Hindawi
Mathematical Problems in Engineering
Volume 2018, Article ID 7171486, 12 pages
https://doi.org/10.1155/2018/7171486

Research Article

Systemic Congestion Propagation in the Airspace Network

Wen Tian, Xiaoxu Dai, and Minghua Hu

National Key Laboratory of Air Traffic Flow Management, Nanjing University of Aeronautics and Astronautics, China

Correspondence should be addressed to Wen Tian; tianwen0665@qq.com

Received 25 April 2018; Revised 24 July 2018; Accepted 25 September 2018; Published 6 November 2018

Academic Editor: Rosa M. Benito

To be different from the traditional concept of congestion, congestion propagation based on the correlation between aircraft is given. And the main resource shared and competed for in airspace is the air route network, especially the intersection linking the multiroute. The system composed of congestion propagation units operates in airspace network, which is limited by the network geometry and the correlation between aircraft. This paper presents models based on the congestion and propagation characteristics in complex network, predicting the trend of congestion propagation and the peak of congestion size. By analyzing the relationships between system parameters and congestion propagation and accounting for the effects of propagation across networks, this paper enhances the current dynamics models of congestion propagation in airspace. Firstly, a heterogeneous network model is introduced to reveal the propagation process of aircraft with different degrees of correlation. This is followed by the specification of two simplified models for short-term prediction, just taking the sector capacity, propagation rate, and dissipation rate into account. And the propagation rate and dissipation rate depend on the sector geometry and aircraft distribution. Using them (sector capacity, propagation rate, and dissipation rate), the prediction models are accurate in predicting the evolution of congestion peak and propagation trend in comparison with the sample data of intersections in the sector. Of them, the model with capacity limitation is more accurate on busy hour. And on non-busy hour, capacity is insensitive in predicting congestion clusters. Furthermore, the computing method of propagation rate and dissipation rate is given in our paper. Finally, a numerical analysis is performed, in which it is demonstrated that system capacity, propagation rate, and dissipation rate have different effects on congestion propagation in airspace. The results show that low propagation and high dissipation rates not only are nonlinear but also decrease the level of congestion in the propagation of congestion. In particular, of the three parameters, system capacity affects the rate of convergence, with a low-capacity system reaching a stable state quickly and therefore providing a basis for sector partitioning. The method proposed in this paper should enable air traffic controllers to better understand the characteristics of congestion and its propagation for the benefits of both congestion management and improvement of efficiency. Significantly, airspace designers can take congestion propagation into consideration for optimizing the airspace structure in the future.

1. Introduction

The rapid growth in air traffic is increasing the complexity of airspace/airline operations resulting in higher levels of congestion. As a result, many airports are experiencing significant flight delays. Delay may cause air traffic unit congested in a certain period, and congestion is one of the events causing delay. Both of them usually are applied to describe the traffic condition, and they can be transmitted between flights, airports, or both, having wider impacts across the airspace network [1]. Traditionally, congestion and delay are addressed largely by tactical management of flight scheduling [2], ignoring the evolution of congestion or delay. However, in order to significantly reduce congestion and delay, a detailed analysis of the propagation process and its influencing factors is required. Delay propagation derives from the interdependencies between different scheduled flights [3–5].

Traditionally, delay trees have been used to describe delay propagation, with flights and connectivity represented by the vertices and edges, respectively [6, 7]. Some delay propagation models consider factors such as aircraft rotation, flight connectivity, and airport congestion [8, 9]. However, although delay propagation can be used to describe airport congestion, it is not a direct measure of airspace traffic. Congestion propagation, on the other hand, through the consideration of air traffic and other factors, can enable the understanding of the actual operation of the airspace network. However, it should be noted that there are other causes of airspace congestion, such as adverse weather, equipment failure, and military activities [2, 10, 11]. Furthermore, congestion propagation operates on air routes, which are complex networks [12–15], usually hub and spoke [16–23]. Some studies determine airspace congestion by computing the complexity of flights in airspace [24–26], but they do not take congestion propagation into consideration. Airspace congestion and airport congestion both propagate on a complex network [8, 27–29]. Queueing [30] and aircraft recovery [31] models take into account the constraints of congested airspace and the correlation between flights. Simulation tools [2, 30, 31] and operation data [8, 9, 19, 29] are used for modeling delay time. In order to mitigate airspace congestion, disruption management is used together with flight plans [32, 33] for proactive control of aircraft, but they do not take congestion propagation into consideration.

The correlation between aircraft's activities, for example, trajectory synchronization, is measured with synchronization likelihood to detect differences between two classes of safety-related events [34]. The congestion correlation between road segments is explored, proposing a three-phase framework, and some important patterns leading to a high/low congestion correlation are found [35]. But the correlation between aircraft in congestion propagation on airspace networks is not included in these studies.

This paper develops simple and accurate models based on the correlation between aircraft for congestion propagation. Aircraft in the airspace are divided into different clusters according to the correlation between flights. The correlation between the clusters is then analyzed in turn to capture the propagation of congestion. The factors that influence the correlation between clusters are mainly capacity limitation and geometric construction of air traffic unit. Hence optimal operation should satisfy both the limitations of capability and configuration, while controlling the scale of congestion by regulating the flight distribution. As the operation of flights depends on the airlines, the correlation between flights varies with the structure of air routes. This paper builds on our previous studies [29, 36, 37] in which we apply the model of the propagation of infectious diseases [38–43] to the airspace and airport to develop congestion propagation models that consider flight correlation. The ultimate goal of the research on congestion propagation is to provide theoretical foundations and strategic and tactical choices for congestion management.

2. Congestion Propagation and Congestion Propagation System

Air traffic congestion arises when the demand of an air traffic unit (e.g., airport, air route, terminals, and region) exceeds its capacity. Congestion manifests as high density of aircraft in the airspace and delay of aircraft departure and arrival. This is caused by a number of factors including severe weather, military exercise, and mechanical failure. In actual operation congestion is dynamic (i.e., not static) in space and time similar to the spread of infectious diseases and public sentiment, which have propagation dynamics in complex networks.

In road transport, the relationship between density and flow is described in three phases: free flow, a wide moving traffic jam, and synchronized traffic flow [44]. In this paper, a new concept of congestion propagation based on congestion causes is given. As it is known, the sharing and competing of resources generate the correlation between aircraft. So we can divide the aircraft into congested cluster and discrete cluster according to the correlation intension/number. And the conversion process between congested cluster and discrete cluster is defined as congestion propagation. Air routes are the main resources shared and competed for in airspace, and they consist of parallel routes, cross routes, and their intersections. The conflict (congestion) always occurs on the cross network, especially on the intersection. A congestion that occurs in a sector or intersection of a complex airspace network spreads and is only limited by the airspace configuration. The various elements in which operations take place can be referred to as a system consisting of the airspace configuration (i.e., sectors) and the associated traffic entering and leaving the sectors. In the event of a disturbance, the system deviates from the stable state and the resulting congestion state is transmitted to the aircraft involved, creating a congestion propagation system as shown in Figure 1.

