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Simulation Analysis on Flight Delay Propagation Under Different Network Configurations

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ABSTRACT This paper investigates flight delay propagation in air transportation networks (ATNs) by considering both network structures and airport operation performance. An airport susceptible-infected-recovered (ASIR) model is established based on the mechanism of epidemic spreading, where the focus is on the impact of the infection rate in order to properly map and understand the probability of delay propagation. Different network configurations are abstracted under complex network theory, in which the ASIR model can be simulated upon. The simulation results show that the original airport traffic, airport connection and the level of airport turnaround services play important roles in influencing delay propagation in different airports. In addition, changes of network structure such as the emerging of secondary hubs can also influence the delay propagation.

INDEX TERMS Flight delay propagation, infection rate, network structures, ASIR model, flight delay simulation.

I. INTRODUCTION

The global aviation industry has experienced an unprecedented growth in terms of supply and demand. Since 2000, annual growth rates of 37 % have been recorded [1]. Moreover, by 2030, it is expected that the total number of flights will double and the total number of passenger-kilometers flown will nearly triple [2]. This growth can be considered as desired from an economic point of view, but will also have a number of important drawbacks, one of which is serious flight delays. Flight delays will not only lead to economic losses [3], [4] but also have a negative impact on the environment [5] and social effects. Any delay related to resources of upstream flights, such as late inbound aircraft, crew, and passengers will further impact its connected downstream flight [6]. When flight delays impact and spread over an entire network, implying that delays originating from an upstream flight infect downstream flights, this process is referred to as flight delay propagation [7]. There will also be a number of spatial implications following flight delay propagation: congestion/disruption at hub airports, unequal distribution of route traffic, emergence of secondary hub airports, and varied operation capabilities among airports [8], [9].

A range of aspects has been investigated to deal with mechanisms of flight delay propagation. Baspinar *et al.* analyzed the impact of airport capacity on the total delay time and found that airports with capacity below a critical threshold can prolong the total delay time [10]. Delay time is considered by Wu et. al. when they produce recovery plans to solve the flight disruption problems. In their opinion, delay propagation is the consequential disruption of the downstream flights which affects the airline operations much more than the initial delay [11]. AhmadBeygi *et al.* concluded that redistributing buffer time during scheduling can reduce the influence of upstream flight delays on the sequential flights [12]. Recently, researchers paid more attention on how network and airport-related attributes influence the delay propagation from a network perspective. For instance, delay propagation can be magnified in terms of number of delayed flights and total delay time if airports are strongly connected

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to each other [13]. The connected resources shared in airports significantly influence the initiation and progression of delay propagation [6], [14].

Complex network theory has been used in network structuring in a comprehensive way. Network growth, routing traffic, and hub capacity etc. are found to have large impact on network structure as well as to model dynamics (e.g. epidemic spreading and delay propagation) of ATNs [15], [16]. Furthermore, Baspinar and Koyuncu [17] innovatively combined the SIR model with complex theory to examine the delay propagation in ATNs, follows its similarity with epidemic spreading. In particular, they paid attention on the mechanism of delay propagation in ATNs with scale-free characteristics that can be found in most of ATNs. However, they considered neither the factors that can also influence the probability of delay propagation in ATNs when establishing the network nor did they take account of the changes of network structure. We have applied the epidemic spreading mechanism into a flight delay model in our previous work [18], where we try to connect the flight delay infected rate with flight operation factors such as distance, buffer time, etc. We compare different airline networks in the aspect of their operation and scheduling, but ignore the evolution rules of ATN itself. As a result, the impact of networks evolution and their different configuration during different evolving process that may influence flight delay propagation might be underestimated.

Therefore, this paper not only apply the SIR model to the air network as Baspinar and Koyuncu [17] did, but also redefines the probability of delay propagation from the perspective of network configuration such as airport connectivity (i.e. airport degree k) and factors that effect airport operation performance (e.g. airport annual passenger flow, airport turnaround service efficiency, etc.) to explore in what ways these factors may influence the flight delay propagation as the ATNs structure develops. Meanwhile, as it is hard to simulate flight delay propagation in a real air network with fixed nodes and edge connection, an abstract simulation environment for ATNs is generated based on complex network theory.

This paper is organized as follows. In Section 2, we first introduce how epidemic spreading mechanism were used in studying flight delay propagation and then the ASIR model were constructed based on SIR model. Factors impact to the probability of delay propagation (i.e. the infected rate) were also discussed. Section 3 presents three different ATNs which is the developing process of China's air transport network from year 2007 to 2017. Complex network theory was used to abstract the real ATNs into simulation ones which is easier and clearer for further characteristics simulating of flight delay propagation. Section 4 presents the simulation results and discussion. Section 5 concludes and puts forwards some avenues for further research.

