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A Spatial–Temporal Network Perspective for the Propagation Dynamics of Air Traffic Delays

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ABSTRACT

Intractable delays occur in air traffic due to the imbalance between ever-increasing air traffic demand and limited airspace capacity. As air traffic is associated with complex air transport systems, delays can be magnified and propagated throughout these systems, resulting in the emergent behavior known as delay propagation. An understanding of delay propagation dynamics is pertinent to modern air traffic management. In this work, we present a complex network perspective of delay propagation dynamics. Specifically, we model air traffic scenarios using spatial–temporal networks with airports as the nodes. To establish the dynamic edges between the nodes, we develop a delay propagation method and apply it to a given set of air traffic schedules. Based on the constructed spatial-temporal networks, we suggest three metrics—magnitude, severity, and speed—to gauge delay propagation dynamics. To validate the effectiveness of the proposed method, we carry out case studies on domestic flights in the Southeastern Asia region (SAR) and the United States. Experiments demonstrate that the propagation magnitude in terms of the number of flights affected by delay propagation and the amount of propagated delays for the US traffic are respectively five and ten times those of the SAR. Experiments further reveal that the propagation speed for US traffic is eight times faster than that of the SAR. The delay propagation dynamics reveal that about six hub airports in the SAR have significant propagated delays, while the situation in the United States is considerably worse, with a corresponding number of around 16. This work provides a potent tool for tracing the evolution of air traffic delays.

1. Introduction

Air transport is pivotal to modern traffic, as it facilitates our lives. Characterized by its high level of safety and fast speed, air transport is prioritized by travelers, resulting in the phenomenal growth of air traffic demands [1,2]. Air transport is associated with air transport systems, which encompass manifold components interacting with one another, usually in a nonlinear fashion [3,4]. The complex dynamics of air transport systems, together with a variety of uncertainties such as inclement weather, airspace restriction, mechanical failures, and so forth, result in intractable air traffic delays [5] which can be extremely difficult for air traffic controllers to deal with. This situation could worsen in the coming decade, as air traffic demands are envisaged to increase.

Air traffic delay is one of the most challenging tasks being addressed by modern air traffic management (ATM). It not only harms entities such as passengers, airlines, and airports, but also results in economic losses [6,7]. Furthermore, air traffic delay increases the pollution load on the natural environment [8,9]. It should be pointed out that air traffic delay is bound to happen, due to a wide range of factors [5,10]. Many efforts have been made in the past several decades to probe the reasons for delays and their internal causalities [11,12]. After building a comprehensive understanding of the relationships among the causal factors and various components of air traffic delays, scientists have spared no efforts in seeking remedies to mitigate them [13–15]. Representative initiatives include Air Traffic Flow Management (ATFM) [16,17], Ground Delay Programs (GDPs) [18,19], and Collaborative Decision-Making (CDM) [20–22]. All these procedures have proven to be valuable in reducing air traffic delays.

While tremendous collaborative efforts are still needed in the research on air traffic delay mitigation, a very fundamental yet challenging task pertaining to modern ATM is delay prediction [23,24]. Prediction of flight delays is significant to those working in aviation, especially during their decision-making process [25,26]. Thus far, researchers have developed many delay prediction methods. In particular, the data sciences represented by

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machine learning techniques are gaining notable momentum in delay prediction [27–30]. A comprehensive literature survey on delay prediction can be found in Ref. [26]. Despite the abundance of methods for delay prediction, it is cumbersome to develop models or methods that can predict precisely, given the vast amount of flight operation data available and the high complexity of air transport systems [26].

In reality, airlines construct flight schedules with the intent of maximizing passenger movements. As a result, an aircraft normally operates a number of flight "legs" or "hops" (where a leg or hop refers to a flight between two airports that is part of the aircraft's itinerary). Consequently, the delay of an upstream flight can spread to downstream flights causing reactionary delays, and the reactionary delays of one aircraft will continue to cause a cascade of reactionary delays for other aircraft. Air traffic delays therefore display the "ripple effect," which is detrimental to aviation workers [31]. According to the ripple effect, also known as delay propagation [32] primary flight delays grow and propagate within complex air transport systems. Studies on delay propagation have attracted an enormous amount of attention from researchers not only in the field of aviation, but also in the fields of computer science, management science, system science, and more [33,34]. Compared with studies on delay prediction, studies on delay propagation may be more appealing, as they can assist in locating the origins of delays, calculating reactionary delays, and understanding how delays evolve, making it possible for efficient measures to be taken to counterbalance the ripple effect [31].

Dozens of studies have investigated flight delay propagation. In the literature, researchers have explored delay propagation phenomena in regions such as the United States [32,35,36], Europe [37], and China [38]. In order to gauge the amount of propagated delays, researchers have devised several metrics, including the delay multiplier (DM) index [39]. In order to trace how primary delays propagate, scientists have mainly utilized agent-based methods to model the propagation process [32,35,37]. Because of delays, multiple flights may simultaneously request services. To resolve this conflict, scientists have predominantly applied the queuing theory [36].

Delay propagation is a collective phenomenon, as air traffic involves a variety of interacting components [5,40,41]. It is natural and straightforward to introduce complex network theories and tools to research on air traffic [40,42,43]. Although complex network modeling for air transport has a short history [44,45], its systemic view is injecting new blood into ATM. While the majority of existing studies on delay propagation focus on the estimation of reactionary delays, several studies on network models for delay propagation analysis have already shown great potential [35,36,46]. However, to the best of our knowledge, Refs. [35,36,46] failed to make use of the spatial–temporal properties of the constructed networks. Consequently, those works cannot provide a comprehensive understanding of delay propagation dynamics.

In this study, we present a dynamic network perspective of the propagation dynamics of air traffic delays. More specifically, for a given set of aircraft itineraries, each of which has a one-day cycle, we model the daily traffic scenario with a spatial–temporal network, given that each aircraft has a departure delay for the first flight leg. We suggest a simple yet effective delay propagation mechanism to transfer the delays as the aircraft implement their rotations. In case multiple flights request services simultaneously at the same airport due to delays, we apply our developed delay assignment strategies to prioritize the flights. At a given time point, we construct a spatial airport network with the delayed departure flights as the edges. For a one-day duration, we then construct a spatial–temporal network. Next, we analyze the degree properties of the constructed spatial–temporal network to quantify the delay propagation dynamics in terms of magnitude, speed, and severity. To verify the effectiveness of the proposed network perspective, we carry out case studies on domestic flights in the SAR and the United States that were operated in the last part of 2016. The experimental results demonstrate that the proposed network-based method can provide spatial–temporal details of the delay propagation process. The experiments also reveal that the delay propagation dynamics of flights in the SAR differ substantially from those in the United States in terms of magnitude, severity, and speed.

2. Related backgrounds

2.1. Spatial networks

Network modeling has proven to be a potent tool for capturing the systemic behaviors of complex systems [44,45]. Generally speaking, a network is a set of nodes and edges. The nodes of a network denote the components of the focal network or networked system, while the edges represent the interactions or relationships between components. Mathematically, a network is denoted by $G = \{V, E\}$ with $n = |V|$ being the cardinality of the node set V, and $m = |E|$ the cardinality of the edge set E. A network is generally represented by its adjacency matrix A, with the entry a_{ij} quantifying the relationship between nodes i and j.

In this work, we study the delay propagation dynamics of air traffic. In order to capture systemic delays, we construct airport networks with airports as the nodes. For an airport network G, if a flight flies from airport i to airport j, then an edge $e_{ij} \in E$ connecting nodes $v_i \in V$ and $v_j \in V$ is created.

The constructed airport networks can be weighted and/or directed, depending on the specific calculation purposes. As the airports include geographical information, the constructed networks are spatial networks [47].

2.2. Temporal networks

Complex systems in reality are usually time-evolving; that is, their structures change over time. In order to trace their evolution, scientists have developed an effective tool: temporal networks [48]. Mathematically, for a given time period $[t_0, t_{\text{end}}]$, a temporal network G can be denoted by a network sequence, that is, $G = \{G^{t_0}, G^{t_1}, \ldots, G^{t_{\text{end}}}\}$, with G^{t_i} being the snapshot at time point t_i.

In this study, we construct airport networks. The edge constructions of the networks depend on the air traffic demands, which are time-evolving. Therefore, we can generate a sequence of airport networks to form temporal airport networks. As mentioned above, airports include geographical information. Consequently, the constructed airport networks are spatial–temporal networks.

2.3. Air traffic delay

The notion of delay is common in the transportation domain. In the air traffic domain, delay is normally defined as the difference between the scheduled and actual flight operation times. According to the definitions provided by the Federal Aviation Administration (FAA), a flight is considered to be delayed if it is 15 min or more past its scheduled time [49]. For research purposes, we consider a flight to be delayed in this work if its delay is positive.

The flying process of a flight generally encompasses two phases: the ground phase, which includes the departure and approach; and the airborne phase (from wheels off to wheels on), which covers the flight stages of climbing, cruising, and descending. Flight delay can occur in every phase. In the ground phase, the following five types of delay are mainly encountered:

- Departure delay: There is a difference between the actual and scheduled gate-out times.
- Taxi-out delay: There is a difference between the actual and scheduled taxi-out times.
- Taxi-in delay: There is a difference between the actual and scheduled taxi-in times.
- Arrival delay: There is a difference between the actual and scheduled gate-in times.
- Turn time delay: There is a difference between the actual and scheduled turn times.

In the airborne phase, the airborne delay is determined to be the difference between the actual and scheduled airborne times.

3. Research problem and contribution

3.1. Problem description

This work is dedicated to investigating the propagation dynamics of air traffic delays by using dynamic network modeling and analysis. Fig. 1 presents a graphical illustration of the research problem and the core idea of the network-based approach.

Fig. 1(a) depicts an air traffic scenario in which a set of aircraft are implementing their flight itineraries. The condition is that the first flight leg for each aircraft has a departure delay. For example, as shown in the bottom part of Fig. 1(a), the flight departing from Makassar to Jakarta is delayed for 10 min. Due to the flights' rotations, the primary delays can propagate and elicit delays in other flights. Our research purpose is to understand the delay propagation dynamics. More specifically, we aim to answer these questions: ① How much is the propagated delay? ② How long will the delay propagation last? ③ How fast can the delay propagate?

In order to probe answers to these questions, we suggest a dynamic network perspective. We first convert the air traffic scenario into a spatial–temporal airport delay network, with the nodes being the spatial airports and the edges being the delayed departure flights (Fig. 1(b)). We then analyze the degree properties of the constructed spatial–temporal networks in order to quantify the delay propagation dynamics in terms of magnitude, severity, and speed.