According to the correlation between aircraft and propagation process, there are aircraft in discrete, congested, and recovered clusters. The aircraft in the discrete cluster are independent, and a strong correlation exists between aircraft in the congested cluster. The correlation increases with the congestion degree. Focusing on the aircraft in the congested cluster C, the aircraft entering the airspace according to the flight schedule s constitute those in the discrete cluster U. When disturbed by a congestion incident, U becomes C, and its propagation rate is expressed as α. The relief from C with a dissipation rate β forms the aircraft in the recovered cluster R. These are shown in Figure 1. The operation of the system depends on the control of three parameters, flight schedule s, propagation rate η/α, and dissipation rate β. In particular, we assume that flights move from one community to another with a diffusion rate η, and U is affected by congested aircraft at the rate α. However, the four parameters are affected by the limitation of airspace capacity L and aircraft propagation correlation degree k. Here we assume that k is the number of aircraft affected directly by one aircraft in the congested cluster. As shown in Figure 1, it influences to some extent the propagation rate and dissipation rate. L limits the growth of s, at the same time limiting the size of U and hence the negative feedback loop among L, s, and U and positive feedback loop among η/α, k, and β.

Based on the congestion propagation system, we can model a congestion propagation tree (in next section) to reveal the domino effect of aircraft in congestion cluster. And the correlation between aircraft is the key to the model. By modeling congestion propagation, we can understand how the factors (propagation rate, dissipation rate, capacity limitation, and so on) influence congestion propagation; this is beneficial for predicting evolution of aircraft in congestion cluster.

3. Model

The dynamical complexity of the network can be characterized by the interactions among its nodes. The congestion

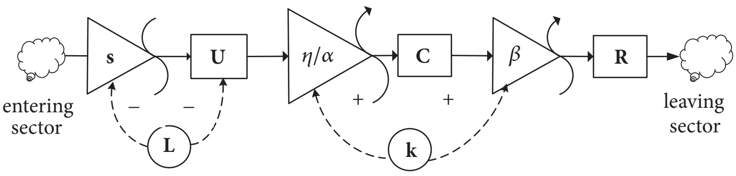


Figure 1: Congestion propagation system.

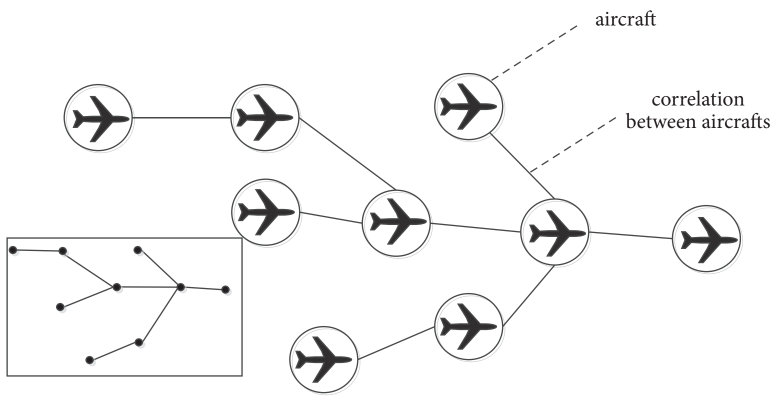


Figure 2: Congestion propagation network.

propagation network in two-dimensional space (Figure 2) is constructed with aircraft as the nodes and the correlation between aircraft as the edges. The model of congestion propagation focuses on the propagation correlation within heterogeneous network. This is the key to finding the nature of the propagation correlation between two aircraft, on the basis of spatiotemporal complexity.

Figure 3 presents a simple example of congestion correlation on a cross network, which is constituted by three inbound routes and one outbound route. If congestion propagation can be seen as a queueing problem, it is easy to understand the cause of congestion and the process of propagation. The intersection can be seen as a single server; in fact, the congestion propagation on crossing routes is the queueing system with multiple queues and a single server. The competition for resources causes aircraft correlation to be close, and the sharing of resource makes the aircraft be associated, generating congestion propagation. The resources competed for and shared in Figure 3 are the air routes, especially the intersection. The aircraft operated on the cross traffic are marked as $A_1, A_2, A_3, \ldots$. The correlation degree among aircraft is diverse. For example, the operation of aircraft A_3 is affected by the aircraft A_2 and A_4, satisfying the limitations of lateral separation and intersection service capacity. At the same time, flight of A_3 needs to take the horizontal separation with former aircraft A_1 into account. In contrast, the operation of A_8 is mainly affected by the longitudinal interval with the aircraft A_5. So the congestion propagation on a cross network constitutes a heterogeneous network. The congestion clusters with k can be denoted as C_k. According to the correlation intension, aircraft on crossing routes can be divided into some clusters/communities, such as $C_1, C_2, C_3, \ldots$, which are shown in Figure 3, and the correlation intension between aircraft in different clusters/communities can be denoted as $T_{C_1}, T_{C_2}, T_{C_3}, \ldots, T_{C_1} \gg T_{C_2} \gg T_{C_3}$. The research on congestion propagation focuses on the cluster/community C_1, that is, aircraft passing the intersection in a short time. The time lag can be set as 5 minutes or 15 minutes according to the prediction demand.

$P(k)$ denotes the probability that an aircraft has correlation degree k and $P(i \mid k)$ is the conditional probability of joining two aircraft with correlation degrees i and k, respectively. U_k and C_k are the aircraft in discrete and congested clusters on the route with correlation degree k, respectively. U_i denotes the set of U with correlation degree i. The congestion propagation with different correlation degrees is formulated as follows:

$$\begin{aligned}\frac{dU_k}{dt} &= s - \eta U_k + k\sum_{i=1}^{n} P(i \mid k)\frac{\eta}{i}U_i - \alpha U_k C_k + \beta C_k \\ \frac{dC_k}{dt} &= \alpha U_k C_k + k\sum_{i=1}^{n} P(i \mid k)\frac{\eta}{i}U_i - \beta C_k\end{aligned} \tag{1}$$

Although model (1) is more close to pratical operation, controllers still need to do a lot of work. Of them, statistical analysis of correlation degree, conditional probability, and cluster analysis spend a lot of time. For short-term prediction, for example, prediction in one hour, time, and accuracy are the keys to the controllers. And the most congested area is the intersection in Figure 3. So the congestion cluster C_1 is our research priority. Simplified models based on model (1) can be introduced for short-term prediction.