II. THE ASIR MODEL

This section introduces how to model delay propagation in weighted ATNs by considering the impacts of network structure, airport traffic and turnaround operations. In particular, the methodology used to express the process of delay propagation is based on the conventional susceptible-infected-recovered (SIR) model which originally applied in the epidemic spreading discipline. Similar to Baspinar and Koyuncu [17], flight delay propagation mechanism can be corresponded to some epidemic spreading such as smallpox which can no longer be infected again once recovered. That is because, data from our examined time scales (always in one day time) shows flights for passenger transfer are mostly scheduled before midnight and rare flights will delayed late to midnight without cancellation. For this reason, we can see there is no departure or arrival flights in the end of the operation day, in other words, no delay can be propagated from these airports. Therefore, what we focus on is how these delays propagate between airports in a day time.

To be explicit, delay propagation progression in ATNs is described as follow. There are three types of airports in the network, and Fig. 1 depicts the origination and progression of delay propagation across airports. When delays occur in a 'susceptible' airport, airports connected to the susceptible airport may be 'infected' through flights and become delayed airports. As flights are scheduled subsequently from one route to another, delays can thus be propagated to other airports that are not directly connected to the original susceptible airports, i.e., along the entire network [20]. Following the measures taken to mitigate delays, the infected airports can be 'recovered'.

FIGURE 1. The progression of delay propagation across airports in a network.

This process is determined by two subsequent transition states - infected and recovered rates as denoted by β and μ respectively. β refers to the probability that a susceptible airport becomes a delayed airport; μ refers to the probability that a delayed airport becomes a recovered airport. As this paper examines the delay propagation pattern from a network-wide perspective, recovered rate only effects the time scale definition of spreading [19].

A. MODEL EXPLANATION

Based on the aforementioned process of delay propagation, we propose an airport susceptible-infected-recovered (ASIR) model as expressed by the following differential equations (1).

$$\begin{cases} S_k(t) + I_k(t) + R_k(t) = 1 \\ \dfrac{dI_k(t)}{dt} = -\mu I_K(t) + \beta k S_k(t)\,\Theta_k(\mathrm{t}) \\ \dfrac{dS_k(t)}{dt} = -\beta k S(t)\,\Theta_k(\mathrm{t}) \end{cases} \quad (1)$$

where:

(1) k refers to the degree of an airport in the network, which indicate the total number of its connected airports.

(2) t refers to time step, $t \in [1, T]$, where T is a value close to infinity to guarantee the model convergence.

(3) $S_k(t)$, $I_k(t)$ and $R_k(t)$ refer to the proportion of susceptible, infected, and recovered airports among airports with degree k at time$t$, respectively. The sum of these three parameters should be equal to 1.

(4) $\Theta_k(t)$ refers to the probability that an airport with degree$k$ connects to a delayed airport at time t. As higher degree of airports does not mean larger probability connecting to a delayed airport in ATNs [21], the value of $\Theta_k(t)$ is thus linearly influenced by the degree distribution of a network and the proportion of delayed airports with degree k at time t, as measured below (2) [19].

$$\Theta_k(t) = \sum\nolimits_k kP(k) I_k(t) / < k > \tag{2}$$

where, $P(k)$ is the degree distribution of a network. $< k >$ is the average degree of a network and measured as $< k >= \sum_{k\in N} k * P(k)$, with N the total number of airports in a network.

(5) Equation (1) refers to the changing rate that susceptible airports are transformed into infected airports, and the probability that infected airports changed back to susceptible airports respectively. Therefore, the effective infected rate can be rewrite as $\lambda = \beta/\mu$. In this paper, it is a function of airport category α which is influenced by both airport traffic and its turnaround efficiency q. We will define λ in the following section.

B. EFFECTIVE DELAY PROPAGATION PROBABILITY

The effective delay propagation probability λ is the core of this model and can be influenced by several factors [22]. We mainly consider three factors – network configuration, airport traffic and turnaround service level, and explore in what ways these three factors influence the delay propagation. Therefore, λ is first measured as follows (3).

$$\lambda(a) = (S_a/S_{max})^q \tag{3}$$

where, S_a refers to the annual traffic of airport a and S_{max} refers to the maximum traffic among all airports in the same network. q refers to the level of airport turnaround services and is set to be between 0 and 1. The value of q in this paper is given based on the score of airport annual service evaluation report which depend on how well the airport react when facing with flight delays. The higher the score is, the faster the airport reacts, therefore, the less probability flight may delay.

