure 1A to represent a spatial-temporal network.

In the literature, most spatial-temporal network modeling for complex systems deals with unweighted and undirected networks,[16,18] which is not appropriate for air traffic system. This is because that an unweighted and undirected network modeling cannot reflect the true properties of the system. Different to existing studies, we in this study model an air traffic system using weighted and directed networks.

3.1.2 | System properties

After constructing a directed and weighted spatial-temporal network for an air traffic system, then it comes to the second question, that is, what properties of the network we should consider in the subsequent analysis. In this study, we propose to analyze the following properties of the constructed spatial-temporal networks.

In-/out-degree: For a given network, the degree of a node represents the edges associated with the node. For the constructed airport networks, we analyze the in-degrees (edges pointing to a node) and out-degrees (edges pointing from a node) of the airports to build a microscopic view at the airport level of the focal networks.

Degree distribution: The degree distribution measures how the degrees of the nodes of an airport network are distributed. We analyze the degree distribution to build a holistic view of the structural organization of the focal network.

Traffic delay distribution: For air traffic, delay is an important indicator of the performance of the air traffic systems. We analyze the delay distribution to obtain a systemic view toward the overall efficiency of an air traffic system.

Adjacency matrix similarity: The similarity between two adjacency matrices measures how two networks are structurally similar. We analyze the similarity between a pair of adjacency matrices to see whether a high structural similarity leads to similar distributions of the traffic delay.

Network resilience: For an airport network, it is very important to assure a high resilience of the network in the face of perturbations such as attacks and/or airport closures. We investigate the resilience of the constructed airport networks to assist network managers with better air traffic system planning.

3.2 | Spatial-temporal network construction

When constructing a spatial network, we construct the directed and weighted edges between the nodes in the following way. If a flight, say flight with tail number N311DN, departs from airport SLC to airport LAS, then we construct a directed edge pointing from node representing airport SLC to node representing airport LAS. For a given time period t, if the aircraft N311DN flies from SLC to LAS for 10 times, then the weight for the directed edge SLC–LAS is 10.

Based on the above method we can get an asymmetric and weighted adjacency matrix $\mathbf{A}_{wtd}^t = \{a_{ij}^t\}$ representing the directed and weighted airport network G_{wtd}^t for time period t. Note that in this study we construct both weighted and unweighted networks. The adjacency matrix $\mathbf{B}_{uw}^t = \{b_{ij}^t\}$ for the unweighted network G_{uw}^t corresponding to G_{wtd}^t is calculated as follows:

$$\begin{cases} \mathbf{B} = \mathbf{A} + \mathbf{A}^{\mathrm{T}} \\ \mathbf{B}\left(b_{ij}^t > 0\right) = 1 \end{cases} \tag{2}$$

in which $\mathbf{A}^{\mathrm{T}}$ is the transpose of $\mathbf{A}$. We set every non-zero elements in $\mathbf{B}$ obtained via the first equation to be 1 so as to obtain the finally binary matrix $\mathbf{B}$.

3.3 | Degree calculation

For a given weighted network G_{wtd}^t with n nodes, we use $d_{i,t}^{in}$ and $d_{i,t}^{out}$ to denote the in-degree and out-degree of node i in network G_{wtd}^t. The degrees $d_{i,t}^{in}$ and $d_{i,t}^{out}$ are respectively calculated as

$$d_{i,t}^{in} = \sum_{j=1}^{n} a_{ji}^t, \tag{3}$$

$$d_{i,t}^{out} = \sum_{j=1}^{n} a_{ij}^t. \tag{4}$$

For a given unweighted network G_{uw}^t, since it is undirected and the adjacency matrix is symmetric, we therefore do not distinguish the in-degree and out-degree. We calculate the degree $k_{i,t}$ of node i as

$$k_{i,t} = \sum_{j=1}^{n} b_{ij}^t. \tag{5}$$

3.4 | Degree distribution analysis

After getting the spatial-temporal airport networks G_{uw}^t and G_{wtd}^t, we calculate the degree for each node of the networks. Then we get the in-degree and outdegree sequences

$$\boldsymbol{d}_t^{in} = \left\{d_{i,t}^{in} | \forall\ i \in [1, n]\right\}, \tag{6}$$

$$\boldsymbol{d}_t^{out} = \left\{ d_{i,t}^{out} | \forall\ i \in [1, n] \right\}. \tag{7}$$

Analogously, we can have $\boldsymbol{k}_t = \{k_{i,t} | \forall\ i \in [1, n]\}$. We then analyze the probability distributions $P(d_{i,t})$ and $P(k_{i,t})$ for the degrees.

3.5 | Delay distribution analysis

When constructing the edges of the spatial-temporal networks, we also record the traffic delays on the edges. Then for a given weighted and directed network G_{wtd}^t, we get to know the arrival delay sequence as

$$\boldsymbol{\varphi}_{arr}^t = \left\{ \varphi_{arr}^{i,j,t} | \forall\ i, j \in [1, n] \right\}. \tag{8}$$

Analogously, we have the departure delay sequence as

$$\boldsymbol{\psi}_{dep}^t = \left\{ \psi_{dep}^{i,j,t} | \forall\ i, j \in [1, n] \right\}. \tag{9}$$

The symbol $\varphi_{arr}^{i,j,t}$ represents the arrival delay for flight flying from airport i to airport j at given time period t. Analogously, the symbol $\psi_{dep}^{i,j,t}$ is the departure delay. We than analyze the probability distributions $P(\varphi_{arr}^{i,j,t})$ and $P(\psi_{dep}^{i,j,t})$.

3.6 | Matrix similarity calculation

For a given pair of networks, we calculate the similarity between the two adjacency matrices to investigate the structural similarity of the two networks. To do so, we adopt three widely used similarity indices, i.e., Cosine index, Pearson Correlation Coefficient, and Tanimoto Coefficient.

Given two vectors $\boldsymbol{x} = (x_1, x_2, ..., x_n)$ and $\boldsymbol{y} = (y_1, y_2, ..., y_n)$ with same length of n, the calculations of the similarities between the two vectors with respect to the four indices are given as follows:

$$S_{\text{Cosine}} = \frac{\boldsymbol{x}\boldsymbol{y}^{\mathrm{T}}}{||\boldsymbol{x}||\,||\boldsymbol{y}||}, \tag{10}$$

$$S_{\text{Pearson}} = \frac{\sum_i^n (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_i^n (x_i - \overline{x})^2}\sqrt{\sum_i^n (y_i - \overline{y})^2}}, \tag{11}$$

$$S_{\text{Tani}} = \frac{\boldsymbol{x}\boldsymbol{y}^{\mathrm{T}}}{||\boldsymbol{x}||^2 + ||\boldsymbol{y}||^2 - \boldsymbol{x}\boldsymbol{y}^{\mathrm{T}}}. \tag{12}$$

In the above equations, $\overline{x}$ and $\overline{y}$ represent the mean of $\boldsymbol{x}$ and $\boldsymbol{y}$, and $||\cdot||$ represents the norm of a vector. To calculate the similarity between a pair of matrices, we first turn the matrices into vectors by stretching the square matrices into row vectors. We then calculate the similarities between the two rows vectors using the above mentioned metrics. The larger the value of the similarity index, the more similar the two vectors in a hyper-plane space.

Note that there are a dozen of similarity indices in the literature.[34–36] In this study we only adopt three of them. This main reason is that the above four indices will yield smaller values of the similarities than other indices like Euclidean distance do without any need of vector normalization. This is because that we construct weighted networks and the values of the elements of the stretched vectors could be very large.