3.2. Research contribution

This work suggests a complex network perspective towards understanding the delay propagation dynamics of air traffic. This work contributes to ATM in the following aspects.

(1) **It provides a fine-grained view of delay propagation dynamics.** Complementary to existing studies on delay propagation, which only provide a coarse-grained view, this work provides a fine-grained view of spatial–temporal resolution by making use of dynamic network modeling and analysis. The network-based approach can trace the evolution process of delay propagation at given airports at given times and time durations.

(2) **It assists with strategic ATM.** This study investigates delay propagation dynamics in terms of magnitude, severity, and speed. The proposed network approach can be implemented in real time. Therefore, the outcome of this study could facilitate airlines in enabling quality pre-assessment of flight schedules in terms of reactionary delays, such that they could adjust the schedules accordingly in order to mitigate air traffic delays. Furthermore, since the network approach can trace the delay propagation process with a spatial–temporal resolution, the outcome of this study will assist air navigation service providers and airports to provide better service.

(3) **It contributes to CDM**. CDM is recognized as a promising paradigm for modern air traffic control. This work carries out case studies on domestic flights in the SAR and the United States, and reveals that only hub airports encounter significant delay propagation. As the proposed approach can estimate temporal propagated delays in real time for given airports, aviation players can choose the proper time to apply CDM to hub airports in order to mitigate the impact of delay propagation. Upon the implementations of several CDM initiatives, the proposed approach can be re-applied to the updated traffic scenario in order to assist decision-makers with further ATM.

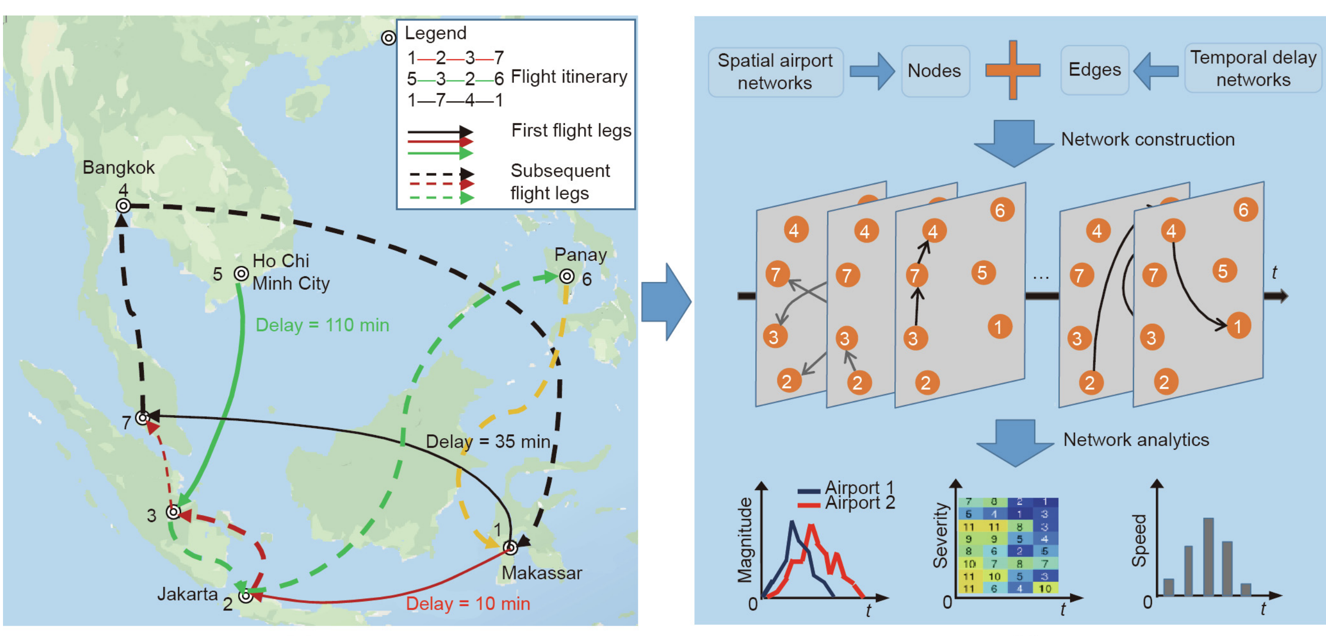

Fig. 1. A conceptual diagram of the studied problem and the core idea of the proposed dynamic network approach for understanding the propagation dynamics of air traffic delays. (a) A traffic scenario in which four aircraft (distinguished by color) are implementing their flight itineraries, and each aircraft has a departure delay for the first flight leg. (b) A summary of the idea of the proposed network approach for understanding the delay propagation dynamics.

4. Research methodology

4.1. Method overview

In order to solve the research problem, we first present an overview of the proposed approach and delineate its procedures in Fig. 2.

It can be seen from Fig. 2 that the core idea of the proposed approach is to construct a spatial–temporal airport network. To achieve this goal, we develop a delay propagation mechanism and a delay assignment mechanism. In what follows, we will elaborate each of the two key components in detail.

4.2. Primary departure delay

In this work, we refer to the primary departure delay as the delay of the first flight leg in an aircraft's itinerary. The primary departure delay is utilized as the stimulus to elicit the reactionary departure and arrival delays. There are two ways to work out the primary departure delays: obtaining them from data or sampling from a given distribution.

Here, we directly derive the primary departure delays from the real-world flight operation data. The reasons for doing so are twofold. First, it is straightforward and easy to obtain the primary departure delays from real data. Second, the sampling-based method requires prior knowledge such as the delay distribution.

4.3. Delay propagation mechanism

The delay propagation mechanism is utilized to capture the reactionary delays. Putting it another way, for all flights $f_i \in [1, N_f]$, the propagation mechanism is used to estimate the actual departure time $t^{f_i}_{AD}$ and actual arrival time $t^{f_i}_{AA}$, where N_f is the total number of flights. The delay propagation mechanism works on the basis of the following assumptions.

(1) **No flight can depart more than 5 min earlier.** In real-world scenarios, airlines can bring forward their flight plans, resulting in earlier departures (these can be several hours ahead of schedule, as reported in real cases). Apart from flight plan adjustment, some flights can depart slightly earlier than scheduled once all necessary preparation procedures—such as refueling, payload loading, and passenger embarkation—have been done. In our model, we hypothesize that the earliest departure cannot be more than 5 min before the scheduled departure.

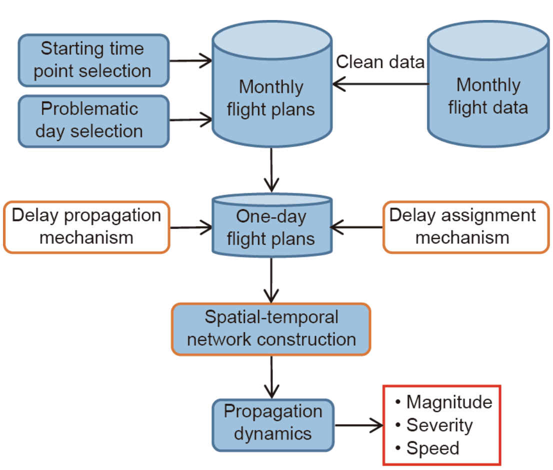

Fig. 2. Flowchart of the proposed network approach for the propagation dynamics of air traffic delays.

(2) **Departures from and arrivals at the same airport are served by different runways.** Flight departures and arrivals require airport runway services. In this work, we assume that each airport accommodates the departures and arrivals separately by using different runways. In real life, some airports may only have single runways. However, this assumption simplifies the subsequent modeling.

(3) **The minimum time separation to alleviate the wake turbulence is set to be 2 min.** To alleviate the wake turbulence, we fix the minimum separation time for departures/arrivals to be 2 min. As a result, each runway can serve a maximum of 30 flights per hour. The setting of the minimum separation time is based on the wake turbulence category [50] promulgated by the International Civil Aviation Organization (ICAO), based on the fact that the majority of the aircraft in this study are of medium size.

(4) **Delay can occur to a flight in the air.** In reality, arrival delay can occur to a flight due to various factors such as convective weather, airspace restriction, airport congestion, and so forth. Unlike existing studies on delay analysis, which assume that delay does not occur during the en-route phase, we introduce the airborne delay of flights to our model. More specifically, we assume that the airborne delay of a flight is a nonlinear function of its departure delay and its scheduled flying time. This assumption also provides the probabilities for flights to absorb delays in the air.

Based on the above assumptions, we then estimate $t^{f_i}_{AD}$ and $t^{f_i}_{AA}$ for all $f_i \in [1, N_f]$ in the following way.

(1) If f_i is the first flight leg of an aircraft's itinerary, then we estimate $t^{f_i}_{AD}$ as follows:

$$t^{f_i}_{AD} = t^{f_i}_{SD} + T^{f_i}_{DD} \tag{1}$$

where $t^{f_i}_{SD}$ and $T^{f_i}_{DD}$ represent the scheduled departure time and departure delay of flight f_i.

(2) If f_i is an intermediate flight leg of an aircraft's itinerary, then we estimate $t^{f_i}_{AD}$ in the following ways.

$$\begin{cases} t^{f_i}_{AD} = t^{f_i}_{SD} & \text{if} \quad t^{f_{i-1}}_{AA} + T^{f_{i-1}}_{TA} \le t^{f_i}_{SD} \\ t^{f_i}_{AD} = t^{f_{i-1}}_{AA} + T^{f_{i-1}}_{TA} & \text{if} \quad t^{f_{i-1}}_{AA} + T^{f_{i-1}}_{TA} > t^{f_i}_{SD} \end{cases} \tag{2}$$

where $T^{f_{i-1}}_{TA}$ represents the minimum turnaround time for flight f_{i-1}, which is the previous leg of f_i.

Note that different aircraft have different minimum turnaround times. Normally, aircraft with larger sizes require longer minimum turnaround times. For a given set of flight plans, we categorize the aircraft into three classes: medium size, large size, and heavy size. We then set the minimum turnaround times T_{TA} respectively to 60, 90, and 120 min.

(3) Based on $t^{f_i}_{AD}$, we then calculate actual arrival time of flight $t^{f_i}_{AA}$ as follows:

$$t^{f_i}_{AA} = t^{f_i}_{AD} + T^{f_i}_{EF} = t^{f_i}_{AD} + T^{f_i}_{SF} + \tau^{f_i} \tag{3}$$

in which τ^{f_i} is a random variable signifying the deviation between scheduled flying time $T^{f_i}_{SF}$ and estimated flying time $T^{f_i}_{EF}$.