Focusing on the cluster C_1, the relationships between different parameters are distinct in expressions (2) and (3). Expression (2) takes system/sector capacity L into account as

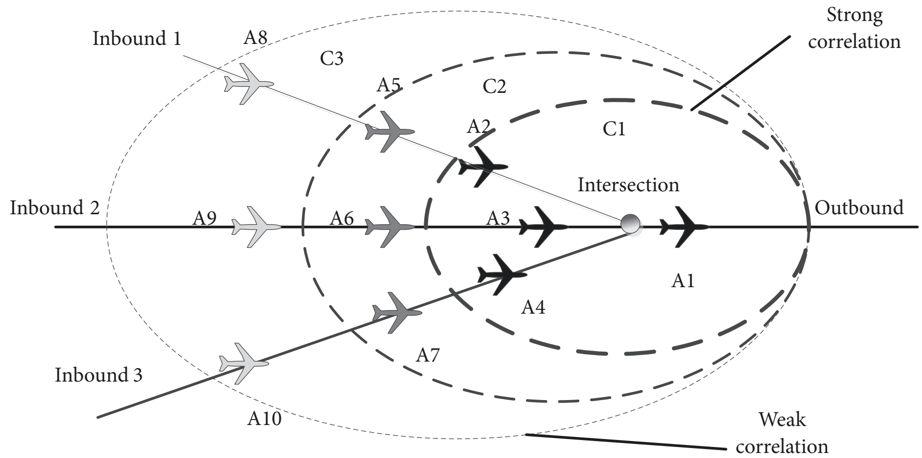


Figure 3: Congestion propagation correlation in a cross network.

a limitation of s. And expression (3) can reveal the relationship between α and β directly. The computing method of α and β is introduced in next sections.

$$\begin{aligned}\frac{dU}{dt} &= \alpha U\left(1-\frac{U}{L}\right)-\alpha UC\\ \frac{dC}{dt} &= \alpha UC-\beta C\end{aligned} \tag{2}$$

$$\begin{aligned}\frac{dU}{dt} &= s-\alpha UC\\ \frac{dC}{dt} &= \alpha UC-\beta C\end{aligned} \tag{3}$$

For either model (2) or (3), the system threshold value is $U^* = \beta/\alpha$. When $U > U^*$, the congestion is aggravated; otherwise, there is no propagation. The characteristics of congestion data and accuracy of models are introduced in next section.

4. Parameter Calculation

The operation of aircraft in sectors/airspace is based on the structure of hub-and-spoke network, in which the intersection of air routes is the basic unit as seen in Figure 4. The congestion characteristics diffuse on the airspace network depending on the network structure. The propagation capability of an intersection can be expressed by node degree (correlation degree) k, the number of routes connecting the assigned intersection.

In general, the flow distributions are similar in two sectors, in which the number and distribution of intersections are similar. If the capacities of two sectors are similar or the same, the consistency of flow distribution is more obvious. Take two sectors in Shanghai area for example; the construction graph of the Shanghai sectors with sector partition and route distribution is shown in Figure 5(a). Comparing the sectors (ZSSSAP09 and ZSSSAP12), the number of intersections, sector capacity, and degree distribution (for details of this analysis, see the Supplemental Material [S2 Results]) are similar as seen in Table 1. If the aircraft in the congestion cluster can be defined as the ones exceeding the capacity of sector, the evolution of congestion flights exhibits similarities in peak, trend, and congestion periods as seen in Figure 5(b). Hence, the congestion evolution in airspace is closely associated with the route distribution and capacity, with the intersection (node) structure being the key to congestion propagation.

For model prediction, the other sector (GYA) data are used. GYA is known to be one of the most congested intersections in Guangzhou Approach, China. It has three inward and one outward air routes. The average inbound traffics for each route are 0.823, 0.108, and 1.031 aircraft per 5 minutes, with the respective standard deviations of 1.012, 0.353, and 1.219 (for details of this analysis, see the Supplemental Material [S1 Dataset]). Let $F(t)$ denote the flow passing the intersection at time t; then α is determined as

$$\begin{aligned}M &= \frac{F(t)-AvgF(t)}{AvgF(t)}\\ G &= if\,(M<0,0,M)\\ \alpha &= AvgG\end{aligned} \tag{4}$$

The propagation rate on GYA $\alpha = 0.27$ (for details of this analysis, see the Supplemental Material [S1 Results]) and the average degree $\langle k\rangle = 10/7$. The average values and standard deviations of three in-routes linked to GYA are diverse. Denote I_i, $i = 1, 2, 3$, as the average values of three inputs, respectively, and σ_i, $i = 1, 2, 3$, as the corresponding standard deviations of three in-routes, and the dissipation rate of GYA can be formulated as

$$\beta = \frac{1}{\sum_{i=1}^{3}(\sigma_i/I_i)} \approx 0.17 \tag{5}$$

5. Comparison with Model Prediction

Supposing the timespan as 5 minutes, the comparison between the historical data and prediction result with model (3) is shown in Figure 7(a). At the same time, considering the

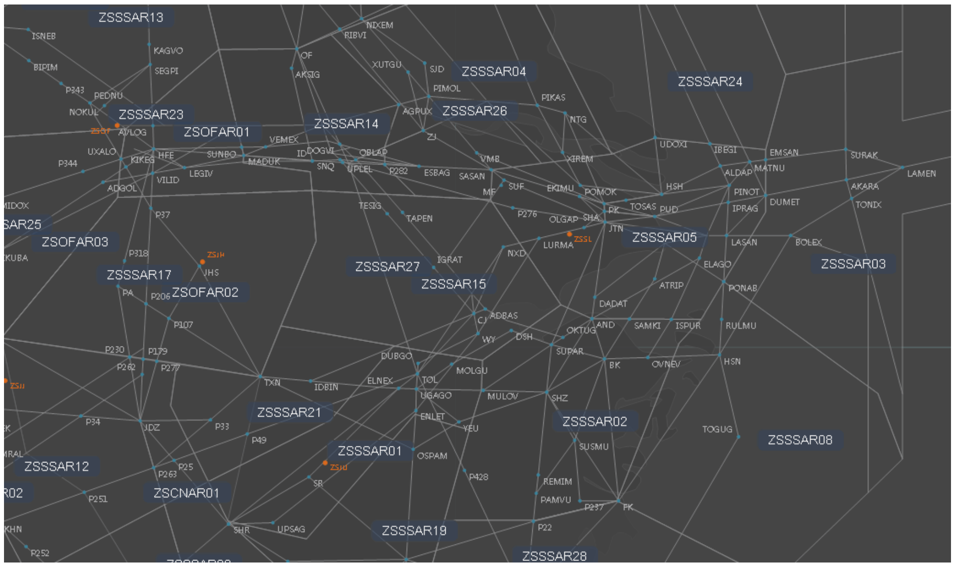
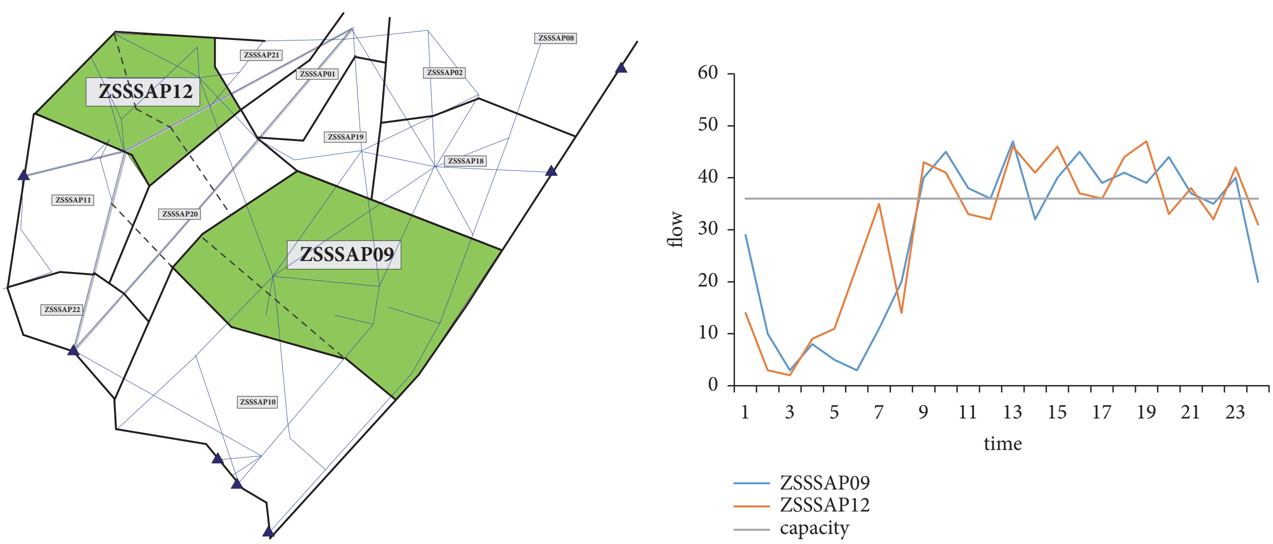


Figure 4: Part of airspace construction of Shanghai in China (2015).