The format design of formulation (3) demonstrates the simplified non-linear relationship between the delay propagation probability $\lambda(a)$, airport traffic S_a and turnaround service level q. In general, higher airport traffic may lead to more congestion therefore more delay flights; on contrary, higher level of airport turnaround operation performance may largely ensure on-time arrival and departure, especially for these connecting flights [21], [22]. As the algorithm presented by Chunki *et al.* pointed out that the average per flight delay was reduced by 30 % even when the transit times are only permitted to increase by 5 % [23]. It is reasonable to say that airport turnaround efficiency should be considered.

Furthermore, the impact of network structure is investigated by considering airport degree k into delay propagation probability. Even with the same airport traffic or turnaround performance, airports with different degree may have different connectivity, hence may show different propagation ability. In this way, λ in formulation (3) can be measured as follows (4).

$$\lambda_k(a) = \left(\frac{S_k(a)}{S_{max}}\right)^q \tag{4}$$

In which for the airport with the same degree and/or traffic proportion (i.e. S_a/S_{max}), the higher value of q leads to lower possibility of effective infected rate λ, on the other hand, for airport with the same turnaround service level, the higher value of k and/or S_a/S_{max} denotes the busier the airport is, therefore more likely to be delayed.

And the ASIR model can be rewritten as:

$$\begin{cases} S_k(t) + I_k(t) + R_k(t) = 1 \\ \dfrac{dI_k(t)}{dt} = -I_K(t) + \lambda_k(a) kS_k(t)\Theta_k(\mathrm{t}) \\ \dfrac{dS_k(t)}{dt} = -\lambda_k(a) kS(t)\Theta_k(\mathrm{t}) \end{cases} \tag{5}$$

From the established ASIR model, flight delay propagation is not only related to airport traffic and turnaround service level, but also influenced by different network configurations. Based on the degree distribution, the proportion of all delayed and susceptible airports in the network at time t can be respectively obtained by the following equation: $I(t) = \sum_k I_k(t) * P(k)$ and $S(t) = \sum_k S_k(t) * P(k)$.

III. DEVELOPMENT OF AIR TRANSPORTATION NETWORKS

A. GROWTH MECHANISM OF ATNs

As China's air network is proved to exhibit an obverse complex network characteristic [24], we use a weighted preferential attachment mechanism stemming from complex network theory, where the nodes are airports and the edge weight is route traffic. At the beginning of the formation of the network, airports are more willing to connect with busy airports and the airport degree seems to be an important connection factor. However, with the development of network, it is more difficult for busy airports to directly connect with those newly emerged small airports. As a result, routes with high passenger flow become the consideration factor for these airports. Different from node preference attachment, the connection between airports (i.e. high passenger flow) is more concerned and emphasized in the edge preferential attachment model.

Considering the growing route traffic, the rule in this paper is designed as the new introduced airport tends to connect to airports linked by routes with the largest traffic. The algorithm used to establish such a network is designed as follows:

(1) Step1 (Initial setting): At time $t\_growth = 0$, the initial state is set as an ATN consisting of three fully connected airports. The initial weights of all three edges are assumed as 1 for model simplicity (Fig. 2).

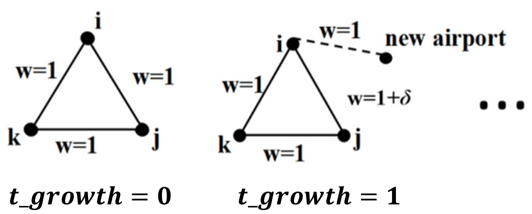

FIGURE 2. A toy network for edge preferential attachment mechanism.

(2) Step 2 (Weighted preferential attachment mechanism): From time $t\_growth = 1$, a new airport is subsequently added to the network at each time step t_growth. The connection process of each new added airport is as follows:

- The new airport selects an existing edge based on a so-called preferential selecting probability $\Pi(e_{ij})$, which is measured as $\Pi\left(e_{ij}\right) = w_{ij}/\sum w_{ij}$, which proportion to route traffic.
- The two endpoints of the new selected edge are equally selected throughout this paper.
- The new generated route is then given a weight 1, i.e., the same as the initial weights. Correspondingly, the weight of the selected edge increases by a given increment δ. Different values of route traffic increment δ will lead to varied configurations of network structure, thus in a long time period, the abstract network can represent the development results of China's networks and upon which the ASIR models are executed.

(3) Step 3 (Stopping rule): the growth of the network stops until the total number of airports reaches a pre-set value.

B. CONFIGURATION OF ATNs

Different network structure and airport types will influence the delay propagation as network develops, it is necessary to investigate how network structure evolves and airport emerge during time goes. Fig.3 shows the changes of network structure as the total number of airports increases where the route traffic increment $\delta = 1$. As can be seen, a more hierarchical network structure tends to emerge with a larger scale.

As the development of ATNs needs a long time scale, airports are highly stable over time, hence, in order to further explore the impact of different network configurations on the delay propagation, we examine the development results of three network structure under different time scale (i.e. 2007, 2012, 2017) (Fig.4).