In this study, we use multivariable nonlinear regression to estimate τ^{f_i}. Specifically, we assume that τ^{f_i} is calculated as follows:

$$\tau^{f_i} = a_0 + a_1 T^{f_i}_{DD} + a_2 \left(T^{f_i}_{SF}\right)^2 \tag{4}$$

with the parameters a_0, a_1, and a_2 being learned from the historical flight operation data.

4.4. Delay assignment mechanism

Due to air traffic delays, multiple flights may request departure services simultaneously at the same airport. Likewise, multiple flights may arrive at the final approach fix at the same time. Consequently, it is necessary to prioritize all departure and arrival flights, and assign delays to the flights that request departure/arrival services. With regard to this, we suggest the following mixed departure and arrival delay assignment mechanisms to further update $t^{f_i}_{\mathrm{AD}}$ and $t^{f_i}_{\mathrm{AA}}$.

Algorithm 1 defines the way to update $t^{f_i}_{\mathrm{AD}}$ when multiple flights request to depart simultaneously from the same airport, as flight f_i does. In Step 6 of Algorithm 1, the variable T_δ represents the minimum time separation to avoid the wake turbulence of departures/arrivals.

Algorithm 1. Departure delay assignment mechanism.

1. For a given airport at time t, identify the departure flight sequence $F = (f_1, f_2, ..., f_n)$ with $t^{f_i}_{\mathrm{AD}} = t, \forall i \in [1, n]$.
2. $T^F_{\mathrm{DD}} = \left\{ t^{f_i}_{\mathrm{AD}} - t^{f_i}_{\mathrm{SD}} | \forall f_i \in F \right\}$; //departure delays for all $f_i \in F$.
3. If size$\left(\text{unique}\left(T^F_{\mathrm{DD}}\right)\right) == 1$, i.e., all the flights have the same delay, then idx $=$ SortRandom$\left(T^F_{\mathrm{DD}}\right)$, i.e., obtain a sequence idx for all $i \in [1, n]$ based upon the random sorting of T^F_{DD}; otherwise, do the following:
   a. idx $=$ SortDecend$\left(T^F_{\mathrm{DD}}\right)$, if max$\left(T^F_{\mathrm{DD}}\right) \le 0$;
   b. idx $=$ SortAscend$\left(T^F_{\mathrm{DD}}\right)$, if min$\left(T^F_{\mathrm{DD}}\right) \ge 0$;
   c. If min$\left(T^F_{\mathrm{DD}}\right) < 0 \wedge$ max$\left(T^F_{\mathrm{DD}}\right) > 0$, then
      i. idx1 $=$ SortAscend$\left(T^F_{\mathrm{DD}}\right) \ge 0$;
      ii. idx2 $=$ find$\left(T^F_{\mathrm{DD}} < 0\right)$;
      iii. idx $=$ [idx1, idx2].
4. Set $F = F(\text{idx})$; //reordered flight sequence.
5. Set $t^{f_1}_{\mathrm{AD}} = t$; //the first flight in F departs at time t.
6. Set $F' = F$ and $t^{f_i}_{\mathrm{AD}} = t + T_\delta, \forall f_i \in F'$; //each of the rest flights is delayed for T_δ min.

In order to update $t^{f_i}_{\mathrm{AA}}$ when multiple flights request to arrive simultaneously at the same airport, as flight f_i does, we further develop the arrival delay assignment mechanism. The proposed arrival delay assignment mechanism works in exactly the same manner as what is shown in Algorithm 1. Both of the mechanisms are implemented simultaneously.

4.5. Spatial–temporal network construction

The purpose of the above exhausted delay propagation and assignment mechanisms is to estimate the actual departure/arrival times for all the flights. Based on the estimated actual departure times, for a given time horizon $[t_0, t_{\mathrm{end}}]$, we construct a spatial-temporal network $G = \left\{G^{t_0}, G^{t_1}, ..., G^{t_{\mathrm{end}}}\right\}$ at a time resolution of one minute, that is, $t_1 - t_0 = 1$ min. Each snapshot G^{t_i} captures the delayed flights that depart at time t_i. Specifically, for network G^{t_i}, we build the edges between their origin–destination (OD) pairs with the weights of the edges being the departure delays (measured in minutes) of the corresponding flights that depart at time t_i. For example, if a flight departs at time t_i from airport a, is 10 min later than scheduled, and is heading for airport b, then we construct an edge between nodes a and b of the network G^{t_i} with the edge weight being 10. Note that G^{t_i} could be empty, since all the flights could be in the air and/or on the ground at time t_i.

As per FAA instructions, a flight f_i is considered to be delayed if, assuming that the departure is considered, $T^{f_i}_{\mathrm{DD}} \ge 15$. When constructing G^{t_i}, we construct an edge between the OD pair of flight f_i as long as $T^{f_i}_{\mathrm{DD}} \ge 1$. The benefit from doing so is that the constructed spatial–temporal network can analyze the delay propagation at different delay levels by extracting the corresponding subnetwork from G^{t_i} with respect to a given delay threshold, such as 15 min, 30 min, and so forth.

4.6. Delay propagation dynamics

In the literature, the most widely used metric for gauging reactionary delay is the DM index, which can be formulated as $\mathrm{DM} = (D + I)/I$, where I and D respectively denote the primary delays and the reactionary delays. In this work, we take the predicted departure delay $t^{f_i}_{\mathrm{DD}}$ as the D for flight f_i, since the prediction of $t^{f_i}_{\mathrm{DD}}$ is the outcome of the collaborative behavior of the delay propagations of all the flights.

The DM metric is straightforward and effective for providing an overall view of the magnitude of the reactionary delays. However, its main advantage is also its main disadvantage. The DM metric cannot reflect the spatial–temporal dynamics of the delay propagation process, and this is the very motivation for proposing the spatial–temporal network-based perspective.

For the constructed spatial–temporal network G, we use A^{t_i} to denote the adjacency matrix of its snapshot G^{t_i}. Let δ be a time duration. We further define a matrix $A^{\phi\delta}$ as follows:

$$A^{\phi\delta} = \sum\nolimits_{t_i \in \Gamma} A^{t_i} \tag{5}$$

where $\Gamma = [t_0 + (\phi - 1)\delta, t_0 + \phi\delta]$ and $\phi \in \Phi = [1, (t_{\mathrm{end}} - t_0)/\delta]$. ϕ is an integer within the range of Φ. The matrix $A^{\phi\delta}$ represents the cumulative network of the snapshot G^{t_i} within time period Γ. As pointed out in Subsection 4.5, the snapshot G^{t_i} could be empty. By defining $A^{\phi\delta}$ we can avoid analyzing empty networks directly, since they contribute little to the research problem.

We then analyze the spatial–temporal degree properties of $A^{\phi\delta}$ and quantify the delay propagation dynamics in the following ways.

(1) **Magnitude.** We quantify the delay propagation magnitude in terms of the number of flights that suffer from reactionary delays, hereafter denoted by DP-mag1, and the amount of delays, hereafter denoted by DP-mag2. Let $a^{\phi\delta}_{ij}$ be the entry of $A^{\phi\delta}$. Then DP-mag1 and DP-mag2 with respect to Γ are calculated as follows:

$$\text{DP-mag1} = \left\{ d^{\phi\delta}_{i1} \middle| d^{\phi\delta}_{i1} = \left\| \left\{ a^{\phi\delta}_{ij} \middle| j \in [1, n] \right\} \right\|_0, \forall i \in [1, n] \right\} \tag{6}$$

$$\text{DP-mag2} = \left\{ d^{\phi\delta}_{i2} \middle| d^{\phi\delta}_{i2} = \sum\nolimits_{j=1}^{n} a^{\phi\delta}_{ij}, \forall i \in [1, n] \right\} \tag{7}$$

In the above equations, elements $d^{\phi\delta}_{i1}$ and $d^{\phi\delta}_{i2}$ respectively represent the unweighted and weighted degrees of node i of the network characterized by matrix $A^{\phi\delta}$. The magnitude metric therefore captures the number of delayed flights as well as the amount of delays each single airport will encounter during the given time period Γ.

(2) **Severity.** Based on the definitions of magnitude, we further define the delay propagation severity for the time window $[t_0, t_{\mathrm{end}}]$ as follows:

$$\begin{aligned} \text{DP-sev1} = \Big\{ d_{i1} \Big| d_{i1} = & \max\left(\phi \in \Phi^{\arg} d^{\phi\delta}_{i1} \ge \overline{d^{\phi\delta}_{l1}}\right) \\ & - \min\left(\phi \in \Phi^{\arg} d^{\phi\delta}_{i1} \ge \overline{d^{\phi\delta}_{l1}}\right), \forall i \in [1, n] \Big\} \end{aligned} \tag{8}$$

$$\text{DP-sev2} = \left\{ d_{i2} \middle| d_{i2} = \max\left(\phi \in \Phi^{\arg} d_{i2}^{\phi\delta} \geq \overline{d_{l2}^{\phi\delta}}\right) - \min\left(\phi \in \Phi^{\arg} d_{i2}^{\phi\delta} \geq \overline{d_{l2}^{\phi\delta}}\right),\ \forall i \in [1,\ n] \right\} \tag{9}$$

where the terms $\overline{d_{l1}^{\phi\delta}}$ and $\overline{d_{l2}^{\phi\delta}}$ are respectively calculated as follows:

$$\overline{d_{l1}^{\phi\delta}} = \frac{\delta}{t_{\text{end}} - t_0} \sum\nolimits_{\phi} d_{i1}^{\phi\delta} \tag{10}$$

$$\overline{d_{l2}^{\phi\delta}} = \frac{\delta}{t_{\text{end}} - t_0} \sum\nolimits_{\phi} d_{i2}^{\phi\delta} \tag{11}$$

One can observe from the above equations that the delay severity practically measures the time duration between the time point from which the magnitude starts to surpass its mean and the time point from which the magnitude starts to decrease from the mean. Therefore, the delay severity captures the duration of time the propagation magnitude can last.

(3) **Speed.** Based on the definitions of magnitude and severity, for a given time window $[t_0,\ t_{\text{end}}]$, we quantify the propagation speed as follows:

$$\text{DP-spe} = \left\{ d^{\phi\delta} \middle| d^{\delta} = \frac{1}{n} \sum\nolimits_{i=1}^{n} d_{i1}^{\phi\delta},\ \forall \phi \in \Phi \right\} \tag{12}$$

As can be seen from Eq. (12), $d^{\phi\delta}$ specifies the average delay propagation magnitude across all the airports in terms of the number of delayed flights. Note that the definition of the delay propagation speed with respect to $d_{i2}^{\phi\delta}$ is omitted, as it has a similar form as the definition formulated above.