(a) (b)

Figure 5: Flow of different sectors with similar/same degree.

limitation of capacity, the comparison between the result of model (2) and the flow of GYA is shown in Figure 7(b). In our previous paper [36], we have used model (2), model of SIR with logistic, to describe the trend and maximum size of congestion in cross network. Compared with model based on probability [5], the prediction result of model (2) is more close to the historical data from amplitude difference and phase difference, which is shown in Figure 6. Based on the above research results, we divide the hour into busy and non-busy hour and select the sample data on non-busy hour as sample 1 and the sample on busy hour as sample 2. We have carried out a case study based on operation data from October 16, 2016, 00:00:00 to October 23, 2016, 23:50:00 of the intersection GYA in Guangzhou area of China.

In Figures 7(a) and 7(b), up-down bars (black and white bars) are used to reveal the gap between the prediction results of models and sample 1. The historical data used in comparison is from the radar track of GYA in October 19, 2016, from 00:00:00 to 23:59:59. The time slice is 5 minutes. We use some descriptions to compare the prediction results and sample 1 (Table 2). We can find that the standard deviation, variance, and standard error of mean of prediction result using model (3) are close to the sample data, comparing with them using model (2). Table 3 describes the difference value

Table 1: Similarity of two sectors in Shanghai area in China.

Sector	Similarity			
	Intersection number	Capacity	Probability of node degree 2	Average node degree $\langle k \rangle$
ZSSSAP09	18	38	50%	4.1
ZSSSAP12	18	38	50%	4.2

Table 2: Descriptions of sample 1 and prediction results.

Comparison	Maximum	Minimum	Standard deviation	Variance	Standard error of mean
Sample 1	8	0	2.178	4.744	0.604
Result of model (3)	7.7	1	2.1656	4.690	0.6006
Result of model (2)	7.8	1	1.6213	2.629	0.4497

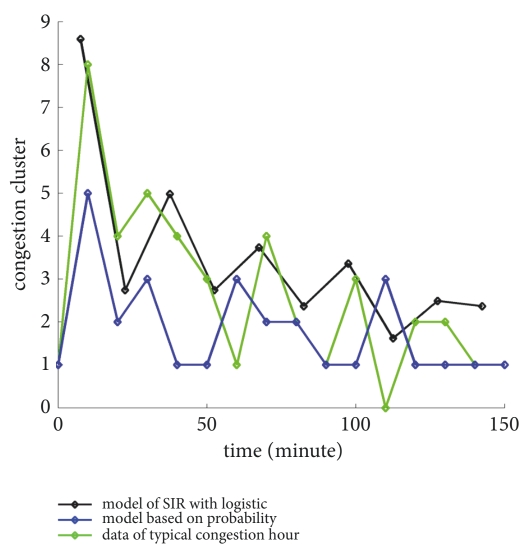


Figure 6: Comparison of model with reality and model with model [36].

between sample 1 and different models. Maximum, minimum, standard deviation, variance, and standard error of difference value using model (3) are less than them using model (2). In a conclusion, comparing model (2), the prediction result using model (3) is more close to sample 1.

Notably, capacity does not limit the propagation process in this case because our sample 1 is insensitive to sector capacity. For short period prediction, large variations in sector or intersection are infrequent. Furthermore, the predicted values are most of the time higher than the historical data. This is because human factors have a significant influence on the actual operation. Both models predict the maxima of congestion clusters accurately. Model (2) describes the fluctuation of congestion propagation and dissipation as a waveform, and model (3) makes the trend and stable state of propagation more explicit.

Being different from sample 1, sample 2 is GYA flow on busy hour. Descriptions of sample 2 and prediction results using model (2) and model (3) can be seen in Table 4. Table 5 describes the difference value between sample 2 and different models. Maximum, minimum, standard deviation, variance, and standard error of difference value using model (2) are less than them using model (3). In a conclusion, model (2) is of higher accuracy predicting congestion clusters on busy hour, compared with model (3).

6. Numerical Analysis

For the case of a homogeneous network, both model (2) and model (3) are able to describe the congestion propagation system. Numerical analysis of model (2) and model (3) can reveal how the factors of propagation rate α, dissipation rate β, and system capability L (in fact, L has a direct effect on s) affect congestion propagation. In both models (Figures 8(a), 8(b), 9(a), and 9(b)), the congestion clusters grow with the values of α and decrease with the values of β as seen in Figures 8(a) and 8(b), both nonlinear.

The factor of capability L affects the convergence rate of the system in theory, as seen in Figures 10(a)–10(d) (phase plots with running time $t = 300$). When disturbed by a congestion incident, the propagation system fluctuation is obvious, with the amplitude fading until it finally reaches a steady state. The time to regain the steady state is longer in the high-capability system, as seen from the comparison of Figures 10(a)–10(d). As sector partitioning is a way of decreasing capability, dividing the airspace system into smaller sectors is beneficial for controlling congestion propagation in actual operation. But sector partitioning is a complex work, it needs to take many factors into consideration, and congestion propagation will be one of the factors.

For the largest congestion cluster per unit time, (a) for the parameter setting $\beta = 1/3$ and (b) for the parameter setting $\alpha = 0.1$.

For the largest congestion cluster per unit time, (a) for the parameter setting $\beta = 1/3$ and (b) for the parameter setting $\alpha = 0.1$.

The proportion of discrete aircraft and congestion aircraft with setting $\alpha = 0.1$, $\beta = 1/3$, $C_0 = 3$, $U_0 = 10$, and $t = 300$: (a) $L = 12$, (b) $L = 17$, (c) $L = 22$, and (d) $L = 27$.