The real networks of three different years were abstracted into complex networks in Fig. 4. With the actual amounts of airports, and their traffic and degree, the fitting curve (green line) shows that $\delta = 1, 2, 4$ is appropriate to describe the real developing process of ATNs respectively. In the interval [1, 100] of degree, compare with the theorical correlation function curve (red line) based on the network model, each linear correlation R-square can be reached around 0.8, indicating a better fitness. As the volume of route traffic increases, the network structure tends to develop into a much more hierarchical structure with the gradual emerging of several secondary hub airports. It is considered to be properly corresponding to the internal growing mechanism of China domestic network.

In fact, after changing for decades, China's airport network has been completely different from the original one. It tends to have more multi-airport system and focus on the development of regional airports in recent years. Although airport network in China yet has not appeared to be a typical hub-and-spoke one, airports in the network are more clustered and has developed obvious hub airports. In this case, how delays spread among airports is the significance research of this paper.

C. AIRPORT CLASSIFICATION ON ATNs

A simple classification scheme is introduced to classify airports into four categories based on the proportion of its annual traffic in a network. The percentages for the domestic air transport network in China is calculated based on the data collected from Airport Council International (ACI) classification.

TABLE 1. Percentage of different types of airports under different network scales.

Airport category (S_a/S_{max}) / Number of airports / year	A $\geqslant$0.5	B [0.2,0.5)	C [0.03,0.2)	D [0,0.003)
2007 (Network 1, N=149)	3	6	30	110
2012 (Network 2, N=183)	3	8	32	140
2017 (Network 3, N=229)	4	16	29	180

The interval of traffic proportion for each category airport in three different networks are calculated in Table 1. Category A airports are the most important airports in a network can be considered as hub airports with the largest number of routes and traffic. Category B airports rank just behind the category A and can be secondary hub airports handling most of a country's domestic traffic. Category C airports may function as regional airports mainly dealing with a region's traffic within a country, whereas Category D airports are the small airports that account for the largest percentage in a network.

IV. SIMULATION RESULTS

Drawing on the proposed ASIR model, this section investigates the impact of airport traffic, the level of airport

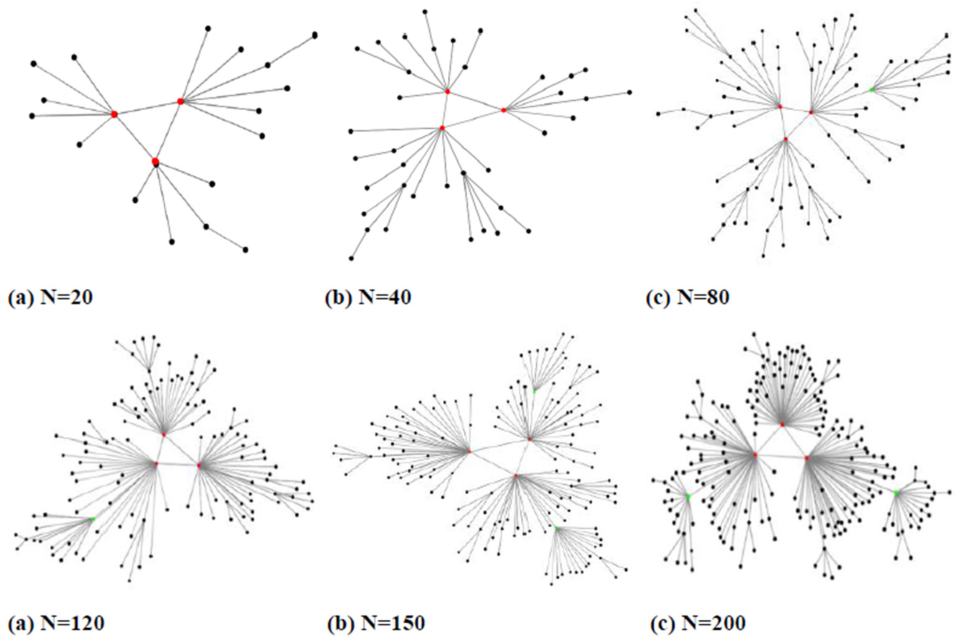

FIGURE 3. Simulation of network evolution.