5. Experimental study

5.1. Testing instances

Section 4 elaborated in detail the proposed network approach for understanding the propagation dynamics of air traffic delays. This section will demonstrate the applications of the proposed approach to the real-world flight plan data.

5.1.1. Flights in the SAR

In this study, we use the flights in the SAR as the first case study. The SAR is a subregion of Asia that consists of 11 countries with a total land area of ~4.5×10^6 km^2. After South Asia and East Asia, SAR is now the third most populous geographical region in the world, with a total population of over 641 million. Therefore, the SAR plays an important role both in the world's economic development and in air transport (there are more than 700 airports in the SAR).

We abstract the flight schedules for the SAR from the automatic dependent surveillance-broadcast (ADS-B) data provided by the Civil Aviation Authority of Singapore (CAAS). The ADS-B data provided by CAAS covers domestic and global flights and spans a period of six months (June, July, September, October, November, and December) in the calendar year 2016. From the six-month ADS-B data, we filter out the schedules for the flights in the SAR.

Fig. 3 displays the spatial airport network derived from the six-month ADS-B data. The weight of an edge is equal to the number of flights that have flown between its two connected airports. The network shown in Fig. 3 has 139 nodes and 376 edges. For the SAR airport network, we further calculate the degrees of the nodes. We then rank the nodes based on their degrees.

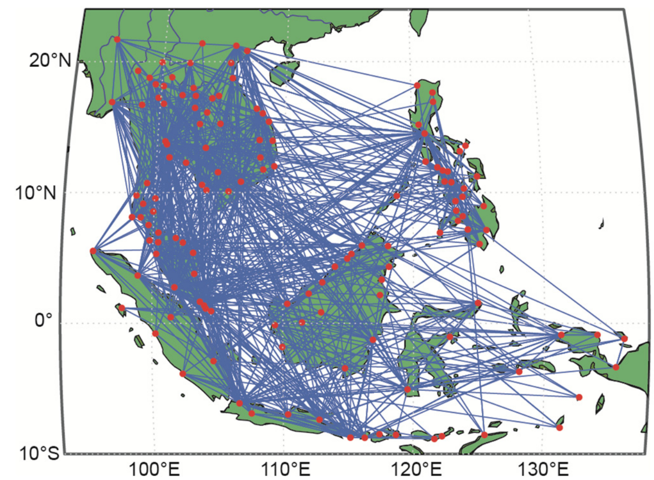

Fig. 3. Overview of the SAR airport network constructed using six-month ADS-B data collected for the calendar year 2016. An edge is created if there is a flight between its two endpoints.

The top part of Table 1 summarizes the basic information for the top 22 busiest airports in the SAR. It can be seen from Table 1 that node WMKK has the largest unweighted degree of 51, followed by node WSSS with a degree of 42. The Malaysian airport WMKK has the greatest number of connections with other airports in the SAR. Although the Singapore airport WSSS is the second largest tie, the weighted degree k_w values as recorded in Table 1 show that the Indonesian airport WIII accommodates more flights than the Singapore airport does. In general, Malaysia and Thailand have the busiest airports in the SAR.

5.1.2. Flights in the United States

The second case study was carried out on US flights. In the literature, validations on US flight data have been widely implemented. The key reason is that the collection strategy of US flight data is well established and the data is available to the public. It is easy to obtain ten-year US flight operation data from a handful of websites.

For the sake of better comparison, we obtained US domestic flight schedules from the Bureau of Transportation Statistics (BTS) website for the same time period as the SAR data. Based on the six-month US domestic flight schedules, we constructed a corresponding airport network (Fig. 4).

The network shown in Fig. 4 has 302 nodes and 2160 edges. The US airport network is more complicated than the SAR airport network in terms of the number of nodes and edges. The bottom part of Table 1 summarizes the basic information for the top 22 busiest airports (sorted by their weighted degrees) in the United States.

It can be seen from Table 1 that the values of unweighted degree k for the US airports are much larger than those for SAR airports. Each of the 22 top airports in the United States has more connections with other airports than each top airport in the SAR does. Each airport in the SAR is connected to 2.7 airports on average, while US airports are connected to an average of 7.2 airports. The greater numbers of airports and airport connections lead to larger throughputs, as reflected by the weighted degree k_w.

5.2. Flight itinerary construction

This work aims to investigate the propagation dynamics of reactionary delays. To do so, we need to work out the flight itineraries so as to trace the delay propagation between consecutive flight legs. The flight operation data obtained above contains tail numbers for all the flights. A tail number is a unique identifier that

Table 1
Properties of the top 22 airports in the SAR and the top 22 airports in the United States.

Region/country	Airport	Country	City	k	k_w
SAR	WMKK	Malaysia	Selangor	51	70 611
	WIII	Indonesia	Tangerang	27	59 199
	WSSS	Singapore	–	42	44 002
	VTBS	Thailand	Bangkok	23	28 831
	VTBD	Thailand	Bangkok	39	27 343
	RPLL	Philippines	Manila	36	25 312
	VVTS	Vietnam	Ho Chi Minh	24	15 374
	WADD	Indonesia	Bali	15	13 930
	WARR	Indonesia	Sedati	12	12 261
	VTSP	Thailand	Phuket	11	11 323
	VVNB	Vietnam	Hanoi	24	9 757
	WMKP	Malaysia	Penang	15	9 397
	WBKK	Malaysia	Sabah	12	8 664
	WBGG	Malaysia	Sarawak	9	8 566
	VTCC	Thailand	Chiang Mai	15	7 916
	RPVM	Philippines	Cebu	14	7 273
	WIMM	Indonesia	Medan	9	7 239
	VTSM	Thailand	Koh Samui	7	5 992
	VVDN	Vietnam	Da Nang	11	5 055
	WAAA	Indonesia	Makassar	10	4 861
	VDPP	Cambodia	Phnom Penh	8	4 204
	RPMD	Philippines	Davao	6	3 869
United States	ATL	USA	Atlanta	162	379 484
	ORD	USA	Chicago	146	240 736
	DEN	USA	Denver	135	225 428
	LAX	USA	Los Angeles	83	214 620
	DFW	USA	Dallas-Fort Worth	128	189 947
	SFO	USA	San Francisco	81	171 022
	PHX	USA	Phoenix	87	155 204
	LAS	USA	Las Vegas	74	148 706
	SEA	USA	Seattle	74	134 638
	IAH	USA	Houston	109	132 419
	MSP	USA	Minneapolis	118	129 429
	DTW	USA	Detroit	108	123 411
	BOS	USA	Boston	59	120 176
	MCO	USA	Orlando	69	115 166
	EWR	USA	Newark	87	113 181
	SLC	USA	Salt Lake City	84	108 153
	CLT	USA	Charlotte	6	107 916
	BWI	USA	Baltimore	61	97 194
	LGA	USA	New York	64	93 118
	JFK	USA	New York	58	89 522
	MDW	USA	Chicago	65	87 325
	SAN	USA	San Diego	47	78 294

k: unweighted degree; k_w: weighted degree.

specifies a certain aircraft. Flights with the same tail number correspond to the same aircraft. Based on the tail numbers of the flights, we then construct the flight itineraries by sorting all the flights chronologically based on their scheduled departure time.

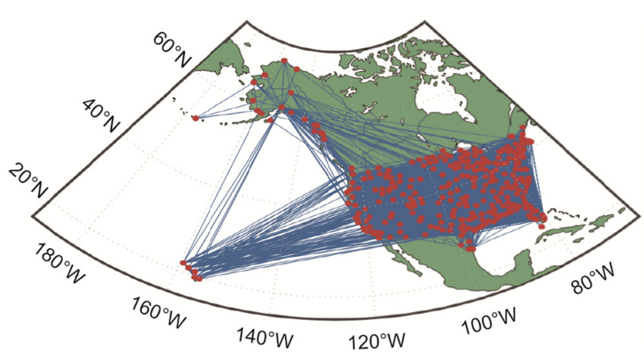

Fig. 4. Overview of the US airport network constructed using six-month flight schedule data collected for the calendar year 2016. An edge is created if there is a flight between its two endpoints.

5.3. Delay statistics overview

The SAR and the US flight schedules provide both the scheduled and actual times of the flights, based on which we know the real delays for the flights. In what follows, we first present the fundamental statistical studies on the delays.

It can be clearly seen from the upper part of Fig. 5 that the number of operated airports in the SAR in each of the studied six months is around 130, which is almost one third of the number operated in the United States. Furthermore, the number of monthly operated flights in the SAR is around 50 000, which is nearly one tenth of the number in the United States. It can also be seen from the upper part of Fig. 5 that the flights in the SAR have smaller arrival and departure punctualities than those in the United States. Nevertheless, the average flight delays in the SAR are much lower than those in the United States.

The middle and bottom parts respectively visualize the probabilistic distribution of the flight delays in the SAR and the United States, together with the curve fittings for the distributions of the positive delays. During the curve fittings, we have utilized three types of distribution: the Weibull, LogNorm, and exponential distributions, with their probabilistic distribution functions respectively being formulated as follows: $f(x)=\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-(x/\lambda)^k}$, $f(x)=\frac{1}{\lambda\sqrt{2\pi}x}e^{-(\ln x-u)^2/(2\sigma^2)}$, and $f(x)=\alpha e^{\beta x}$, where λ, k, u, σ, α, and β are all constants.

Although the average delays vary in different months, we can see that the delay distributions over different months in both the SAR and the United States share many resemblances. With regard to the curve fittings, the Weibull distribution obtains the best fittings in terms of the statistical metrics of R^2 and root mean squared error (RMSE). The curve-fitting results indicate that the positive delays obey the Weibull distributions.

5.4. Problematic days selection

The original flight schedule data is recorded by month. With regard to the fact that flight delays on different days in a month can possess unique properties, since air traffic is fraught with technical, operational, and meteorological issues, we analyze the delay propagation dynamics at a resolution of one day. More specifically, we abstract the daily flight schedules from a given monthly data as the basic unit for subsequent analysis.

In this study, we choose four days for every month—two days with the highest average departure delays and two days with the lowest average departure delays—as the problematic days to be studied. The selected days, together with their corresponding basic information, are listed in Table 2.

5.5. Starting time point selection

When a problematic day is determined, we then extract the 24 h flight schedules from the original flight data. To do so, we must determine the starting time point, from which we eventually build the flight itinerary. Different selections of starting time point could lead to different flight itineraries, which may affect the final results.