Even though schedule has been ignored in analysis of parameter relationships, the input distribution of the inbound traffic resulting from upstream schedule is important in calculating the parameters such as propagation and

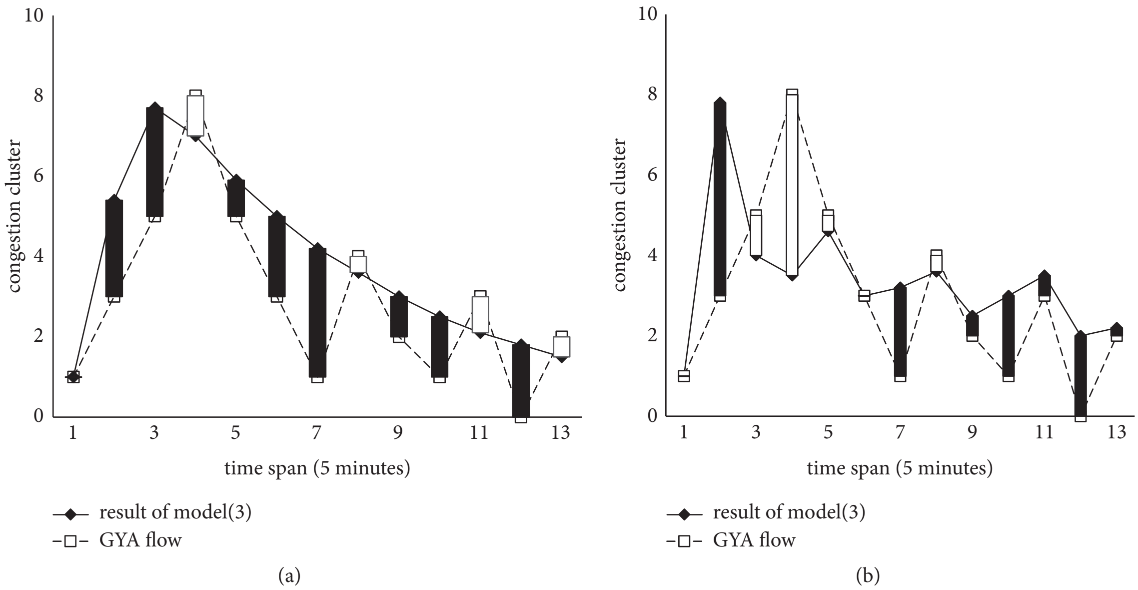


Figure 7: Comparison of model with sample 1.

Table 3: Comparison of difference value between model and sample 1.

Comparison	Maximum	Minimum	Standard deviation	Variance	Standard error of mean
Difference value between sample 1 and model (3)	3.2	-1	1.42604	2.034	0.39551
Difference value between sample 1 and model (2)	4.8	-4.5	2.14694	4.609	0.59545

Table 4: Descriptions of sample 2 and prediction results.

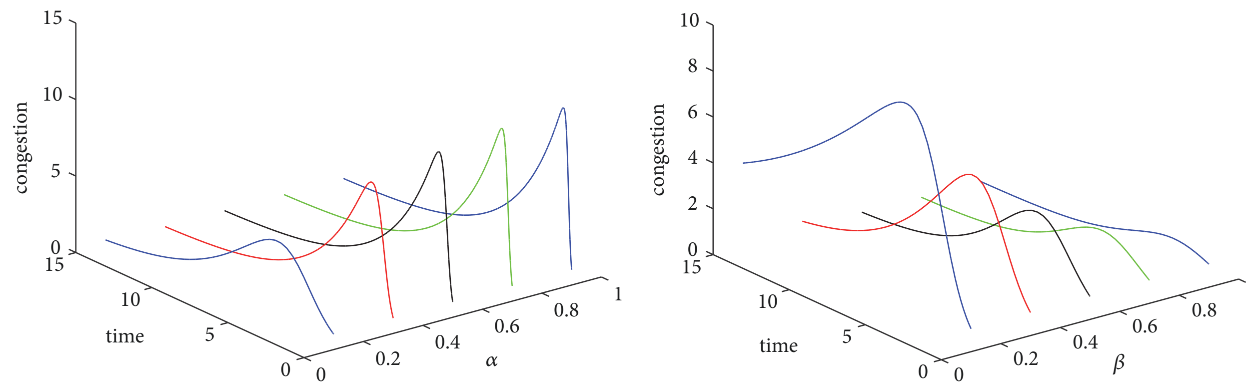
Comparison	Maximum	Minimum	Standard deviation	Variance	Standard error of mean
Sample 2	8	1	2.0817	4.333	0.6009
Result of model (3)	7.9	1	1.9151	3.668	0.5528
Result of model (2)	9	1	2.4325	5.917	0.7022

Table 5: Comparison of difference value between model and sample 2.

Comparison	Maximum	Minimum	Standard deviation	Variance	Standard error of mean
Difference value between sample 2 and model (3)	3	-2	1.5048	2.264	0.4344
Difference value between sample 2 and model (2)	1.8	-3	1.2799	1.638	0.3695

dissipation rates α and β, respectively. Figure 11 shows us the correlation between aircraft in different input distribution. Figures 11(c) and 11(d) are the correlation networks of Figures 11(a) and 11(b), respectively. Congestion spreads backward and sideward, leading aircraft to have influence on trailing ones due to safety separation. The correlation network of Figure 11(a) is more complex than that of Figure 11(b).

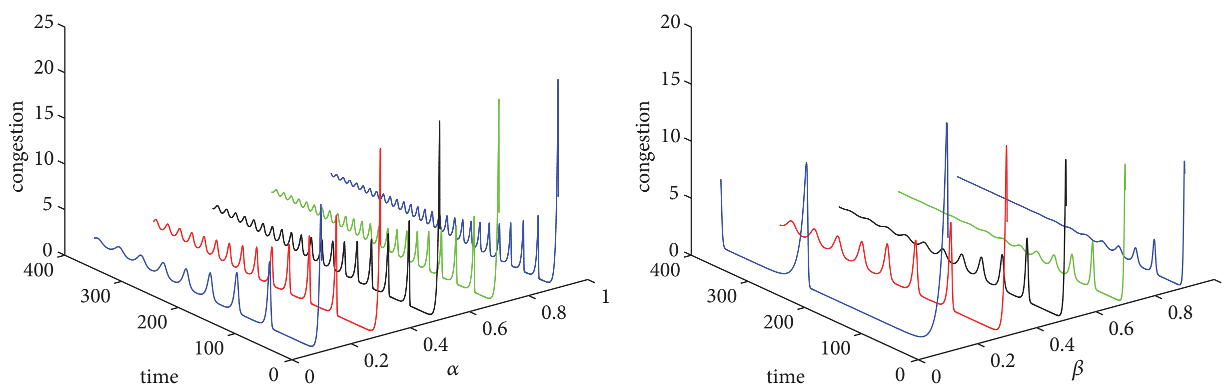
The simulation can be used to reveal the relationship between input distribution and main parameters. Based on the hypothesis of the same geometry of GYA (as seen in Figure 12), the three input lines comply with the exponential distribution. And the service interval of simulated GYA is 10 minutes. The result for the propagation rate can be seen in Figure 13, computing 131,664 samples of simulation. And the average propagation rate of aircraft in simulation is 0.122, less than that in GYA. The inputs of airlines are even, which obey the same distribution law, so the weights of airlines are the same in complex networks. If all the arrivals on routes 1, 2, and 3 are distributed evenly and there is no correlation between them, the dissipation rate can be expressed as



(a) Effect of the main parameter α in model/system (3)

(b) Effect of the main parameter β in model/system (3)

Figure 8



(a)

(b)

Figure 9: Effect of the main parameters in model/system (2).

$$\beta = \frac{1}{k_{in}} = \frac{1}{3} \tag{6}$$

k_{in} is the in-degree of intersection.