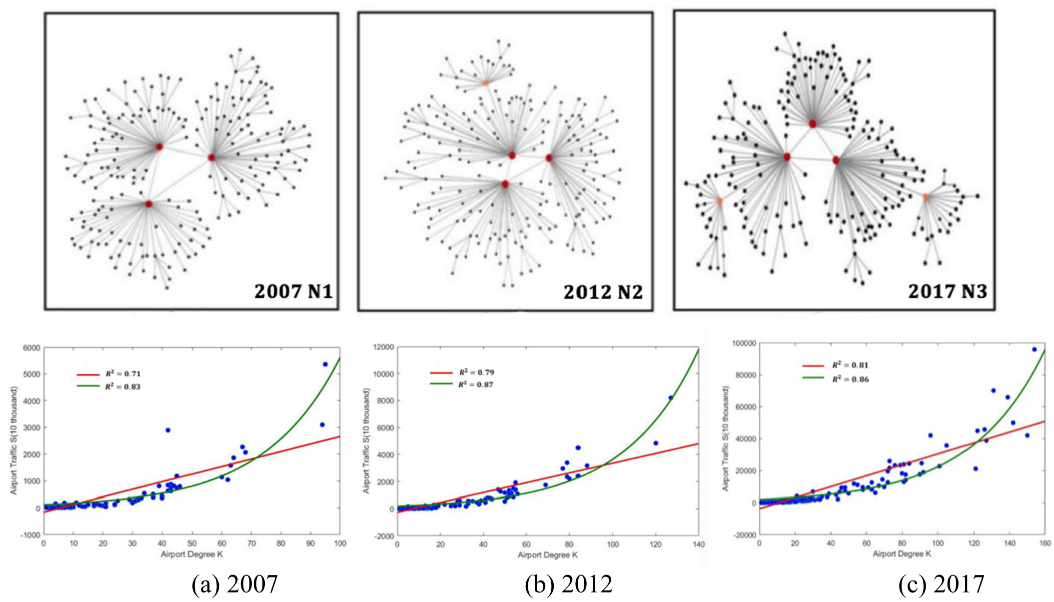

FIGURE 4. The evolution of network structure and modeling effective verification.

turnaround services and network structures on the delay propagation. In particular, the impacts of airport traffic and airport turnaround services level are first investigated in a focused network configuration (i.e. Network 3). Then how network structures influence delay propagation is examined in three different network scenarios. In each simulation, time scale presents the complete time that flight delay propagates among networks. As the ending time for each simulation is 48, it can be seen that two simulation steps correspond to one hour in practices.

A. FACTORS EFFECT DELAY PROPAGATION

Supposing that the turnaround services are at a high level with $q = 0.8$, we consider category B and C airports as the initial susceptible airports. Fig. 5 presents the proportion distribution of delayed airports under different airport types.

As can be seen, the maximum proportion of delayed airports for airport categories with larger traffic (i.e., category B) is much higher than that for the airports with less traffic (i.e., category C). The time to reach the maximum proportion for the former is shorter. Effective way to control the spread

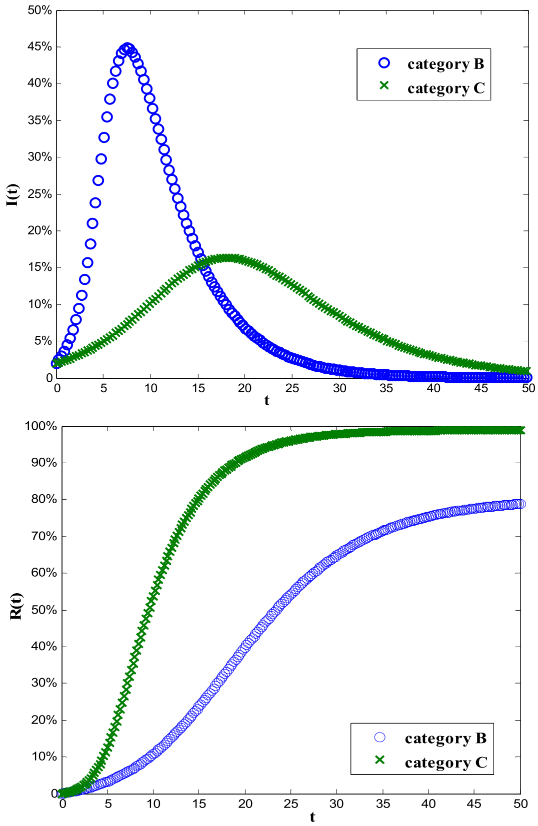

FIGURE 5. Airport traffic effect under different categories.