In order to determine the starting time point, we first visualize the six-month traffic demands over the time horizon from 00:00 to 24:00 at intervals of one hour. The statistics are shown in Fig. 6.

It can be seen from Fig. 6(a) that 20:00 p.m. can be regarded as the peak-off hour, as there are relatively few flights, while Fig. 6(b) suggests that the peak-off time for the US air traffic is 09:00 a.m. In this study, we choose the peak-off hours observed in Fig. 6 as the starting time points to respectively build the daily flight itineraries from the SAR and US flight schedules.

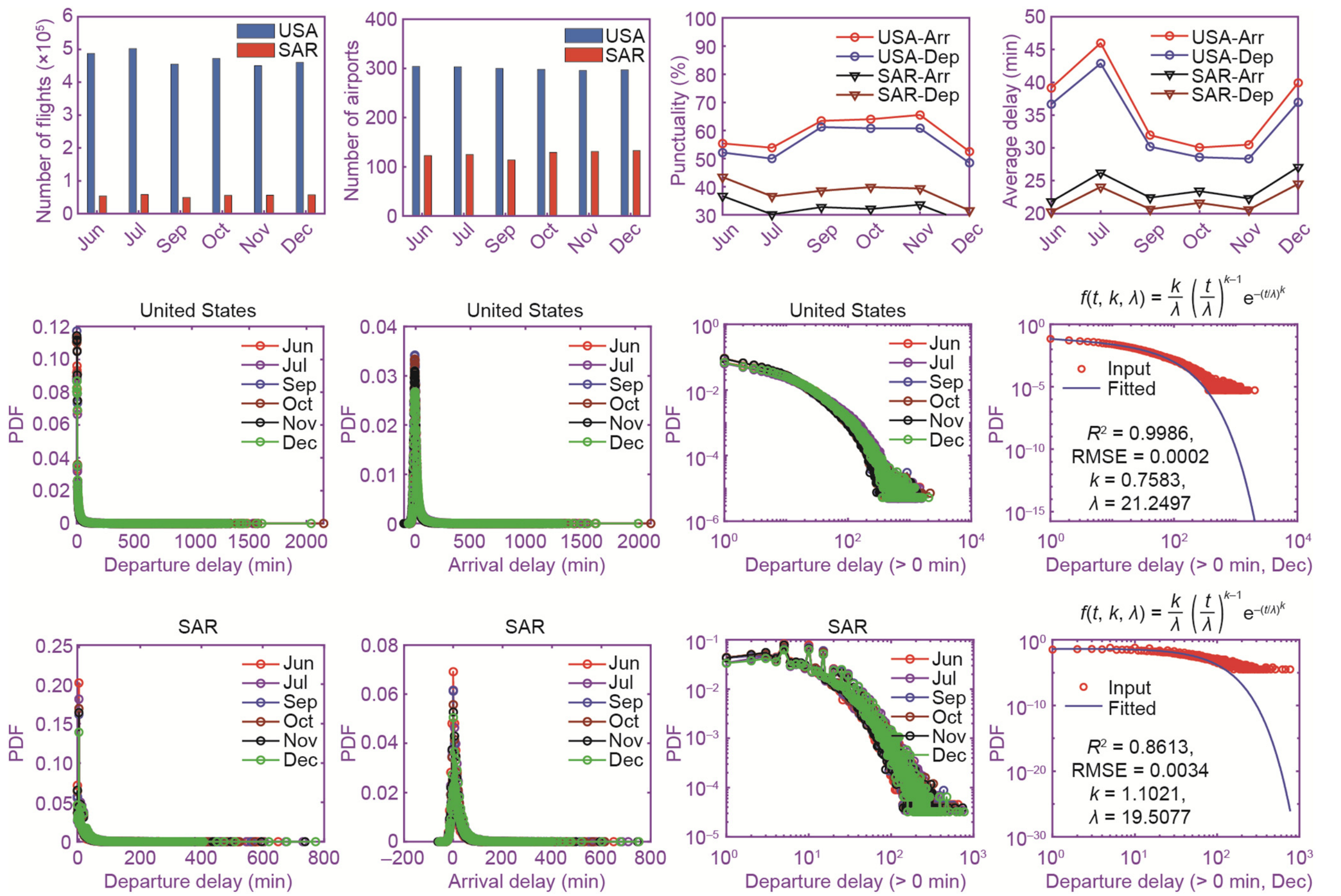

Fig. 5. Delay statistics for the SAR and US flight operation data recorded in the calendar year 2016. Arr: arrival; Dep: departure; PDF: probabilistic distribution of the fight delays; RMSE: root mean squared error.

5.6. Reactionary delay analysis

For each selected problematic day, together with the primary flight delays, we implement the delay propagation and assignment mechanisms to work out the reactionary delays for the remaining flight legs. In order to investigate the difference between the reactionary delays of flights in the SAR and the United States, we calculate the values of the DM metric. Furthermore, based on the estimated reactionary delays, we calculate the classification accuracy for the delayed flights.

Fig. 7(a) visualizes the distributions of the values of the DM metric when applied to the reactionary delays for the studied 24 days. It can be seen from Fig. 7 that the majority of the DM values are in the range 1–2, which indicates that a primary delay of 1 min would cause a reactionary delay of around 1 min.

As for the delay accuracy, we observe from the middle part of Fig. 7 that the delay accuracies for flights with $T_{\rm DD}^{f_i} \geq 1$ and flights with $T_{\rm DD}^{f_i} \geq 15$ are respectively around 78% and 80% for the flights in the SAR, while the corresponding accuracies for flights in the United States are respectively around 72% and 85%. In the literature, the classification accuracies for delayed flights with $T_{\rm DD}^{f_i} \geq 1$ as reported in Refs. [29,30,35] are respectively 70%, 74.2%, and DD 82.7%. The results recorded in Fig. 7 indicate that the proposed delay propagation and assignment mechanisms make sense, and the subsequent analysis on the delay propagation dynamics is therefore reliable.

5.7. Delay propagation dynamics

The DM metric is a widely applied index to quantify the delay propagation effect. However, as can be seen from Fig. 7, the DM metric hardly provides useful insights into the magnitude, severity, and speed of the delay propagation dynamics, which is the very motivation for our suggested dynamic network approach.

Based on the reactionary delays, we then construct the spatial–temporal networks. In order to capture the delay propagation dynamics, we construct the spatial–temporal networks at a granularity of per hour. Specifically, in the network modeling process, we set $\delta = 60$ min; as a consequence, we have $\Phi = [1,\ 24]$.

5.7.1. Delay propagation magnitude

In this paper, we only focus on the departure delays, since the results shown in Fig. 5 indicate that the arrival and departure delays have an approximately linear relation. Fig. 8 exhibits the delay propagation magnitude with respect to DP-mag1. On 18 July, among the top eight airports in the SAR, the three airports WMKK, WIII, and WSSS are found to be most congested, as there are about eight delayed flights per hour at each of these airports, while there are around three delayed flights per hour for each of the remaining top eight airports. On 30 November, since the average delay is smaller than that on 18 July, the top eight airports are relatively less congested. The top three airports are still found to be the most congested.

Regarding the US airports, it can be clearly seen from Fig. 8 that the delay propagation magnitude is higher than that in the SAR. In

Table 2
Selected problematic days for investigating the delay propagation dynamics of flights in the SAR and the United States.

Region/country	Day	N_f	$N_\mathrm{f}^1/N_\mathrm{f}$	$N_\mathrm{f}^{15}/N_\mathrm{f}$	$\bar{T}_\mathrm{DD}$(minute per flight)
SAR	Jun, 17	1381	63.34%	32.34%	24.0
	Jun, 2	1355	62.60%	29.47%	23.3
	Jul, 18	1519	63.79%	31.11%	30.8
	Jul, 8	1617	61.22%	29.27%	30.7
	Sep, 9	1358	70.47%	43.61%	29.3
	Sep, 29	1225	64.08%	32.42%	28.2
	Oct, 14	1501	66.84%	31.27%	28.0
	Oct, 30	1367	59.90%	30.51%	27.0
	Nov, 2	1425	61.14%	32.50%	27.3
	Nov, 1	1355	62.90%	32.63%	25.4
	Dec, 16	1730	76.27%	43.54%	30.4
	Dec, 23	1567	76.57%	42.40%	29.1
	Jun, 9	1202	48.90%	16.17%	15.6
	Jun, 12	911	47.59%	18.17%	16.1
	Jul, 6	1379	58.67%	24.81%	18.7
	Jul, 25	1519	60.22%	24.87%	19.6
	Sep, 13	1186	54.13%	17.71%	16.0
	Sep, 12	1250	61.02%	24.29%	16.9
	Oct, 10	1306	58.61%	20.65%	17.2
	Oct, 21	1470	59.30%	23.42%	17.3
	Nov, 30	1514	59.74%	23.63%	15.9
	Nov, 19	1450	59.07%	21.76%	16.8
	Dec, 14	1454	65.91%	27.71%	17.9
	Dec, 31	1224	58.30%	23.76%	18.4
United States	Jun, 14	10 393	49.62%	26.23%	40.8
	Jun, 28	10 280	51.38%	29.70%	40.5
	Jul, 21	9936	59.07%	37.65%	57.1
	Jul, 28	10 438	51.48%	30.18%	48.9
	Sep, 21	9319	39.50%	19.81%	40.5
	Sep, 2	10 517	44.06%	20.87%	35.7
	Oct, 25	9110	38.09%	17.43%	34.9
	Oct, 30	7701	41.59%	20.85%	34.5
	Nov, 15	9463	41.29%	21.10%	34.8
	Nov, 4	9652	41.08%	19.12%	33.0
	Dec, 17	8766	76.90%	56.55%	71.8
	Dec, 18	9272	77.55%	55.18%	64.0
	Jun, 1	8213	42.91%	18.16%	23.5
	Jun, 20	10 583	41.91%	17.87%	26.7
	Jul, 12	10 113	40.20%	18.21%	27.7
	Jul, 10	9728	42.37%	18.70%	27.9
	Sep, 4	5931	26.32%	10.02%	22.0
	Sep, 15	9916	37.11%	13.00%	22.1
	Oct, 1	6314	33.96%	11.83%	20.2
	Oct, 6	9314	42.14%	16.46%	21.1
	Nov, 25	5363	26.60%	8.24%	18.1
	Nov, 24	7505	25.99%	7.74%	20.2
	Dec, 1	6924	36.52%	13.54%	22.4
	Dec, 2	8980	36.98%	15.44%	24.8

N_f^1: number of flights with $\bar{T}_\mathrm{DD}^{f_i} \geq 1$; N_f^{15}: number of flights with $\bar{T}_\mathrm{DD}^{f_i} \geq 15$.

the United States, of the 40 busiest airports, about 30% are congested on each of the studied days, that is, 21 July and 25 November, while the top two airports, namely ATL and DEN, are the most congested, with around 30 delayed flights in each airport.