In a conclusion, the distribution of inputs has an impact on the propagation rate and dissipation rate. The propagation rate is proportional to the flight density, and the dissipation rate is inversely proportional to the standard deviation of inputs. Let σ_i/I_i denote the variable coefficient; it can be used to measure the inequality of airline inputs. The dissipation rate is inversely proportional to the variable coefficient. If the sum of inputs is equal, the dissipation rate will be maximum when the inputs comply with the same distribution.

7. Conclusion

Congestion propagation can be viewed as the transition between congested cluster and discrete cluster based on the correlation between aircraft in a complex network. In this paper, we have presented reaction-diffusion models including the different factors that can predict the evolution of congestion cluster in a sector. Focusing on the relationships between the main parameters, the propagation rate, dissipation rate, and system capacity have an impact on the propagation of congestion. In particular, the distribution of in-routes has profound influences on the propagation rate and dissipation rate. The numerical study has shown that the dissipation rate is maximum when the inputs of airlines linked to the intersection are equal and that the propagation rate is proportional to the flight density.

We can reveal the relationship between different clusters with model (1) and predict the level of congestion with models (2) and (3) over short time periods. The results from prediction and analysis of the parameters should help air traffic controllers gain better understanding of congestion propagation. For sector designers, it is important to optimize the structure of the sectors. Research on airspace design mostly focuses on the relationship between congestion and geometry of routes. But the congestion propagation is not taken into consideration. Further works will be aimed at the application of congestion propagation models, improving the design of an airspace. For example, sector partitioning should take the system recovery into consideration.

This paper builds on our previous paper [36] for modeling congestion propagation of airspace, by applying SIR with logistic, which reflects the evolution of congestion peaks. It focuses on the system of congestion propagation and analyzes how the factors of the system affect the propagation process. Although the correlation of aircraft in propagation is involved, the measuring method is not given in this paper.

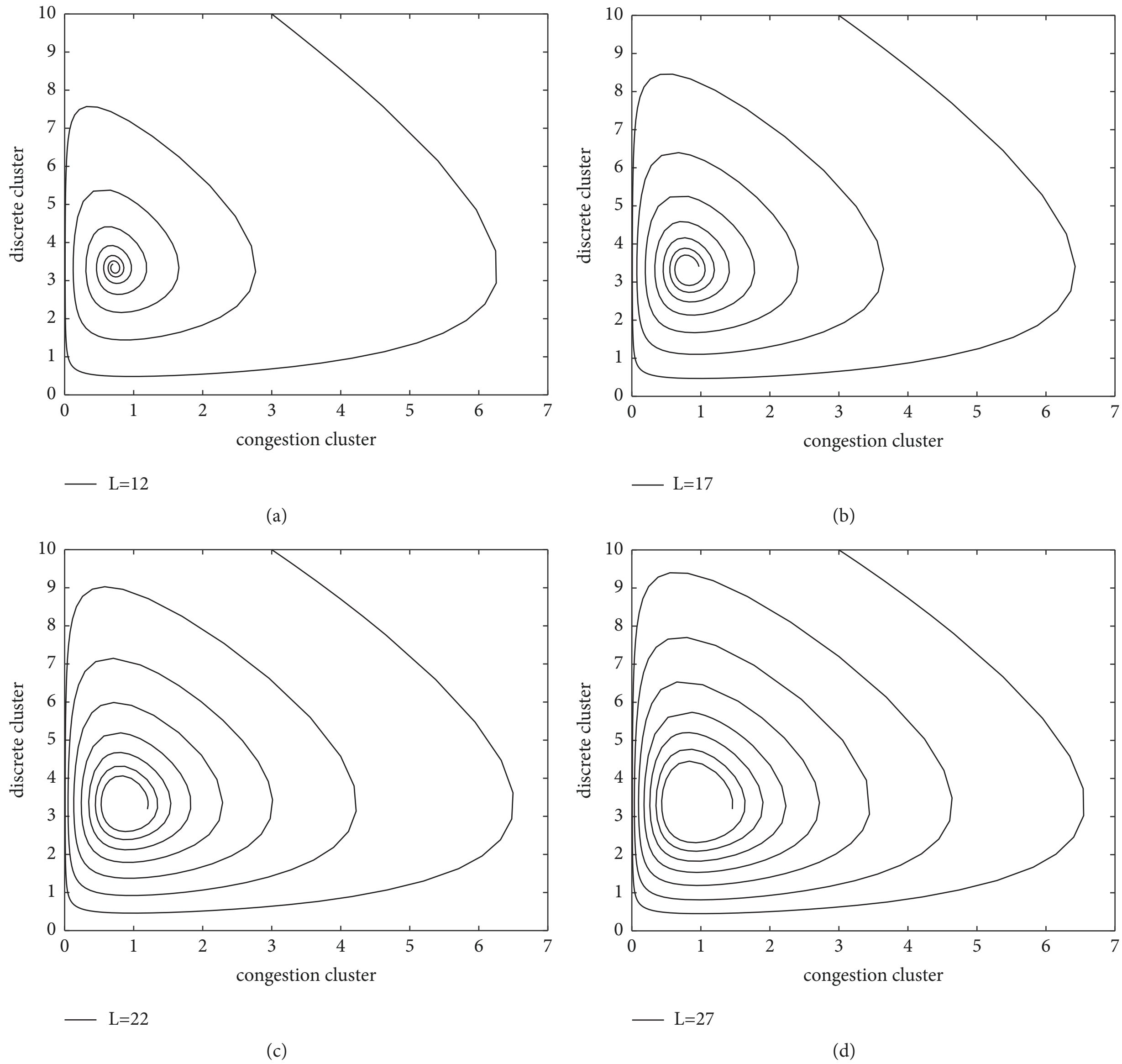


Figure 10: Phase plots with the different system capacity values.

Ignoring the difference of correlations, we get the simplified models. And of them, model with capacity limitation is more accuracy on busy hour, and it is not insensitive on non-busy hour. In the future research, the correlation difference between aircraft will be taken into account.

Data Availability

The [S1 Dataset.xlsx] data used to provide flow distribution of GYA in-routes are included within the supplementary information files. The [S1 Results.xlsx] data used to support the calculating results of parameter from 08:50 to 23:59 in GYA are included within the supplementary information files. The [S2 Results.xlsx] data used to support the degree distribution of sectors (AP09 and AP12) in Shanghai area are included within the supplementary information files.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Wen Tian and Xiaoxu Dai conceived and designed the experiments. Wen Tian performed the experiments. Xiaoxu Dai analyzed the data. Minghua Hu contributed analysis tools. Wen Tian and Xiaoxu Dai wrote the paper.