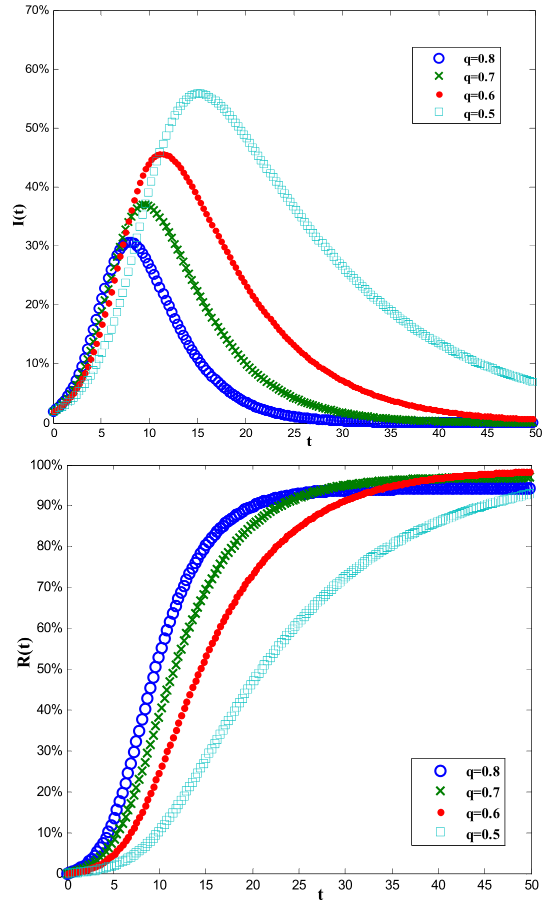

FIGURE 6. Airport turnaround service level effect.

of delays can be taken to restrain delays at airports with larger traffic. For instance, priorities can be given, or longer buffer time can be scheduled for connecting flights at these airports where delay propagation originally occurs with a higher probability.

Theoretically, the departure/arrival delay time can be reduced if the buffer time of aircraft turnaround is appropriately scheduled and airports can provide high level of turnaround services. As have proven above, delays can be easily transmitted starting from airports with large volumes of traffic (i.e., category B airports), we therefore, use category B airports to illustrate whether delay propagation can be controlled by improving the turnaround service level at these airports. A high level of airport turnaround service is assumed to be between 0.5 and 1 in this paper. Fig. 6 shows the impact of the airport turnaround service level on the delay propagation by setting four linearly increased levels (i.e., 0.5, 0.6, 0.7, 0.8).

As the level of the airport turnaround service gradually improves, the proportion of delayed airports decreases nearly in all the time moments and the total time for the delayed airports to diminish is also less. Therefore, airports should strive to improve the level of the turnaround service level by taking effective airport control management, for instance, investing more human resources during peak hours, or applying automatic facilities in the key links of airport turnaround operation, which can help restraining the spread of delays in terms of the scale and speed.

B. NETWORK STRUCTURE EFFECT

We investigate the impact of the network structures on the delay propagation by examining how the proportion of the number of delayed airports $I(t)$ changes under different networks proposed in Fig. 4. Supposing the turnaround service is at a high level with $q = 0.8$, Fig. 7 shows that: (1) the maximum proportion of the delayed airports is reduced as network develops from N1to N3; (2) the time reaching its maximum is also prolonged. This means different network structures can influence the pattern of delay propagation in terms of both scale and speed.

During one decade's evolution, routes in China's network becomes denser and the total passenger volume nearly triple increased. Compare to the high speed in traffic increment, the decline of on time performance (OTP) is slowed down. In fact, the decreasing rate of OTP in 2012 and 2017 is 5.71 % and 4.98 % respectively, which indicate only an average of 0.83 % OTP decline in each year over the whole decade. Despite of the government investment for airport facilities construction supporting, easier connection between airports and the developing of multi-airport system is also one of the

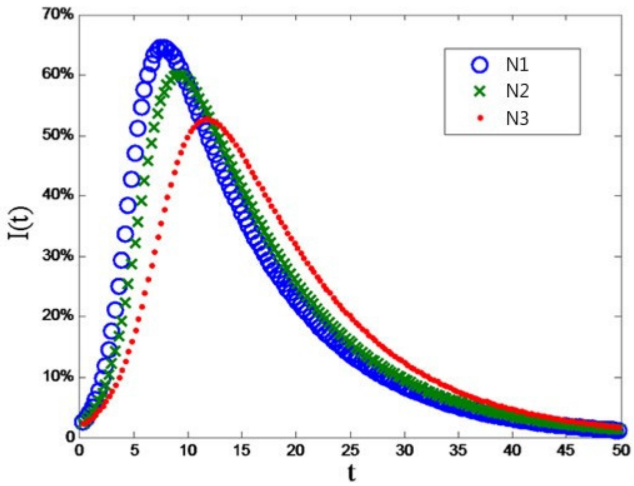

FIGURE 7. Route traffic effect on the delay propagation.

main reasons to restrain delay propagation. The emergency of secondary/regional hub airports illustrate that carriers tend to adopt a multi-hub-and-spoke network structure in order to relieve the congestion and severe schedule delays at their primary hubs. Meanwhile, airlines adopting a medium-traffic expansion strategy should be encouraged to enter small airports with large traffic growth potential without suffering from the loss of delay.