The delay propagation magnitude in terms of the number of delayed flights shows a positive relation with the degrees of the airports. Next, we investigate the delay propagation magnitude in terms of the amount of delays occurring at each airport. The corresponding results are demonstrated in Fig. 9.

It can be seen from Fig. 9 that the WMKK airport suffers from significant delays on 18 July (74 min on average) and 30 November (64 min on average). Given that the airport operates at a maximum throughput, that is, with 30 flights taking off in 1 h, each flight on 18 July has a propagated delay of 2.5 min on average. On 30 November, the average delay is decreased to 2 min, since the traffic on that day is less congested than that on 18 July. The WIII and WSSS airports have significant delays on both of the studied days.

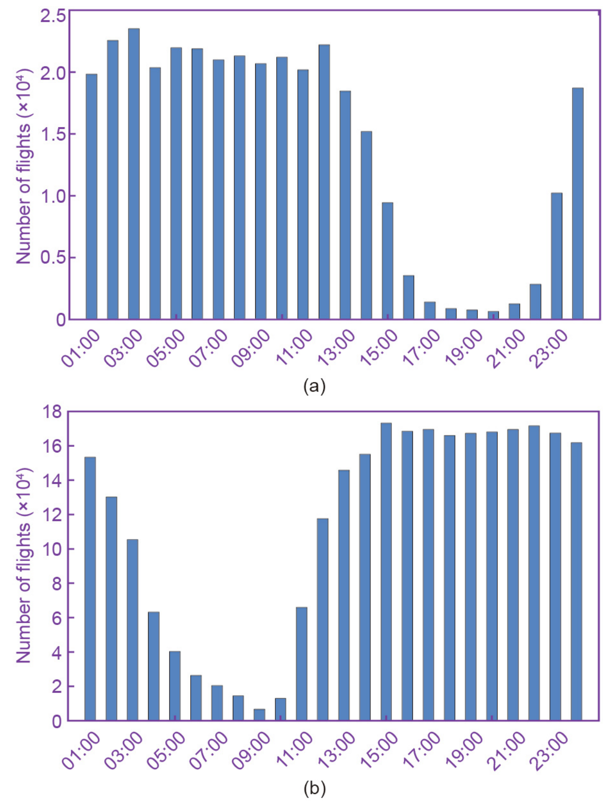

Fig. 6. Distribution of the six-month traffic demands over the time horizon from 00:00 to 24:00 (UTC time) at intervals of one hour. (a) SAR; (b) United States.

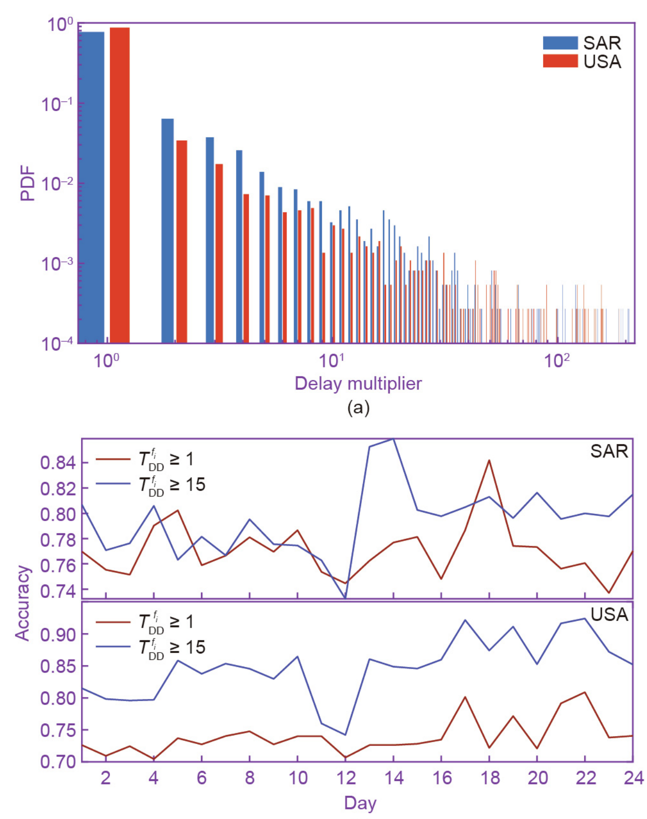

Fig. 7. (a) Distribution of the values of the DM metric and (b) the classification accuracies for the delayed flights for the studied 24 problematic days.

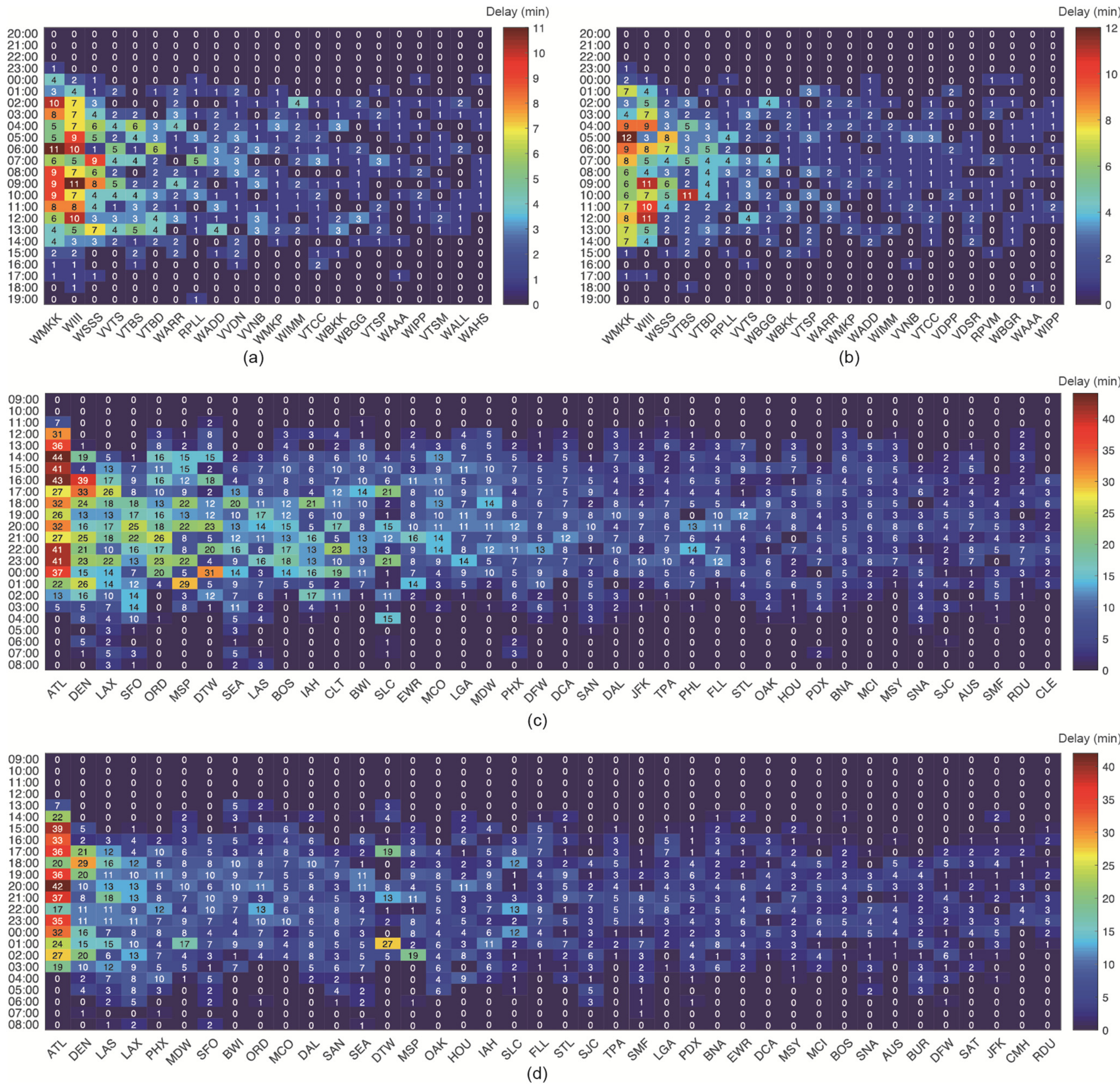

Fig. 8. Delay propagation magnitude with respect to DP-mag1. (a, b) The values of DP-mag1 for the top 22 airports operated in the SAR (a) on 18 July and (b) 30 November. (c, d) The values of DP-mag1 for the top 40 airports operated in the United States on (c) 21 July and (d) 25 November.

Interestingly, for some airports, such as VTCC and WMKP, even though there are not too many delayed flights on the ground, there are still massive delays, as flights are heavily delayed due to reactionary delays.

Figs. 9(c) and (d) reveal that the delay propagation magnitude in terms of delays for the US flights is more significant than that of the SAR. On 21 July, the most congested airport, ATL, suffers from huge delays. As can be seen from Fig. 9, the hourly delays for the ATL airport are around 300 min. Putting it another way, each flight on the ground has a propagated delay of 10 min on average. On 25 November, the average propagated delay per flight is 2 min. Of the investigated 22 top airports in the SAR, around 25% have significant delays. However, around 40% of the 40 top US airports suffer from departure delays.

5.7.2. Delay propagation severity

An analysis of the spatial–temporal airport networks provides a comprehensive understanding of the delay propagation dynamics in terms of magnitude. Here, we continue to analyze the delay propagation dynamics in terms of severity.