3.7 | Network resilience analysis

We investigate the resilience of both unweighted and weighted airport networks under perturbations. In the literature, there are two ways to investigate the resilience of complex networks, that is, the resilience of complex networks under node failures and the resilience of complex networks under edge failures. In this study, we investigate the resilience of airport networks under node failures instead of edge failures because node (airport) failures can cause greater disasters than edges do.

3.7.1 | Node failure model

To quantify the resilience of airport networks under node failures, first we need to simulate the situation of airport failures. For a given airport network G, we assume that q fraction of airports are failed. Putting it another way, we need to remove q fraction of nodes of network G. How to choose the q fraction of nodes is critical as it affects the resilience of G in terms of the four metrics shown above. In this study, we adopt three widely used node failure models which are explained below.

- Mode 1 Random Failure. Literally, this model choose the q fraction of nodes from G randomly.
- Mode 2 From maximum degree nodes to minimum degree node. This model sorts the nodes by their degree in a descend order and choose the former q fraction of nodes.
- Mode 3 From minimum degree nodes to maximum degree node. This model sorts the nodes by their degree in a ascend order and choose the former q fraction of nodes.

3.7.2 | Cascading failure model

When q fraction of nodes are removed from a network G, cascading failures could happen, i.e, other nodes may also fail because of the failure of the q fraction of nodes. In this paper we propose the following cascading failure model.

- Model 1—Undirected network scenario. For a given undirected network G, we detach all the edges previously connected to the q fraction of nodes of network G. Model 1 is in line with the models used by existing studies in Ref. [37,38].
- Model 2—Directed network scenario. For a given directed network G, we propose a cascading failure model to mimic the chain effect of the airport failures on traffic mobility.

The proposed model works as follows. We detach all the edges previously connected to the q fraction of nodes of network G. Afterward, we remove nodes that only have zero in-degrees or out-degrees. At last we delete edges connected to other nodes to balance their in-degrees and out-degrees. Figure 2 presents a detailed illustration of this model.

In Figure 2, node 3 is initially failed due to perturbations. Then we detach all the directed edges connected to node 3. Then we observe that node 4 only has the in-degree. Based on our criterion, we further remove edges connected to node 4. After that we notice that there is an imbalance between the in-degree and out-degree of node 1. Therefore we change the edge weight to reach a balance.

3.7.3 | Resilience metrics

To quantify the resilience of airport networks under node failures, we introduce four metrics based on existing literature.[37–40] Here we denote the four metrics respectively as Rn_GC, Rn_RC, Rm_GC and Rm_RC. Given a network G with n nodes and m edges, we assume that q fraction of its nodes are failed. Then the four metrics are respectively calculated as follows:

$$\text{Rn\_GC} = n_{\text{GC}}(q)/n \tag{13}$$

$$\text{Rn\_RC} = n_{\text{RC}}(q)/n \tag{14}$$

$$\text{Rm\_GC} = m_{\text{GC}}(q)/m \tag{15}$$

$$\text{Rm\_RC} = m_{\text{RC}}(q)/m \tag{16}$$

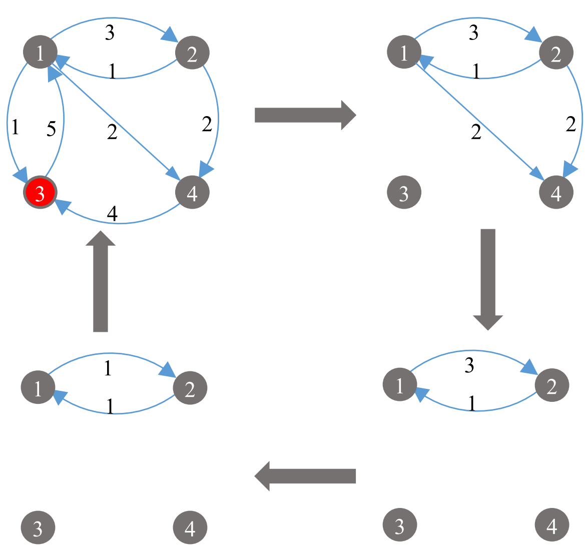

FIGURE 2 Proposed cascading failure model for directed airport networks. The node in red is assumed to fail because of perturbation. The failure of node 3 causes cascading failures and eventually only nodes 1 and 2 survive. [Color figure can be viewed at wileyonlinelibrary.com]

in which GC and RC mean the giant and remained components of G, respectively. The symbols $n_{GC}(q)$ and $m_{GC}(q)$, respectively, denote the remained number of nodes and edges in the GC of G after the failure of q fraction of nodes. The metrics Rn_GC and Rn_RC measure the impact on network structure while the metrics Rm_GC and Rm_RC measure the impact on traffic mobility.

4 | EXPERIMENTAL STUDY

To validate the effectiveness of the proposed graph theories for tracing the evolution dynamics of complex air traffic systems, we do experiments on airport systems as airports are the backbone of air traffic systems. Different to most of the existing studies that focus on unweighted and undirected air traffic networks, we in this paper propose to analyze weighted and directed networks. As a consequence, we need real-world traffic data.

For many airlines or countries, the real traffic data are not free to obtain due to commercial interests. However, the Reporting Carrier On-Time Performance data for the domestic air traffic within the USA are available online. In the experiments, we use this data as the studying material. The traffic data can be obtained from the official website of the Bureau of Transportation Statistics.

4.1 | Traffic data

From the website of the Bureau of Transportation Statistics, we download the data for the year 2019. Although the data for years 2020 and 2021 are also available, we decide not to use them as the traffic demands declined in 2020 and 2021 due to the COVID-19 pandemic, and those data cannot reflect the real capability of the air traffic system.

The original traffic data are organized into csv form. It provides many information. Table 1 shows the key data features that are considered in the subsequent analysis. In Table 1, the city information for the departure airport and the arrival airport is needed. This is because that in the original data the flight time is provided in the local time form. The city information will be used to determine the time zones of the cities.

Note that the traffic data do not provide the geographical location information of the airports. To construct spatial airport networks, we need the location information of the airports. In view of this, we download online the location information of global airports.

4.2 | Data preprocessing

As mentioned earlier that the original traffic data record the traffic time in local time format. To construct temporal networks, we first need to unify the traffic time. Based on the city information, we determine the time zones of the cities. Then based on the time zones we turn all the traffic time as recorded in the data into UTC time.

Note that flights can be canceled due to several reasons such as mechanical failures, convective weather, etc. In the original data, whether a flight is canceled or not is reflected by the data entry "Canceled." Meanwhile, for a normal flight that is not canceled, its information such as destination or origin could be missing due to reasons such as anthropogenic errors.

TABLE 1 Key data features that are considered in subsequent analysis

Entry	Example	Entry	Example
Year	2018	DestAirportID	12,478
Month	1	Dest	JFK
DataofMonth	1	DestCityName	New York, NY
FlightData	1/1/2018	DepTime	547
TailNumber	N5FGAA	DepDelay	−13
OriginAirportID	10721	ArrTime	705
Origin	BOS	ArrDelay	−6
OriginCityName	Boston, MA	Canceled	0

Table 2 presents the basic properties of the original data. In the subsequent analysis, we delete information of flights that are canceled. We also delete flights whose information are missing. Then we get the cleaned flight data (reflected in the last column of Table 2) for each month.

4.3 | Spatial-temporal network construction

After the data preprocessing process, we obtain the cleaned flight data for constructing the spatial-temporal airport networks. For a given time period t, we construct both unweighted and weighted spatial networks, that is, G_{uw}^t and G_{wtd}^t.