C. AIRPORT CATEGORY EFFECT

As both the airport traffic and network structures have changed during the decade, we further investigate how airport category (i.e. the role that the airport plays in the network development) influence the delay propagation in different networks. Supposing that parameters $q = 0.8$, different from the examination in Fig, 7 which calculates all airports in the entire network, Fig. 8 shows the proportion distribution of delayed and recovered airports for category B airports.

We overall observe three sharp proportion distribution curves with high kurtosis and long tails in the left figure in all three networks. As category B airports tend to be hubs with limited capacity, even the slight increase of route traffic can lead to severe delays at these types of airports. However, the steep slope of the $R(t)$ curve implies that as more 'infected' airports are recovered at a high speed, the propagation of delays is controlled at more airports. Airports are also examined in Fig. 9 which present the situations in category C airports.

For category C airports, flatter proportion distributions of delayed airports are observed in the cases of N1 and N2, whereas the similar sharp distribution as the category B airports is discerned in the N3 situation. In addition, a closer comparison shows that the maximum proportions of delayed airports for category B airports are nearly doubled comparing to those for category C airports in both N1 and N2 situations. This implies that the slight traffic increment at category C airports would not lead to severe propagation of

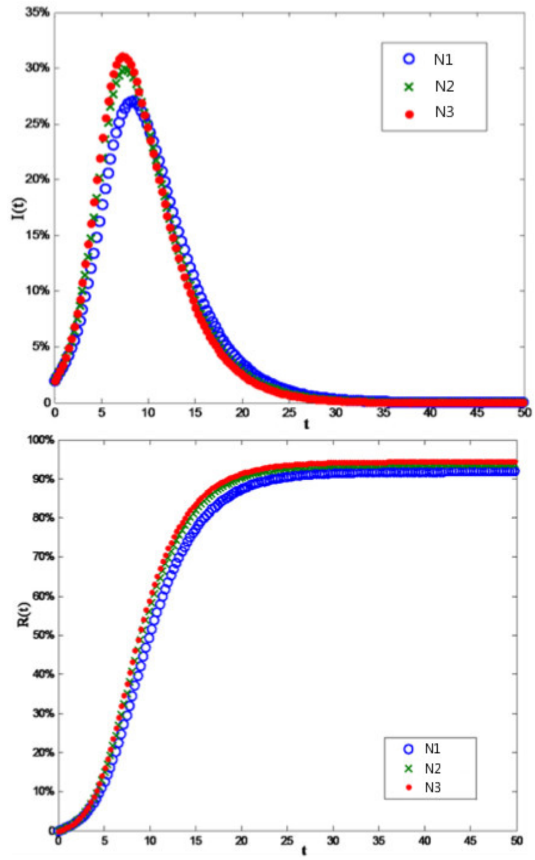

FIGURE 8. The integrated effect for category B airports.

delays. However, as network develops, category C airport plays a more important role in connecting small airports (i.e. category D airports) and large/medium airports (i.e. category A/ B airports). They are often regional hub airports located in large cities in each province and work as bridge airports for passenger transiting, therefore plays a more and more important role in effecting delay propagation. It is, therefore, suggested that carriers that pursuit a moderate route traffic expansion strategy can explore new markets at category C airports with high traffic growth potential, meanwhile without suffering from the loss of delays.

D. COMBINATION EFFECT

Lastly, we consider an integrated effect by designing four scenarios with the level of the airport turnaround service $q = 0.5, 0.7$ and 0.9 (i.e., representing low, medium and high level, respectively) as well as different network structures in Fig 10. As it seems to be unrealistic for an airport to have high volumes of traffic but lower level of turnaround services (i.e., a scenario of N3, p=0.5) or low volumes of traffic but high level of turnaround services (i.e., a scenario of N1, p=0.9), we do not consider these two cases in our simulations.

Four distributions representing the aforementioned four scenarios are labeled as 1, 2, 3 and 4, respectively. When