In this work, we define the delay propagation severity as the time duration for which the propagation magnitude can last. As the magnitude is quantified in two ways, the severity is also measured in two ways. It can be seen from the upper part of Fig. 8 that the peak time (the time when the number of delayed flights starts to exceed the mean value) starts at 03:00 a.m. and ends at 13:00 p.m. for the air traffic in the SAR. The middle and bottom parts of Fig. 8 indicate that the peak time starts at 13:00 p.m. and ends at 03:00 a.m. for the air traffic in the United States. Similar

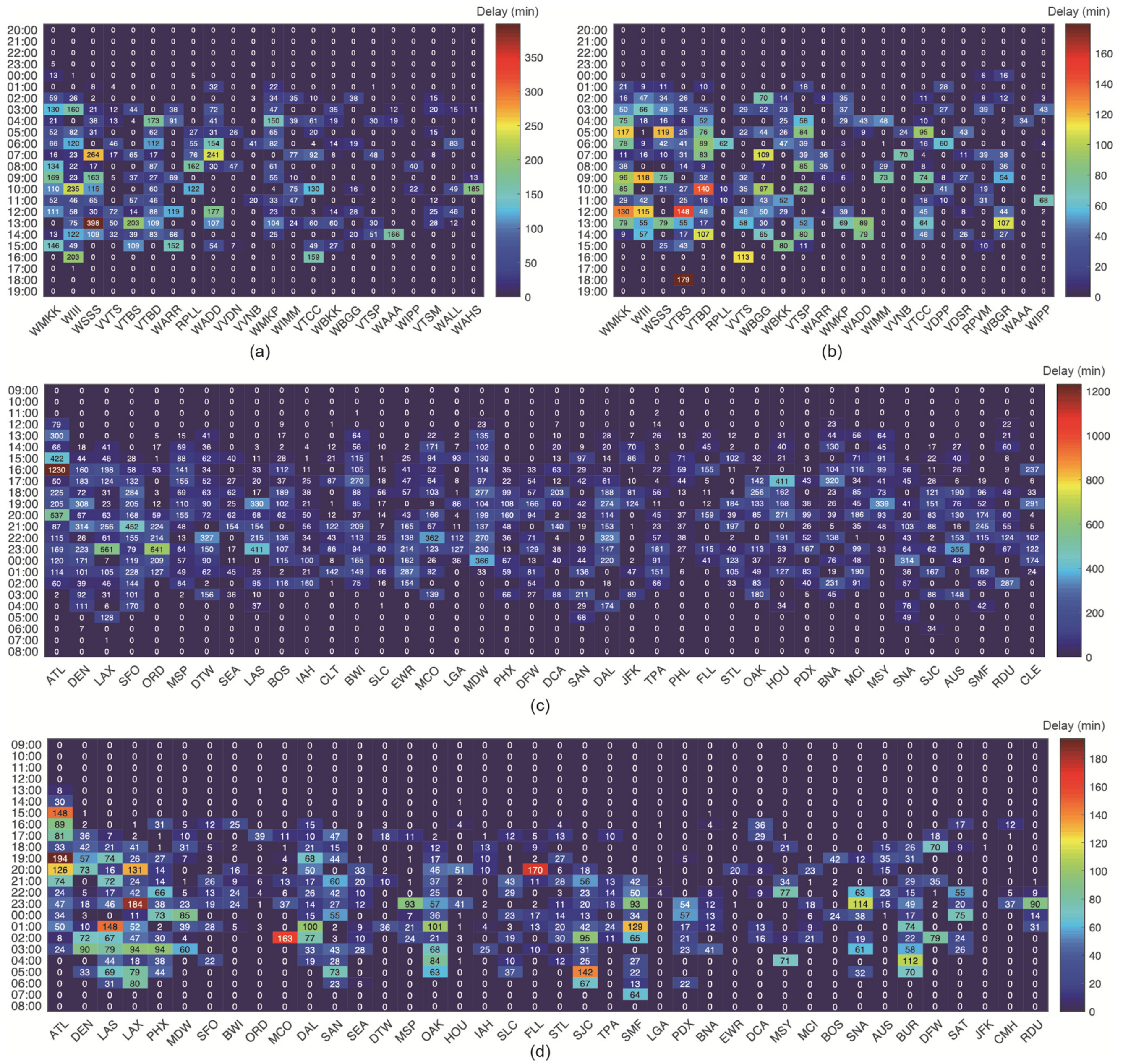

Fig. 9. Delay propagation magnitude with respect to DP-mag2. (a, b) The values of DP-mag2 for the top 22 airports operated in the SAR on (a) 18 July and (b) 30 November. (c, d) The values of DP-mag2 for the top 40 airports operated in the United States on (c) 21 July and (d) 25 November.

phenomena can be observed in Fig. 9. We therefore conclude that the delay propagation for the flights in the United States lasts longer than that of the flights in the SAR, since the propagation severities are 14 and 10 h, respectively.

It can be seen from the above results that the magnitude metric helps to estimate the amount of delays for each flight and airport, given the scheduled flight plans, while the severity metric indicates the duration of time the delay propagation process can last. With regard to this, airlines can estimate in advance whether scheduled flight plans will suffer from significant delays by utilizing the proposed network model and applying the magnitude metric. By doing so, airlines can adjust flight plans to counterbalance the delay propagation effect. Furthermore, air traffic controllers can utilize the proposed metrics to assist with timely monitoring of the air traffic situation. For example, the above results show that the airport ATL suffers from significant delays in terms of magnitude and severity. In this case, air traffic controllers may consider to take strategic ATM measures, such as ATFM, to balance the traffic demand, airspace, and airport capacities. In addition, airlines, air traffic controllers, airports, and other stakeholders can collaborate with each other to come up with effective CDM initiatives for better ATM.

5.7.3. Delay propagation speed

Apart from the delay propagation dynamics in terms of magnitude and severity, aviation workers may want to know how fast the delay can propagate. As per the definition of DP-spe presented in Subsection 4.6, we now calculate the delay propagation speed for the flights in the SAR and the United States.

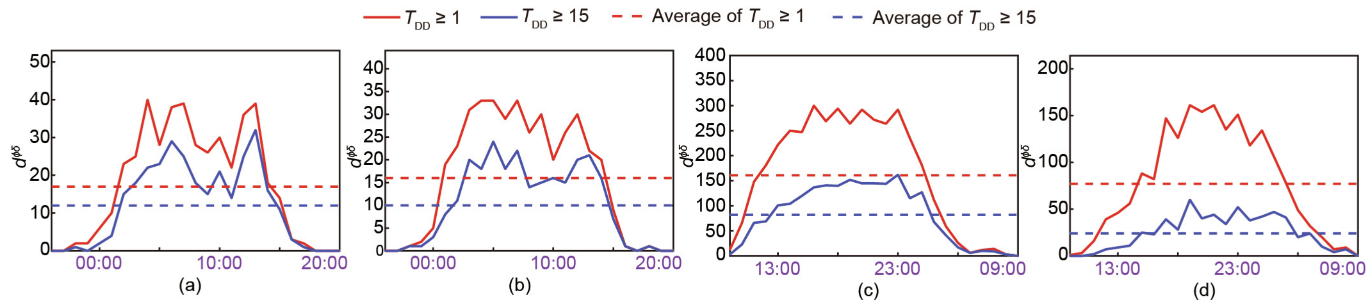

Fig. 10. Delay propagation speed with respect to DP-spe. (a, b). The values of $d^{\phi\delta}$ for the flights operated in the SAR on (a) 18 July and (b) 30 November. (c, d) The values of $d^{\phi\delta}$ for the flights operated in the United States on (c) 21 July and (d) 25 November.

Fig. 10 shows the delay propagation speed for the flights operated on the four days investigated above. In Fig. 10, the red solid curves record the values of $d^{\phi\delta}$ with $\phi \in \Phi$, that is, the averaged degrees of the spatial–temporal network characterized by matrix $A^{\phi\delta}$. As mentioned in Subsection 4.5, the construction of the network G^{t_i} can analyze delay at different levels. Here, we also calculate the average degrees of the network characterized by $A^{\phi\delta}$, excluding edges with $T_{DD} < 15$, which are represented by the blue solid curves.

Note that $d^{\phi\delta}$ reflects the hourly average degree of the network characterized by matrix $A^{\phi\delta}$. In order to better compare the delay propagation speed, we further calculate the mean of $d^{\phi\delta}$, which is represented by the red and blue dashed lines in Fig. 10. Table 3 records the mean values of $d^{\phi\delta}$ for the selected 24 days for the flights in the SAR and United States. It can be seen from the left part of Table 3 that the average delay propagation speeds, Spd1, for the flights in the SAR are around 14, which means that primary delays can elicit delays in 14 flights per hour. When the situation in the United States is compared with that in the SAR, the delay propagation speeds for flights in the United States are about eight times faster than those in the SAR.

6. Conclusion

Air traffic inevitably suffers from internal/external perturbations, giving rise to air traffic delays that harm both the aviation industry and the natural environment. Studies on how delays happen and promising initiatives to mitigate delays are pivotal to aviation workers in modern ATM. Air traffic delays are associated with the high complexity of air transport systems. In order to maximize passenger movements, airlines normally plan an aircraft schedule with multiple flight legs during the aircraft's rotation. As a consequence, a delay for one flight is likely to elicit reactionary delays for other flights, triggering the ripple effect, also known as delay propagation.

Delay propagation is detrimental to air traffic. An understanding of how delays propagate throughout air transport systems is crucial in order to achieve optimal structural design of air transport systems and to delay mitigation. This work presented a complex network perspective on air traffic delay propagation dynamics. Complementary to existing studies, the proposed network perspective can help decision-makers to acquire a comprehensive understanding of delay propagation dynamics in terms of magnitude, severity, and speed.

To validate the effectiveness of the proposed methodology, we carried out extensive case studies on flights in the SAR and the United States. We discovered that delay propagation dynamics for the flights in the SAR vary considerably from those in the United States. The proposed network-based method provides temporal details for the delay propagation dynamics for each airport and therefore contributes to strategic ATM and CDM.

Table 3
Delay propagation speeds for the flights in the SAR and United States.

Region/country	Day	Spd1	Spd15
SAR	Jun, 17	14	8
	Jun, 2	13	8
	Jul, 18	17	12
	Jul, 8	20	13
	Sep, 9	19	14
	Sep, 29	14	10
	Oct, 14	18	13
	Oct, 30	14	9
	Nov, 2	16	12
	Nov, 1	18	13
	Dec, 16	22	16
	Dec, 23	19	13
	Jun, 12	10	6
	Jun, 7	7	3
	Jul, 25	14	9
	Jul, 13	17	10
	Sep, 13	13	9
	Sep, 24	16	12
	Oct, 10	14	10
	Oct, 21	17	10
	Nov, 19	16	10
	Nov, 12	16	10
	Dec, 14	16	10
	Dec, 31	14	9
United States	Jun, 14	148	67
	Jun, 28	149	67
	Jul, 21	161	82
	Jul, 28	147	70
	Sep, 21	136	63
	Sep, 2	142	62
	Oct, 25	125	56
	Oct, 30	125	60
	Nov, 15	135	63
	Nov, 4	139	67
	Dec, 17	177	118
	Dec, 18	206	126
	Jun, 1	139	55
	Jun, 9	149	64
	Jul, 12	133	59
	Jul, 11	145	61
	Sep, 11	69	23
	Sep, 15	130	48
	Oct, 1	88	30
	Oct, 6	137	59
	Nov, 25	77	24
	Nov, 1	65	21
	Dec, 1	123	48
	Dec, 2	119	51

Spd1: average propagation speed for the case of $T_{DD} \geq 1$; Spd15: average propagation speed for the case of $T_{DD} \geq 15$.