Figure 3 visualizes a constructed spatial airport network using the traffic data of January 1, 2019. For simplicity, only the unweighted and undirected network is shown and the time period is set to be one day when constructing the network.

Note that the selection of the time period affects the construction of the temporal networks. In the experiments, we set the time period for constructing temporal networks to be 1 month. This is because that we are using 1 year traffic data. For each month, the traffic movements are quite large as can be seen from Table 2. We in this study analyze the monthly evolution dynamics of the airport networks. However, the proposed approach based on graph theories is generic and the evolution dynamics at a higher resolution can be easily achieved by changing the time period.

4.4 | Network structural properties

For each month of the traffic data, we construct a weighted network and an unweighted network using the way shown above. Both of the networks are directed. The basic structural properties of the constructed networks are summarized in Table 3.

In Table 3, m_{uw} and m_{wtd} represent the number of edges in G_{uw}^t and G_{wtd}^t, respectively. The symbols $\overline{\boldsymbol{k}_t}$ and $\overline{\boldsymbol{d}_t}$ represent the average degrees of networks G_{uw}^t and G_{wtd}^t, respectively.

We can see from Table 3 that for the constructed airport networks, each airport is connected around 16 airports on average as reflected by the values of $\overline{\boldsymbol{k}_t}$. The maximum values of $k_{i,t}$ indicate that there are hub airports in the constructed networks. We also observe from Table 3

TABLE 2 Basic data properties for each of the 12 months traffic data

Month	#Flights	#Canceled	#MissInfo	#Remained
Jan	583,985	16,726	1296	565,963
Feb	533,175	15,255	1606	516,314
Mar	632,074	12,564	1005	618,505
Apr	612,023	14,488	1515	596,020
May	636,390	13,012	2039	621,339
Jun	636,691	13,227	2577	620,887
Jul	659,029	12,928	2320	643,781
Aug	658,461	11,298	1812	645,351
Sep	605,979	10,016	1247	594,716
Oct	636,014	5172	1300	629,542
Nov	602,453	4446	1062	596,945
Dec	625,763	5793	1507	618,463

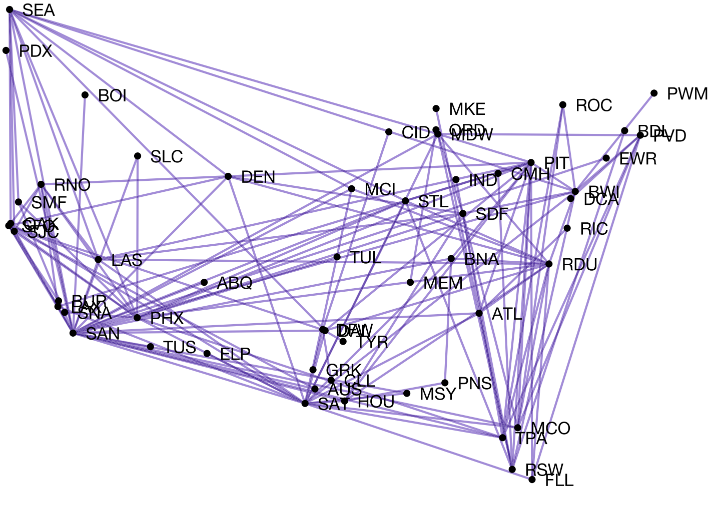

FIGURE 3 Visualization of a constructed unweighted spatial airport network using the traffic data of January 1, 2019. Each airport (black dot) is labeled with a three-letter string. [Color figure can be viewed at wileyonlinelibrary.com]

that the values of m_{wt} are quite stable. This indicates that the monthly traffic mobilities do not change significantly over month.

4.5 | Node degree distributions

In Table 3, the properties of the networks only provide a coarse view of the evolution dynamics of the airport networks in terms of network sizes and node degrees. Decision makers can only see how the size of the airport networks change over time. They also may wish to see how the connections between the airports look like. As a consequence, in this part we analyze the degree distributions of the networks.

Figures 4 and 5, respectively, show the degree distributions of the constructed unweighted and weighted airport networks. In the figures, the curve fittings for the degree distributions are also presented. For the curve fitting, two probability distribution functions (PDFs) are used, that is, the power law distribution and the Lognormal distribution. The PDFs of those two functions are provided below:

$$\text{Power Law: } P(k) = ck^{-\lambda}, \tag{17}$$

TABLE 3 Basic structural properties of the constructed weighted and unweighted spatial-temporal airport networks

Metric	Jan	Feb	Mar	Apr	May	Jun
n	359	359	359	359	359	359
m_{uw}	5552	5472	5592	5564	5574	5890
m_{wtd}	565,963	516,314	618,505	596,020	621,339	620,887
$\max(k_{i,t})$	163	164	168	172	171	177
$\min(k_{i,t})$	1	1	1	1	1	1
$\max(d_{i,t}^{in})$	30,797	27,907	33,762	32,615	34,173	33,802
$\min(d_{i,t}^{in})$	8	7	6	1	4	8
$\max(d_{i,t}^{out})$	30,783	27,936	33,752	32,606	34,137	33,872
$\min(d_{i,t}^{out})$	8	7	4	1	4	8
$\overline{\boldsymbol{k}_t}$	16.05	15.82	16.12	15.90	15.84	16.54
$\overline{\boldsymbol{d}_t^{in}}$	1635.73	1492.24	1782.44	1702.91	1765.17	1744.06
$\overline{\boldsymbol{d}_t^{out}}$	1635.73	1492.24	1782.44	1702.91	1765.17	1744.06
Metric	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
n	359	359	359	359	359	359
m_{uw}	5842	5890	5510	5492	5630	5716
m_{wtd}	643,781	645,351	594,716	629,542	596,945	618,463
$\max(k_{i,t})$	177	177	178	178	175	178
$\min(k_{i,t})$	1	1	1	1	1	1
$\max(d_{i,t}^{in})$	34,957	35,228	31,546	33,554	31,143	32,247
$\min(d_{i,t}^{in})$	8	2	3	8	8	2
$\max(d_{i,t}^{out})$	34,978	35,158	31,668	33,523	31,114	32,174
$\min(d_{i,t}^{out})$	8	2	3	8	8	1
$\overline{\boldsymbol{k}_t}$	16.41	16.54	15.70	15.60	16.22	16.38
$\overline{\boldsymbol{d}_t^{in}}$	1808.37	1812.78	1694.35	1788.47	1720.30	1772.10
$\overline{\boldsymbol{d}_t^{out}}$	1808.37	1812.78	1694.35	1788.47	1720.30	1772.10