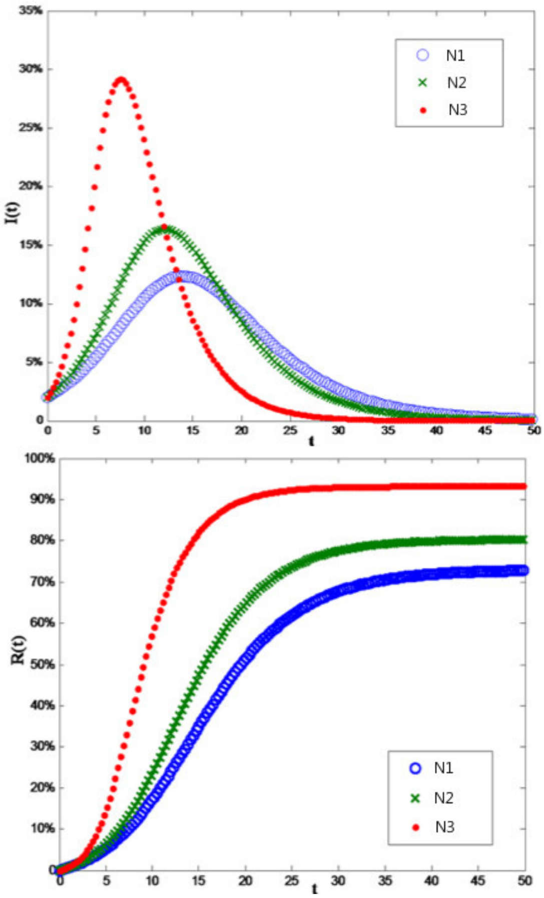

FIGURE 9. The integrated effect for category C airports.

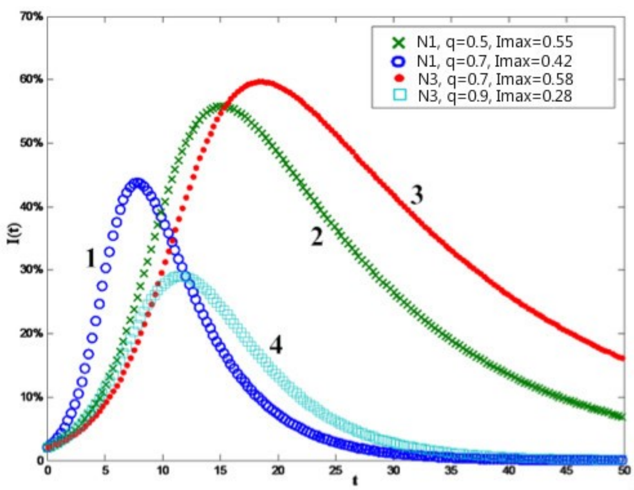

FIGURE 10. Integrated effects of airport turnaround level and route traffic.

the level of airport turnaround services maintains at the medium level (scenario1 and 3), delay propagation in N1 and N3 lead to two different situations before and after $t = 11$. At the initial time moment, the proportions of delayed airports for scenario 1 are higher than those of scenario 3. After $t = 11$, it seems that delays caused by the network with smaller scale and lower traffic (i.e. N1) can be gradually dissolved as long as the airports can provide at least medium level of turnaround services (curve 1). When network evolves into N3 and traffic of each airport become larger, the maximum proportions of delayed airports is nearly 1.5 more than that of N1. That is because more flights will be involved as network enlarged. In addition, as curve 4 is located almost under all the other three curves, it shows that the high level of airport turnaround services can significantly reduce the number of delayed airports and suppress the propagation of delays, even in the case of N3 with larger airports emerged and dense routes.

To summarize, in order to control the delay propagation in term of its scale and time, the increase of airport traffic should match the level of airport turnaround services. Specifically, the ambitious expansion of airport traffic should be guaranteed by the high level of airport turnaround services; if not, a medium level of airport turnaround services combined with a conservative plan with slight increase of route traffic may restrain the spread of delays.

V. CONCLUSION

This paper investigated how airport traffic, turnaround operations and network structure influence the flight delay propagation based on the evolution results of China's air transport networks. We first establish a relationship between delay propagation and network structures by considering both airport connection and the airport traffic and then simulate the flight delay propagation upon.

The ASIR model allows to not only quantify the process of flight delay propagation by considering the scope and lasting time of propagation, but also incorporate factors influencing the delay propagation. In all these three network structures, airports with larger traffic should be effectively controlled so as not to generate delays easily or swiftly spread delays to other airports. As the network appear to be a more typical hub-and-spoke structure, the scope of the delay propagation is more likely to be restrained. This is mainly contributed to the emergency of secondary/regional hub airports which are in the role of sharing traffic effectively. In addition, when more regional/secondary airport emerged, the main effects of delay propagation is gradually transferred from hub airports to these airports. Therefore, resources such as runway and terminals as well as the level of airport turnaround services there should be accelerated developed in order to accommodate its rapid growing traffic.

This paper has been done without limitations that can be improved for further research. First, empirical studies for real air transport networks (e.g., ATNs in China) should be provided to further validate the simulation results. Second, although we explore airport traffic and airport connection as the main factor that drives network change and delay propagation simultaneously, other factors, such as yield and distance, can also be included in the model in the future.

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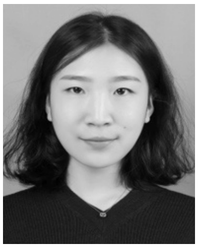

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