Acknowledgments

Our paper gets generous help from Professor Washington Yotto Ochieng, an academician from the Royal Academy of Engineering, in the aspects of article structure and description. Dr. Hu Bin supports the obtaining of the original

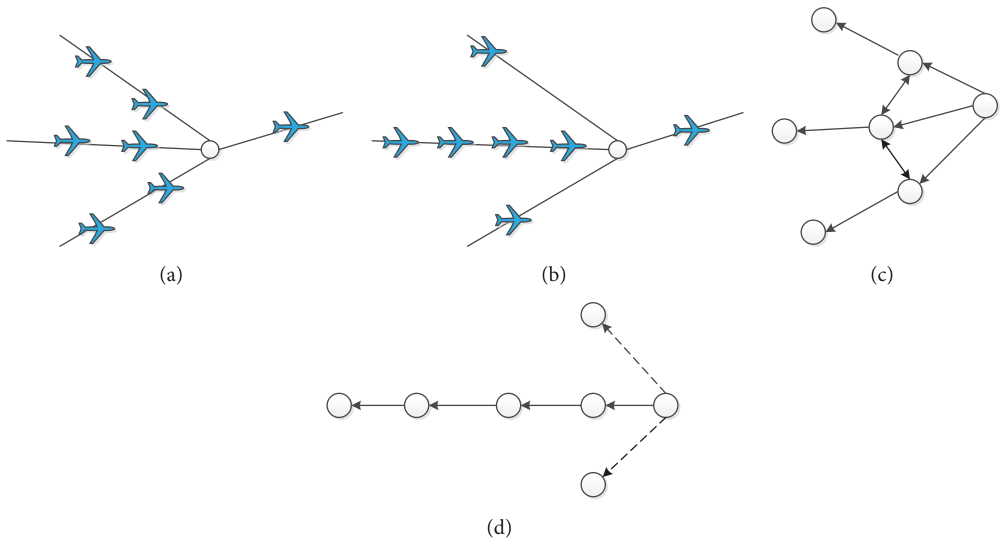


Figure 11: Correlation network in different input distribution.

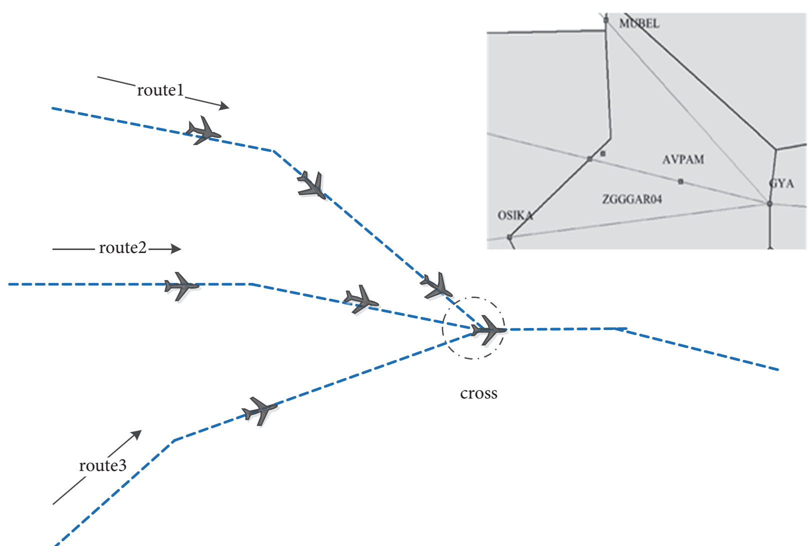


Figure 12: Structure of intersection in simulation and GYA.

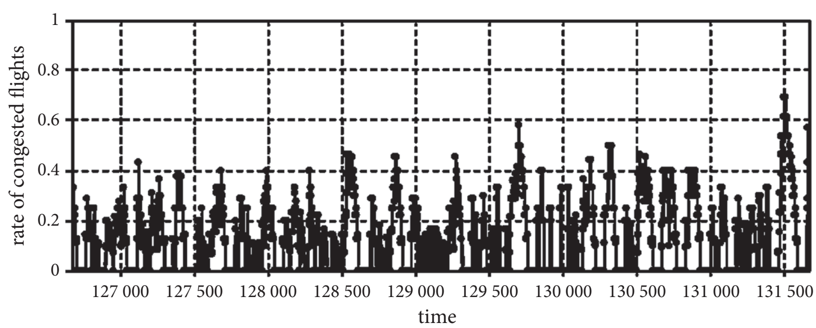


Figure 13: The result of propagation rate in simulation.

data from Aeronautical Information Services Departments of CAAC and the processing charges of paper. This work is partially supported by the National Natural Science Foundation of China (No. 71301074, No. 71731001, No. 61573181, and No. 51608268), and Research Innovation Program for College Graduates of Jiangsu Province (No. KYLX16_0385) and supported by the Fundamental Research Funds for the Central Universities (No. NS2017044).

Supplementary Materials

S1 Dataset: flow distribution of in-routes in GYA. S1 Results: the result of real operation in calculating parameter α on GYA. S2 Results: the result of degree distribution of sectors (AP09 and AP12) in Shanghai area. *(Supplementary Materials)*

References

[1] P. T. R. Wang, L. A. Schaefer, and L. A. Wojcik, "Flight connections and their impacts on delay propagation," in *Proceedings of the The 22nd Digital Avionics Systems Conference - Proceedings*, p. 5.B.4/9, USA, October 2003.

[2] L. Schaefer and D. Millner, "Flight delay propagation analysis with the Detailed Policy Assessment Tool," in *Proceedings of the IEEE International Conference on Systems, Man & Cybernetics*, pp. 1299–1303, Tucson, Ariz, USA.

[3] M. Abdel-Aty, C. Lee, Y. Bai, X. Li, and M. Michalak, "Detecting periodic patterns of arrival delay," *Journal of Air Transport Management*, vol. 13, no. 6, pp. 355–361, 2007.

[4] G. Gentile, L. Meschini, and N. Papola, "Spillback congestion in dynamic traffic assignment: A macroscopic flow model with time-varying bottlenecks," *Transportation Research Part B: Methodological*, vol. 41, no. 10, pp. 1114–1138, 2007.

[5] E. P. Gilbo and S. B. Smith, "New Method for Probabilistic Traffic Demand Predictions for En Route Sectors Based on Uncertain Predictions of Individual Flight Events," in *Proceedings of the FAA & Eurocontrol, The Ninth USA/Europe Air Traffic Management Research and Development Seminar (ATM2011)*, p. 11, 1, 2011.

[6] C. Wanke, L. Song, S. Zobell, D. Greenbaum, and S. Mulgund, "Probabilistic congestion management," in *Proceedings of the 6th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2005*, pp. 50–59, USA, June 2005.

[7] S. AhmadBeygi, A. Cohn, Y. Guan, and P. Belobaba, "Analysis of the potential for delay propagation in passenger airline networks," *Journal of Air Transport Management*, vol. 14, no. 5, pp. 221–236, 2008.

[8] P. Fleurquin, J. J. Ramasco, and V. M. Eguiluz, "Systemic delay propagation in the US airport network," *Scientific Reports*, vol. 3, article 1159, 2013.

[9] P. Fleurquin, J. J. Ramasco, and V. M. Eguiluz, "Data-driven modeling of systemic delay propagation under severe meteorological conditions," in *Proceedings of the 10th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2013*, USA, June 2013.

[10] M. Jetzki, *The propagation of air transport delays in Europe [Ph.D. thesis]*, Department of Airport and Air transportation Research. RWTH Aachen University, Aachen, The Netherlands, 2009.

[11] C. F. Daganzo and J. A. Laval, "Moving bottlenecks: a numerical method that converges in flows," *Transportation Research Part B: Methodological*, vol. 39, no. 9, pp. 855–863, 2005.

[12] A. Gautreau, A. Barrat, and M. Barthelemy, "Microdynamics in stationary complex networks," in *Proceedings of the National Academy of Sciences USA*, vol. 106, pp. 8847–8852, 2009.