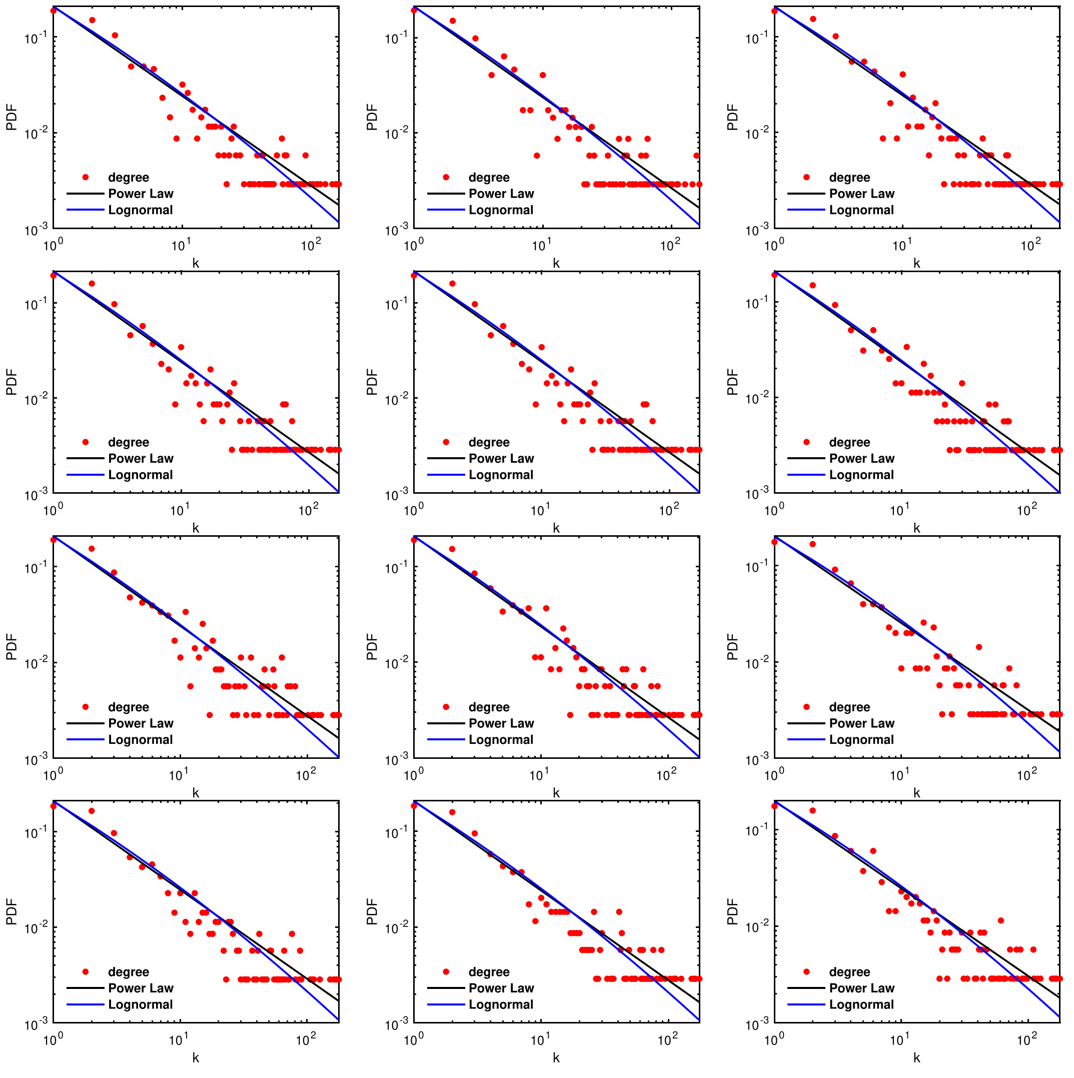

FIGURE 4 Degree distributions together with the corresponding curve fittings for the distributions of the 12 (January to December from lefthand side to righthand side in consecutive order) constructed unweighted airport networks. [Color figure can be viewed at wileyonlinelibrary.com]

$$\text{Lognormal: } P(k) = \frac{1}{\sqrt{2\pi}\,\sigma k} e^{\frac{-(\ln k-\mu)^2}{2\sigma^2}}. \tag{18}$$

We can see from Figure 4 that the degree distributions of the unweighted networks tend to follow the power law as well as the Lognormal distributions, because the scattered points tend to follow the trends of the black and blue curves quite well. However, Figure 5 indicates that the two adopted PDFs do not fit the degree distributions of the weighted networks well since the scattered points deviate too much from the trends of the black and blue curves.

Table 4 records the statistical results for the curve fittings of the degree distributions of the unweighted and weighted networks. The statistical results include the fitted parameters of the corresponding PDFs and the values of the R^2 metric indicating the goodness of the curve

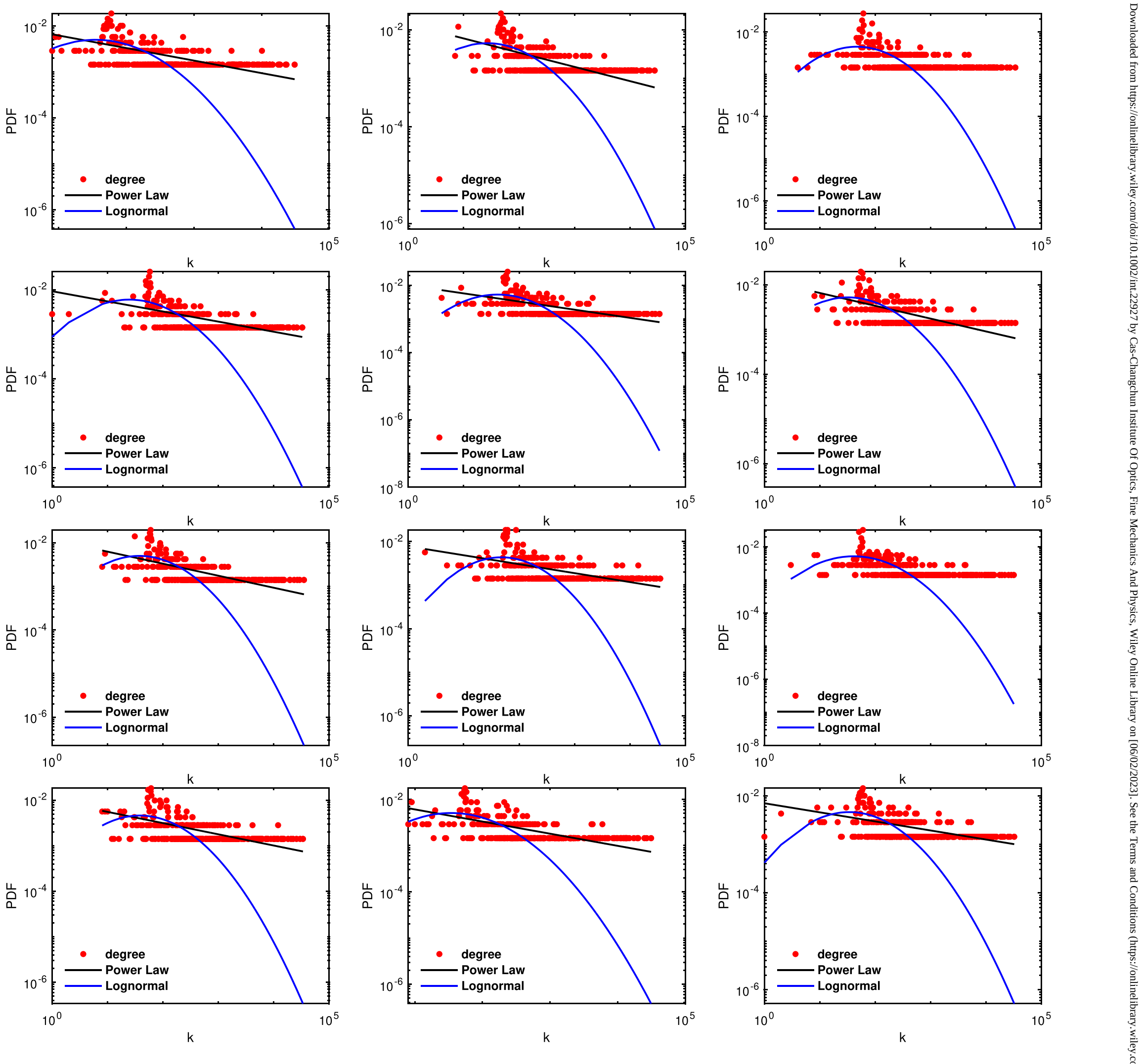

FIGURE 5 Degree distributions together with the corresponding curve fittings for the distributions of the 12 (January to December from lefthad side to righthand side in consecutive order) constructed weighted airport networks. [Color figure can be viewed at wileyonlinelibrary.com]

fittings. We can clearly see from Table 4 that the Lognormal PDF fits better for the unweighted networks. Note that many existing research indicate that the degree distributions of many real-world networks follow the power law distributions.[41,42] However, our research finding is still in line with existing findings. Although the R^2 values for the Lognormal distributions are higher than those of the power law distributions, those values are still quite close to each other. We still can conclude that the degree distributions of the unweighted networks follow the power law distributions.