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Compliance with ethics guidelines

Qing Cai, Sameer Alam, and Vu N. Duong declare that they have no conflict of interest or financial conflicts to disclose.

References

[1] Airbus. Flying by numbers: global market forecast for 2015–2034. Technical Report. Toulouse: Airbus; 2015. Report No.: 14029463.
[2] International Air Transport Association. IATA's annual review 2019 [Internet]. Montreal: International Air Transport Association; 2019 Jun 2 [cited 2019 Sep 21]. Available from: https://www.iata.org/publications/Documents/iata-annual-review-2019.pdf.
[3] Chen CH, Chou JH. Multiobjective optimization of airline crew roster recovery problems under disruption conditions. IEEE Trans Syst Man Cybern Syst 2017;47(1):133–44.
[4] Cao X, Zhu X, Tian Z, Chen J, Wu D, Du W. A knowledge-transfer-based learning framework for airspace operation complexity evaluation. Transp Res Part C Emerg Technol 2018;95:61–81.
[5] Zhou Y, Wan Y, Roy S, Taylor C, Wanke C, Ramamurthy D, et al. Multivariate probabilistic collocation method for effective uncertainty evaluation with application to air traffic flow management. IEEE Trans Syst Man Cybern Syst 2014;44(10):1347–63.
[6] Peterson EB, Neels K, Barczi N, Graham T. The economic cost of airline flight delay. J Transp Econ Policy 2013;47(1):107–21.
[7] Baumgarten P, Malina R, Lange A. The impact of hubbing concentration on flight delays within airline networks: an empirical analysis of the US domestic market. Transp Res Part E Logist Trans Rev 2014;66:103–14.
[8] Ball M, Barnhart C, Dresner M, Hansen M, Neels K, Odoni A, et al. Total delay impact study: a comprehensive assessment of the costs and impacts of flight delay in the United States. Technical Report. National Center of Excellence for Aviation Operations Research; 2010. Report No.: 01219967.
[9] Clewlow RR, Simaiakis I, Balakrishnan H. Impact of arrivals on departure taxi operations at airports. In: Proceedings of the AIAA Guidance, Navigation, and Control Conference; 2010 Aug 2–5; Toronto, ON, Canada; 2010.
[10] Morisset T, Odoni A. Capacity, delay, and schedule reliability at major airports in Europe and the United States. Transp Res Rec 2011;2214(1):85–93.
[11] Sridhar B, Swei SSM. Relationship between weather, traffic and delay based on empirical methods. In: Proceedings of the 6th AIAA Aviation Technology, Integration and Operations Conference; 2006 Sep 25–27; Wichita, KS, USA; 2006.
[12] Lui L, Ball MO, Hansen M, Lovell DJ, Chuang C, Gulding J. Causal analysis of en route flight inefficiency—the US experience. In: Proceedings of the 12th USA/Europe Air Traffic Management Research and Development Seminar; 2017 Jun 27–30; Seattle, WA, USA; 2017.
[13] Jones JC, Lovell DJ, Ball MO. Stochastic optimization models for transferring delay along flight trajectories to reduce fuel usage. Transp Sci 2017;52(1):134–49.
[14] Cai K, Zhang J, Xiao M, Tang K, Du W. Simultaneous optimization of airspace congestion and flight delay in air traffic network flow management. IEEE Trans Intell Transp Syst 2017;18(11):3072–82.
[15] Delgado L, Prats X. Effect of wind on operating-cost-based cruise speed reduction for delay absorption. IEEE Trans Intell Transp Syst 2013;14(2):918–27.
[16] Ma C, Cai Q, Alam S, Sridhar B, Duong VN. Airway network management using Braess's paradox. Transp Res Part C Emerg Technol 2019;105:565–79.
[17] Zhang Y, Su R, Li Q, Cassandras CG, Xie L. Distributed flight routing and scheduling for air traffic flow management. IEEE Trans Intell Transp Syst 2017;18(10):2681–92.
[18] Liu Y, Hansen M. Incorporating predictability into cost optimization for ground delay programs. Transp Sci 2016;50(1):132–49.
[19] Estes A, Ball M. Data-driven planning for ground delay programs. Transp Res Rec 2017;2603(1):13–20.
[20] Ball MO, Chen CY, Hoffman R, Vossen T. Collaborative decision making in air traffic management: current and future research directions. In: Bianco L, Dell'Olmo P, Odoni AR, editors. New concepts and methods in air traffic management. Berlin: Springer; 2001. p. 17–30.
[21] Okwir S, Ulfvengren P, Angelis J, Ruiz F, Guerrero YMN. Managing turnaround performance through collaborative decision making. J Air Transp Manage 2017;58:183–96.
[22] De Almeida CRF, Li W, Meinerz GV, Li L. Satisficing game approach to collaborative decision making including airport management. IEEE Trans Intell Transp Syst 2016;17(8):2262–71.
[23] Chatterji G, Sridhar B. National airspace system delay estimation using weather weighted traffic counts. In: Proceedings of the AIAA Guidance, Navigation, and Control Conference and Exhibit; 2005 Aug 15–18; San Francisco, CA, USA; 2005.
[24] Klein A, Craun C, Lee RS. Airport delay prediction using weather-impacted traffic index (WITI) model. In: Proceedings of the 29th Digital Avionics Systems Conference; 2010 Oct 3–7; Salt Lake City, UT, USA; 2010. p. 2–8.
[25] Baspinar B, Koyuncu E. A data-driven air transportation delay propagation model using epidemic process models. Int J Aerosp Eng 2016;2016:4836260.
[26] Sternberg A, Soares J, Carvalho D, Ogasawara E. A review on flight delay prediction. 2017. arXiv:1703.06118.
[27] Rebollo JJ, Balakrishnan H. Characterization and prediction of air traffic delays. Transp Res Part C Emerg Technol 2014;44:231–41.
[28] Khanmohammadi S, Tutun S, Kucuk Y. A new multilevel input layer artificial neural network for predicting flight delays at JFK airport. Procedia Comput Sci 2016;95:237–44.
[29] Belcastro L, Marozzo F, Talia D, Trunfio P. Using scalable data mining for predicting flight delays. ACM Trans Intell Syst Technol 2016;8(1):5–14.
[30] Chen J, Li M. Chained predictions of flight delay using machine learning. In: Proceedings of the 2019 AIAA Science and Technology Forum and Exposition; 2019 Jan 7–11; San Diego, CA, USA; 2019. p. 1661.
[31] Churchill AM, Lovell DJ, Ball MO. Flight delay propagation impact on strategic air traffic flow management. Transp Res Rec 2010;2177(1):105–13.
[32] Fleurquin P, Ramasco JJ, Eguíluz VM. Characterization of delay propagation in the US air-transportation network. Transp J 2014;53(3):330–44.
[33] Ahmadbeygi S, Cohn A, Lapp M. Decreasing airline delay propagation by re-allocating scheduled slack. IIE Trans 2010;42(7):478–89.
[34] Kafle N, Zou B. Modeling flight delay propagation: a new analytical-econometric approach. Transp Res Pt B Methodol 2016;93(Pt A):520–42.
[35] Fleurquin P, Ramasco JJ, Eguiluz VM. Systemic delay propagation in the US airport network. Sci Rep 2013;3(1):1159.
[36] Pyrgiotis N, Malone KM, Odoni A. Modelling delay propagation within an airport network. Transp Res Pt C Emerg Technol 2013;27:60–75.
[37] Campanelli B, Fleurquin P, Arranz A, Etxebarria I, Ciruelos C, Eguíluz VM, et al. Comparing the modeling of delay propagation in the US and European air traffic networks. J Air Transp Manage 2016;56(Pt A):12–8.
[38] Wu W, Wu CL, Feng T, Zhang H, Qiu S. Comparative analysis on propagation effects of flight delays: a case study of China airlines. J Adv Transp 2018;2018:1–10.
[39] Beatty R, Hsu R, Berry L, Rome J. Preliminary evaluation of flight delay propagation through an airline schedule. Air Traffic Control Q 1999;7(4):259–70.
[40] Hossain MM, Alam S, Symon F, Blom H. A complex network approach to analyze the effect of intermediate waypoints on collision risk assessment. Air Traffic Control Q 2014;22(2):87–114.
[41] Du W, Zhang M, Zhang Y, Cao X, Zhang J. Delay causality network in air transport systems. Transp Res Part E Logist Trans Rev 2018;118:466–76.
[42] Du W, Zhou X, Lordan O, Wang Z, Zhao C, Zhu Y. Analysis of the Chinese airline network as multi-layer networks. Transp Res Part E Logist Trans Rev 2016;89:108–16.
[43] Hossain MM, Alam S. A complex network approach towards modeling and analysis of the Australian airport network. J Air Transp Manage 2017;60:1–9.
[44] Rocha LE. Dynamics of air transport networks: a review from a complex systems perspective. Chin J Aeronaut 2017;30(2):469–78.
[45] Hossain M, Alam S, Abbass H. A dynamic multi-commodity flow optimization algorithm for estimating airport network capacity. In: Electronic Navigation Research Institute, editor. Air traffic management and systems II. Tokyo: Springer; 2017. p. 205–20.
[46] Campanelli B, Fleurquin P, Eguíluz VM, Ramasco JJ, Arranz A, Etxebarria I, et al. Modeling reactionary delays in the European air transport network. In: Proceedings of the Fourth SESAR Innovation Days; 2014 Nov 24–27; Madrid, Spain; 2014.
[47] Barthélemy M. Spatial networks. Phys Rep 2011;499(1–3):1–101.
[48] Holme P, Saramäki J. Temporal networks. Phys Rep 2012;519(3):97–125.
[49] Federal Aviation Administration. Definitions of variables [Internet]. Washington, DC: Federal Aviation Administration; [cited 2019 Jun 21]. Available from: https://aspmhelp.faa.gov/index.php/APM:_Analysis:_Definitions_of_Variables.
[50] International Civil Aviation Organization. Wake turbulence category [Internet]. Montreal: International Civil Aviation Organization; [cited 2019 Apr 21]. Available from: https://www.skybrary.aero/index.php/ICAO_Wake_Turbulence_Category.