Note that both Figure 5 and Table 4 demonstrate that the two adopted PDFs do not fit well the degree distributions of the weighted networks. It seems that the degree distributions of the weighted networks do not follow any known probability distributions. We have tried 10 other well-known PDFs. However, the fitting results are worse than those shown in Table 4.

TABLE 4 Statistical results for the curve fittings of the degree distributions

Month	Power law	LogNormal	Month	Power law	LogNormal
Jan	c = [0.2093, 0.0117]	σ = [1.5844, 0.6765]	Jul	c = [0.2097, 0.0118]	σ = [1.618, 0.6641]
	λ = [0.9394, 0.2728]	μ = [1.0012, 2.5971]		λ = [0.9413, 0.2762]	μ = [0.9569, 2.5878]
	R^2 = [0.9343, 0.2534]	R^2 = [0.9434, 0.3115]		R^2 = [0.939, 0.2318]	R^2 = [0.9454, 0.2881]
Feb	c = [0.2132, 0.013]	σ = [1.6227, 0.7201]	Aug	c = [0.2073, 0.0077]	σ = [1.6359, 0.6431]
	λ = [0.955, 0.293]	μ = [0.903, 2.6171]		λ = [0.9448, 0.205]	μ = [0.9694, 2.6338]
	R^2 = [0.9283, 0.2381]	R^2 = [0.9359, 0.2712]		R^2 = [0.9384, 0.1472]	R^2 = [0.9455, 0.1899]
Mar	c = [0.207, NaN]	σ = [1.5603, 0.6423]	Sep	c = [0.2039, −906.6123]	σ = [1.4746, 0.6372]
	λ = [0.9296, NaN]	μ = [1.0519, 2.6176]		λ = [0.9049, NaN]	μ = 1.1466, 2.5446]
	R^2 = [0.9219, NaN]	R^2 = [0.9315, 0.2002]		R^2 = [0.9105, NaN]	R^2 = [0.923, 0.2156]
Apr	c = [0.216, 0.0093]	σ = [1.5963, 0.7083]	Oct	c = [0.21, 0.0098]	σ = [1.5377, 0.6745]
	λ = [0.9529, 0.2279]	μ = [0.8986, 2.5459]		λ = [0.9308, 0.2467]	μ = [1.0374, 2.6299]
	R^2 = [0.9315, 0.2005]	R^2 = [0.9394, 0.2987]		R^2 = [0.9256, 0.1953]	R^2 = [0.9364, 0.2302]
May	c = [0.2141, 0.0101]	σ = [1.5689, 0.6311]	Nov	c = [0.2079, 0.011]	σ = [1.5864, 0.6788]
	λ = [0.9414, 0.2423]	μ = [0.9565, 2.5317]		λ = [0.9374, 0.2626]	μ = [1.0144, 2.5974]
	R^2 = [0.9408, 0.1835]	R^2 = [0.9491, 0.2644]		R^2 = [0.9323, 0.2437]	R^2 = [0.9419, 0.2962]
Jun	c = [0.2094, 0.0127]	σ = [1.6415, 0.6828]	Dec	c = [0.1987, 0.007]	σ = [1.5291, 0.6983]
	λ = [0.9496, 0.2871]	μ = [0.9346, 2.584]		λ = [0.9067, 0.187]	μ = [1.1667, 2.6536]
	R^2 = [0.9425, 0.2572]	R^2 = [0.9491, 0.306]		R^2 = [0.9194, 0.2105]	R^2 = [0.9301, 0.2889]

Note: Regarding the parameters, the first column represents the results for the unweighted networks and the second the weighted ones.

This phenomenon can be attributed to the specific traffic flow patterns as the weights of the networks are the traffic flows between the airports.

4.6 | Traffic delay distributions

Air traffic systems are very complicated. Any delay to a certain flight can cause the ripple effect, that is, the delay can propagate in the system affecting a large body of flights.[4,18] It is important to analyze the delay distributions of the constructed airport networks as such analysis can help aviation managers better manage air traffic systems to improve the efficiency of the system. Based on the cleaned traffic data, we obtain the delay information. According to the literature,[4,18] a flight is said to be delayed if the delay is no smaller than 15 min. We then filter out the delay information based on this criterion.

Figure 6 exhibits the distributions of the traffic delays over 12 months. We can see from the first row of Figure 6 that the monthly delay distributions are quite similar. In the second row of Figure 6, we choose the delay for January and do the corresponding curve fittings. We have observed that the delay distributions do not follow the power law distributions. Therefore, apart

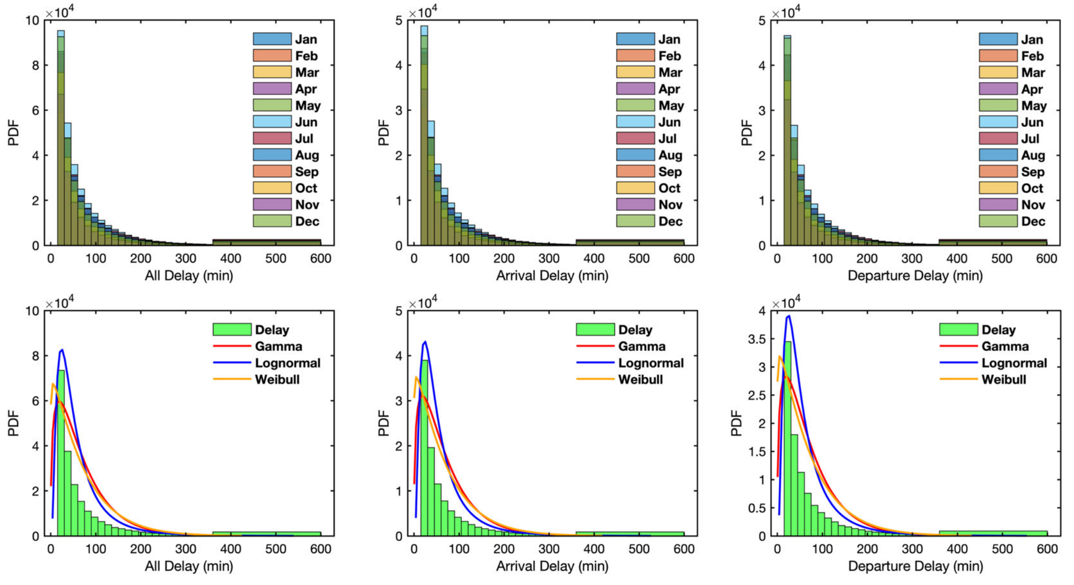

FIGURE 6 Distributions (first row) and curve fittings (second row) of the air traffic delays over time. The R^2 values for the three curve fitting cases are, respectively, $R^2 = [0.9618\ 0.9939\ 0.9639]$; $R^2 = [0.9633\ 0.9930\ 0.9687]$; $R^2 = [0.9620\ 0.9942\ 0.9624]$. [Color figure can be viewed at wileyonlinelibrary.com]

from the Lognormal distribution, we also introduce the Gamma and Weibull distributions. The PDFs of these two distributions are provided below.

$$\text{Gamma: } P(k) = \frac{1}{\Gamma(\beta)\theta^{\beta}} k^{\beta-1} e^{\frac{-k}{\theta}}, \tag{19}$$

$$\text{Weibull: } P(k) = \frac{\beta}{\theta}\left(\frac{k}{\theta}\right)^{\beta-1} e^{-\left(\frac{k}{\theta}\right)^{\beta}}. \tag{20}$$

We observe that the distributions of the delays follow Lognormal distributions as indicated by the R^2 values. The results shown in Figure 6 indicate that the airport system of the USA is quite stable over time in terms of traffic delay.

Figure 7 exhibits the linear relationships between the monthly arrival delays and the departure delays. The curve fittings as shown in Figure 7 clearly indicate the linear relationships between the arrival and departure delays. The coefficients of the linear functions for the 12 months are quite close to each other. This explains the phenomenon shown in the first row of Figure 6.

4.7 | Causal factor

As mentioned earlier, the traffic delay is a key performance indicator for analyzing the dynamics of air traffic system. Air traffic delay is related to the traffic demand and the associated airport network. However, the delay distributions as shown in Figure 6 indicate that the delay distributions do not vary too much over the months. This section aims to analyze the possible causality behind this phenomenon.

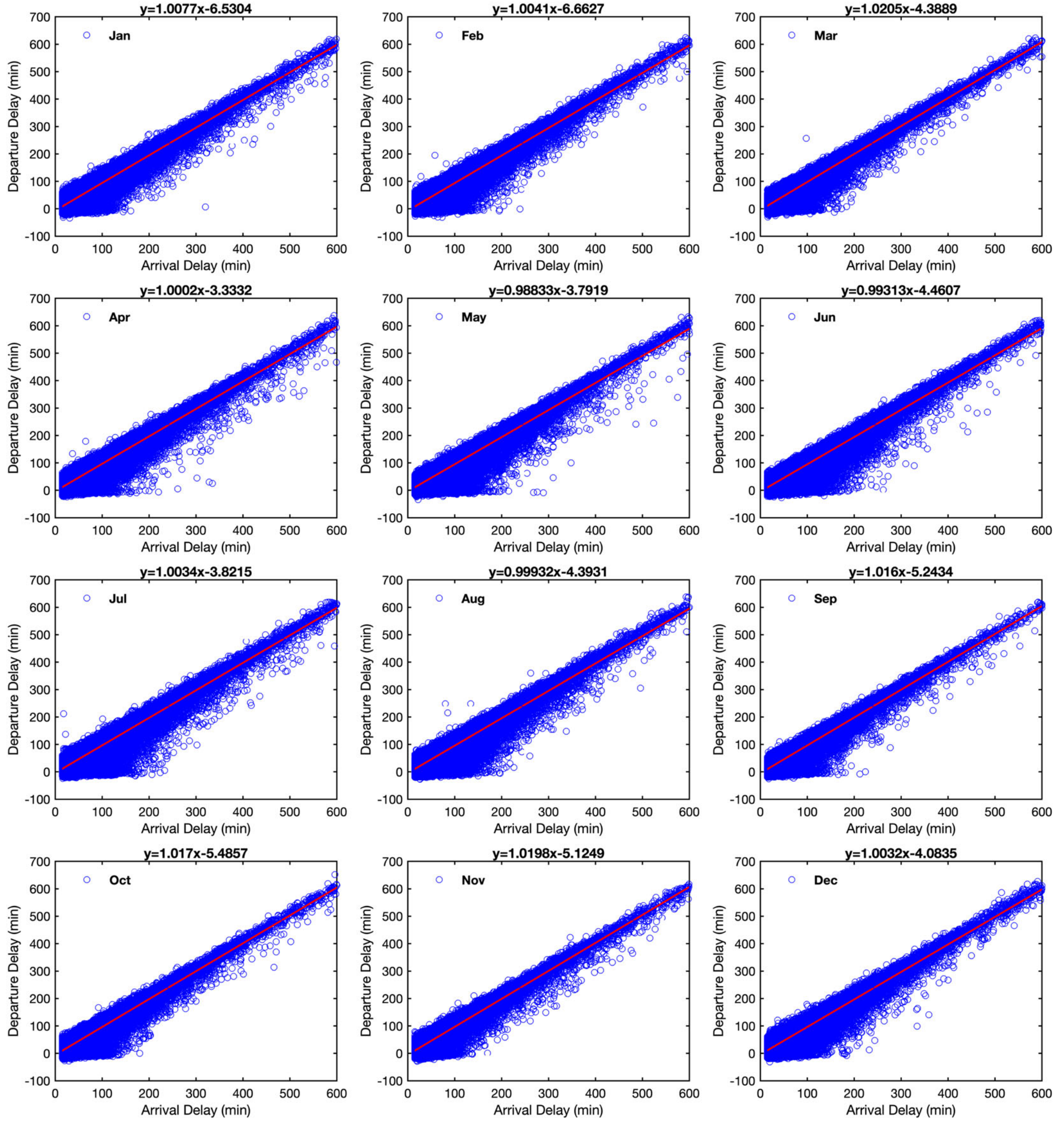

FIGURE 7 Linear relationships between the arrival delays and the departure delays with respect to the 12-month traffic data of the American flights of 2019. [Color figure can be viewed at wileyonlinelibrary.com]

Since delay is closely related to the structure of the airport network, we therefore analyze the similarities between the constructed spatial-temporal airport networks. For a given airport network constructed based on a given month of traffic data, we have its two corresponding adjacency matrices, i.e., the unweighted and weighted matrices. We turn those matrices into vectors. Therefore, we have two vectors, one is a binary sequence and the other one is an integer sequence.

For the 12 unweighted matrices constructed over the 12 months traffic data, we calculate the pairwise similarities using the three similarity indices summarized in Section 3.6. Analogously, we do the same to the weighted networks. The similarity results are presented in Figure 8.

The first row of Figure 8 shows the similarities between the unweighted networks with respect to the three similarity indices presented in Section 3.6. We can clearly see from the first

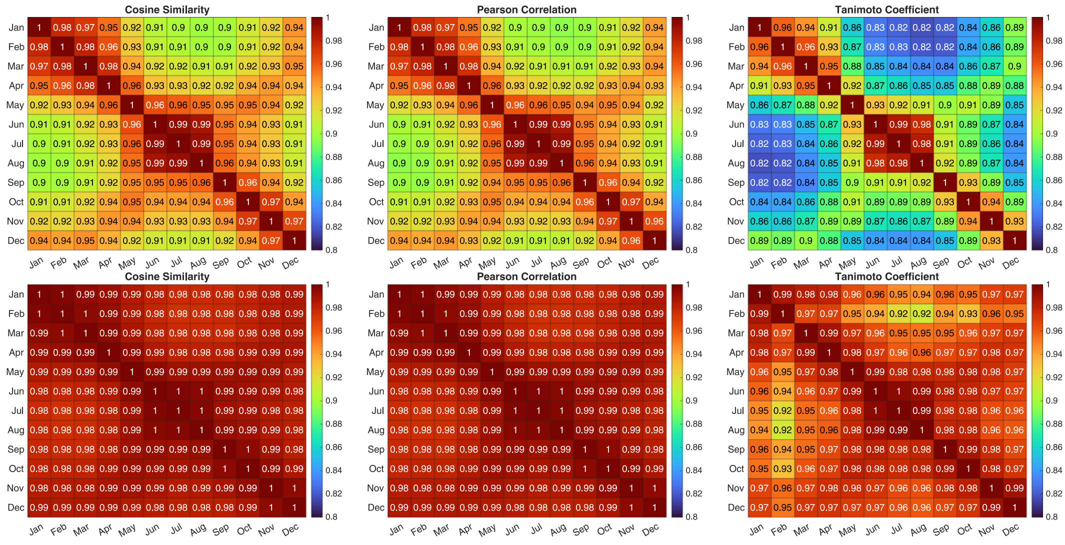

FIGURE 8 Similarities between the constructed unweighted (first row) and weighted (second row) airport networks using the 12-month traffic data of 2019. [Color figure can be viewed at wileyonlinelibrary.com]

row of Figure 8 that the similarities between the unweighted networks based on the Cosine and Pearson indices are quite high (larger than 0.9), while the similarities with respect to the Tanimoto coefficient are also high (larger than 0.8). The unweighted networks only reflect the structural properties of the airport networks. The high similarities indicate that the structures of the American airport networks do not show significant changes over the 12 months of 2019. Putting it another way, no new airports were built and no airports were closed in 2019.

The second row of Figure 8 shows the similarities between the weighted networks whose weights represent the traffic mobilities. We can see from Figure 8 that the similarities between the weighted networks with respect to the Cosine and Pearson indices are around 0.98, while the similarities with respect to the Tanimoto coefficient are around 0.95. The similarities between the weighted networks are also quite high. The high similarities indicate that the traffic mobilities over the 12 months of 2019 do not vary significantly. Putting it another way, the monthly traffic demands and traffic control procedures are stable.

As mentioned earlier, traffic delay is related to both the airport networks and the traffic mobility. The delay of a flight could propagate and magnify on an airport network. The traffic mobility defines the traffic demand which is the source of the traffic delay. However, the results shown in Figure 8 indicate that both the structures of the airport networks and the monthly traffic mobility are quite stable. This is the mainly causality for the stable distributions of the monthly traffic delays as shown in Figure 6.

4.8 | Network resilience

As mentioned earlier, we analyze the resilience of airport networks under airport failures. For a given airport network G with n nodes and m edges, we assume that $q \in [0, 1]$ fraction of the airports, that is, nodes, are failed due to perturbations. Then we quantify the resilience of G using the indices shown in Section 3.7.

In the experiments we set the interval of the range of q to be 0.025. For a given value of q, we apply the failures to a given network for 50 independent times. Thus, we get the average resilience. Figure 9 demonstrates the resilience of the 12 unweighted airport networks under different node failure mechanisms with respect to four resilience metrics.

We can clearly see from Figure 9 that the values of Rn_GC, Rn_RC, Rm_GC, and Rm_RC in the first and third columns of Figure 9 decrease quite slowly as the increase of q. This indicates that the unweighted airport networks are quite robust when random node failures and the failures of nodes in an ascending order of their degrees happen. The values of Rn_GC, Rn_RC,

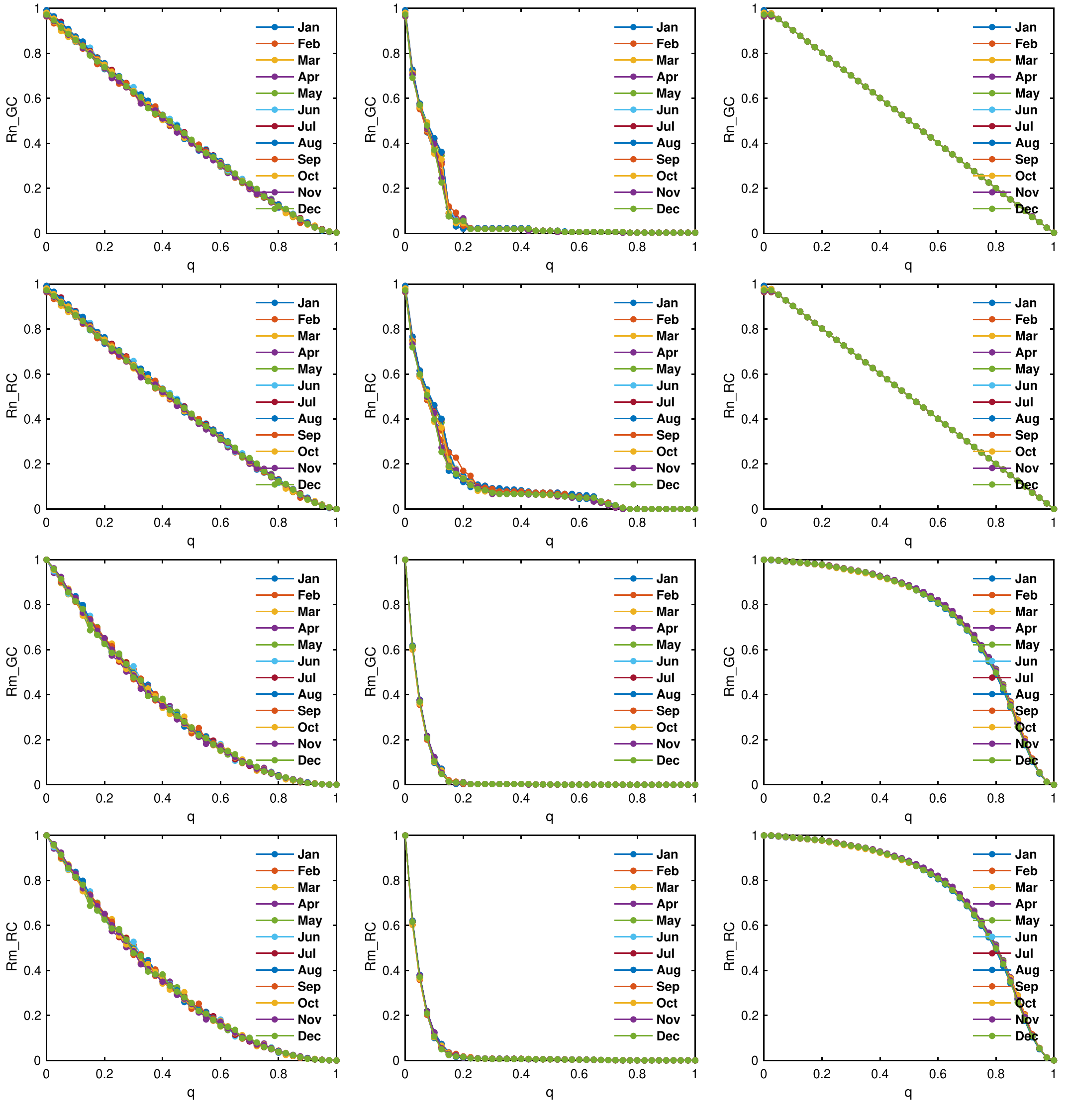

FIGURE 9 Resilience of the unweighted airport networks under airport failures with three different failure models. First column—random failure; Second column—by descend order of node degrees; Third column—by ascending order of node degrees. Results are obtained over 50 independent runs. [Color figure can be viewed at wileyonlinelibrary.com]

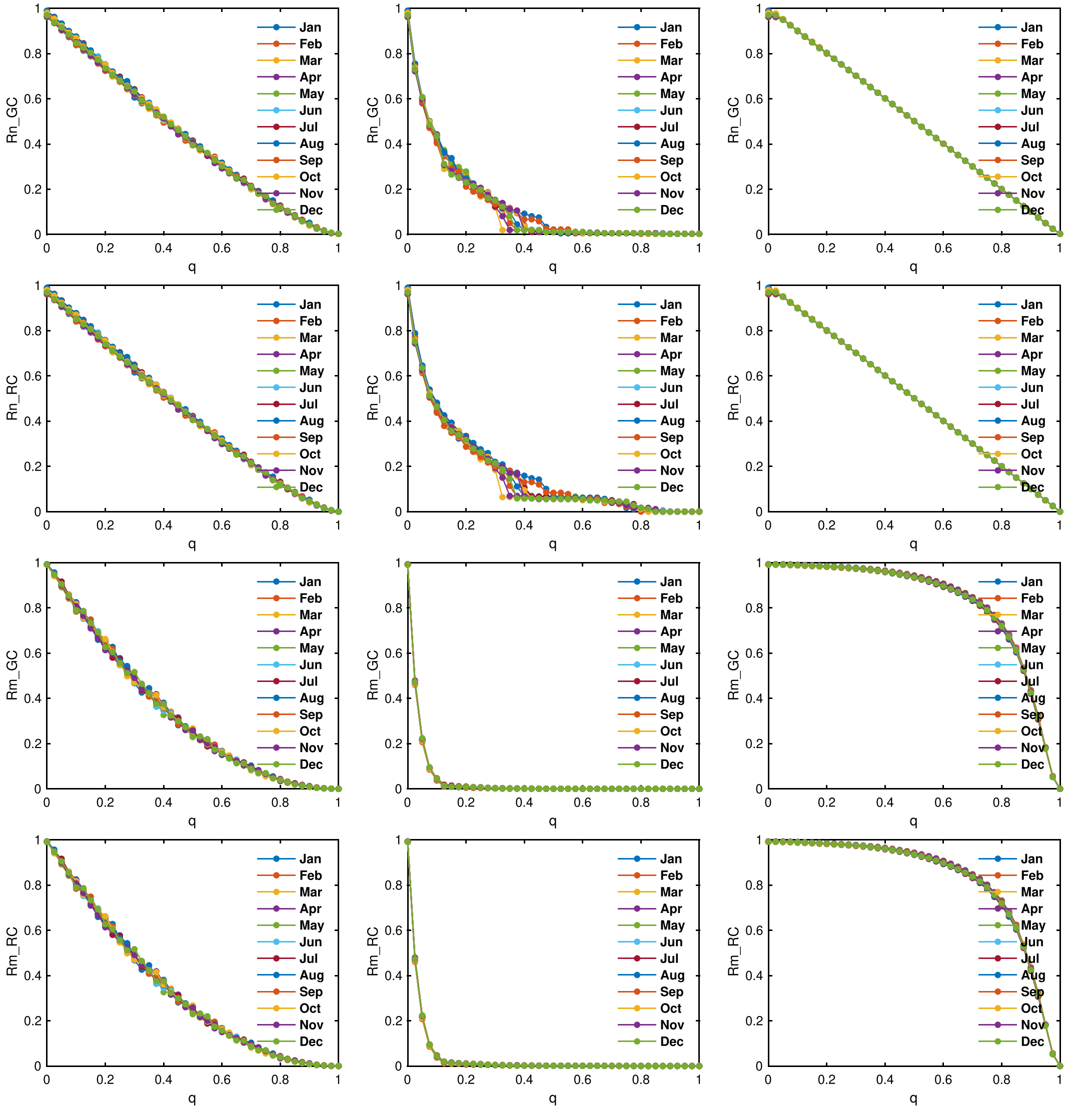

FIGURE 10 Resilience of the weighted airport networks under airport failures with three different failure models. First column—random failure; Second column—by descending order of node degrees; Third column—by ascending order of node degrees. Results are obtained over 50 independent runs. [Color figure can be viewed at wileyonlinelibrary.com]

Rm_GC, and Rm_RC in the second column of Figure 9 decrease quite fast as the increase of q. This indicates that the unweighted airport networks are fragile if hub airports are failed.

The experiments shown in Figure 9 only investigate the resilience of airport networks with respect to the cascading failure model 1 as discussed in subsection 3.7. In other words, the results shown in Figure 9 demonstrate the resilience of the networks in terms of network structures since the networks are unweighted and do not carry any weight information. Therefore, the resilience has nothing to do with the traffic scenarios since in model 1, if an airport is failed, then model 1 only removes the edges attached to that airport. As a consequence, model 1 cannot capture the impact of the failed airport on the traffic. It would be more appealing to aviation decision makers if the impact of airport failures on the traffic can be known.

In view of the above, we in what follows investigate the resilience of the airport networks with respect to the cascading failure model 2 which deals with traffic mobility. Model 2 mimics the impact of a failed airport on the entire traffic. The corresponding results are shown in Figure 10.

We can see from Figure 10 that the resilience of the airport networks with respect to model 2 are a little bit different to what are shown in Figure 9. The results shown in Figure 10 indicate the impacts of the airport failures on the airport network structure (captured by Rn_GC and Rn_RC) and the traffic mobility (captured by Rm_GC and Rm_RC) are quite small. even the cascading failure model 2 is considered. This indicates that the American airport networks and the traffic control are well managed. The results shown in the second column of Figure 10 differ slightly from those in the second column of Figure 9. Overall, we notice that the failure of around 10% of the hub airports could lead to the collapse of the entire traffic network, while the percentage with respect to cascading failure model 1 is 20%. Besides, we notice an interesting phenomenon. Under cascading failure model 2 and node failure mode 2, the portions of remained nodes both in the giant components and the remained components are higher than those with respect to cascading failure model 1. In other words, when some hub airports failed, the entire airport network still can function properly as most airports are still available. This study finding reflects the special design and management of the American airport networks.

5 | CONCLUSION

Air traffic plays a very important role in human society. People rely on air traffic for diverse kinds of purpose. Since air traffic is indispensable to the air traffic systems, it is therefore of great significance to build an efficient and resilient air traffic systems. It would be of great value to aviation decision makers if a comprehensive knowledge about how the air traffic systems evolve over time can be gained. Note that it is quite challenging to trace the evolution process in air traffic systems because an air traffic system is quite complex since it consists of a magnitude of components which often interact with each other.

To trace the evolution dynamics in air traffic systems, the most effective way is to build complex networks representing the air traffic systems and then apply network theories. In this study we proposed a spatial-temporal network approach to investigate the evolution of air traffic systems. Our proposed approach mainly differs from existing studies in two ways. First, our approach modeled air traffic systems by both weighted and unweighted complex networks using real-world traffic data, while most of existing studies only consider unweighted networks. Second, our proposed approach investigated the evolution of air traffic systems by analyzing a couple of network properties, while most of existing studies only pay attention to one or two properties.

To investigate the evolution of air traffic systems, we first constructed spatial-temporal airport networks using real traffic data. We then analyzed the evolution dynamics of the constructed networks in terms of network properties including nodal degrees, degree distributions, traffic delays, causality between graph structures and traffic delays, and system resilience under airport failures. We carried out a case study on the American airport systems with respect to 12-month traffic data. We discovered that the American airport networks are quite stable in terms of network structures over the studied 12 months. We also observed a stable evolution of the traffic movements. A similarity analysis between the structures of the constructed network indicate that the stabilities of the network structures and traffic movements lead to a stable evolution of the traffic delays. We analyzed the resilience of the American airport networks under airport failures. To do so, we proposed two network cascading failure models. We discovered that the airport networks are quite robust to random airport failures. However, if hub airports are failed, then we discovered that failures of respectively 20% and 10% of the hub airports will lead to the collapse of the entire system with respect to the two proposed cascading failure models.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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