[13] W.-B. Du, X.-L. Zhou, O. Lordan, Z. Wang, C. Zhao, and Y.-B. Zhu, "Analysis of the Chinese Airline Network as multi-layer networks," *Transportation Research Part E: Logistics and Transportation Review*, vol. 89, pp. 108–116, 2016.

[14] J. Zhang, X.-B. Cao, W.-B. Du, and K.-Q. Cai, "Evolution of Chinese airport network," *Physica A: Statistical Mechanics and its Applications*, vol. 389, no. 18, pp. 3922–3931, 2010.

[15] W. Du, B. Liang, G. Yan, O. Lordan, and X. Cao, "Identifying vital edges in Chinese air route network via memetic algorithm," *Chinese Journal of Aeronautics*, vol. 30, no. 1, pp. 330–336, 2017.

[16] D. Ni and J. D. Leonard II, "A simplified kinematic wave model at a merge bottleneck," *Applied Mathematical Modelling*, vol. 29, no. 11, pp. 1054–1072, 2005.

[17] P. Roberg-Orenstein, C. Abbess, and C. Wright, "Traffic jam simulation," *Journal of Maps*, vol. 3, no. 1, pp. 107–121, 2007.

[18] L. Lacasa, M. Cea, and M. Zanin, "Jamming transition in air transportation networks," *Physica A: Statistical Mechanics and its Applications*, vol. 388, no. 18, pp. 3948–3954, 2009.

[19] C. Antoniou, M. Ben-Akiva, and H. N. Koutsopoulos, "Dynamic traffic demand prediction using conventional and emerging data sources," pp. 97–104.

[20] S. B. Li, J. J. Wu, Z. Y. Gao, Y. Lin, and B. B. Fu, "Bi-dynamic analysis of traffic congestion and propagation based on complex network," *Acta Physica Sinica*, vol. 60, no. 5, 2011.

[21] K. Bohacova and D. Turgut, "Deniz Turgut. Agent-based approach for analyzing delay propagation in airline networks," *ISC-PIF*, 2008.

[22] J. C. Long, Z. Y. Gao, H. L. Ren, and A. P. Lian, "Urban traffic congestion propagation and bottleneck identification," *Science China Information Sciences*, vol. 51, no. 7, pp. 948–964, 2008.

[23] J. Long, Z. Gao, P. Orenstein, and H. Ren, "Control strategies for dispersing incident-based traffic jams in two-way grid networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 2, pp. 469–481, 2012.

[24] C.-A. Robelin, D. Sun, G. Wu, and A. M. Bayen, "MILP control of aggregate Eulerian network airspace models," in *Proceedings of the 2006 American Control Conference*, pp. 5257–5262, USA, June 2006.

[25] C. R. Wanke, M. B. Callaham, D. P. Greenbaum, and A. J. Masalonis, "Measuring uncertainty in airspace demand predictions for traffic flow management applications," in *Proceedings of the AIAA Guidance, Navigation, and Control Conference and Exhibit 2003*, pp. 11–14, Austin, Tex, USA, August 2003.

[26] D. Delahaye and A. R. Odoni, "Airspace congestion smoothing by stochastic optimization," in *Evolutionary Programming VI*, vol. 1213 of *Lecture Notes in Computer Science*, pp. 163–176, Springer Berlin Heidelberg, Berlin, Heidelberg, 1997.

[27] R. Guimerà and L. A. N. Amaral, "Modeling the world-wide airport network," *The European Physical Journal B*, vol. 38, no. 2, pp. 381–385, 2004.

[28] W. Li and X. Cai, "Statistical analysis of airport network of China," *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 69, no. 4, 2004.

[29] X.-X. Dai, M.-H. Hu, W. Tian, and B. Hu, "Mechanisms of congestion propagation in air traffic management based on

infectious diseases model," *Jiaotong Yunshu Xitong Gongcheng Yu Xinxi/Journal of Transportation Systems Engineering and Information Technology*, vol. 15, no. 6, pp. 121–126, 2015.

[30] H. B. Thiagaraj and C. V. Seshaiah, "A queueing model for airport capacity and delay analysis," *Applied Mathematical Sciences*, no. 69-72, pp. 3561–3575, 2014.

[31] N. Jafari and S. Hessameddin Zegordi, "Simultaneous recovery model for aircraft and passengers," *Journal of The Franklin Institute*, vol. 348, no. 7, pp. 1638–1655, 2011.

[32] B. Vaaben and J. Larsen, "Mitigation of airspace congestion impact on airline networks," *Journal of Air Transport Management*, vol. 47, pp. 54–65, 2015.

[33] S. A. Beygi, A. Cohn, and M. Lapp, "Decreasing airline delay propagation by re-allocating scheduled slack," *Institute of Industrial Engineers (IIE). IIE Transactions*, vol. 42, no. 7, pp. 478–489, 2010.

[34] M. Zanin, "Synchronization likelihood in aircraft trajectories," in *Proceedings of the 10th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2013*, USA, June 2013.

[35] Y. Wang, J. Cao, W. Li, T. Gu, and W. Shi, "Exploring traffic congestion correlation from multiple data sources," *Pervasive and Mobile Computing*, vol. 41, pp. 470–483, 2017.

[36] X. Dai, M. Hu, W. Tian, D. Xie, B. Hu, and W. Du, "Application of Epidemiology Model on Complex Networks in Propagation Dynamics of Airspace Congestion," *PLoS ONE*, vol. 11, no. 6, Article ID 0157945, 2016.

[37] X. Dai, M. Hu, W. Tian, and H. Liu, "Modeling Congestion Propagation in Multistage Schedule within an Airport Network," *Journal of Advanced Transportation*, vol. 2018, pp. 1–11, 2018.

[38] D. Balcan, V. Colizza, B. Goncalves, H. Hu, J. J. Ramasco, and A. Vespignani, "Multiscale mobility networks and the spatial spreading of infectious diseases," *Proceedings of the National Acadamy of Sciences of the United States of America*, vol. 106, no. 51, pp. 21484–21489, 2009.

[39] D. Balcan, H. Hu, B. Goncalves et al., "Seasonal transmission potential and activity peaks of the new influenza A(H1N1): A Monte Carlo likelihood analysis based on human mobility," *BMC Medicine*, vol. 7, p. 45, 2009.

[40] C. C. McCluskey, "Complete global stability for an SIR epidemic model with delay—distributed or discrete," *Nonlinear Analysis: Real World Applications*, vol. 11, no. 1, pp. 55–59, 2010.

[41] T. K. Kar and A. Batabyal, "Stability analysis and optimal control of an SIR epidemic model with vaccination," *BioSystems*, vol. 104, no. 2-3, pp. 127–135, 2011.

[42] X. Meng, L. Chen, and B. Wu, "A delay SIR epidemic model with pulse vaccination and incubation times," *Nonlinear Analysis: Real World Applications*, vol. 11, no. 1, pp. 88–98, 2010.

[43] T. K. Kar and P. K. Mondal, "Global dynamics and bifurcation in delayed SIR epidemic model," *Nonlinear Analysis: Real World Applications*, vol. 12, no. 4, pp. 2058–2068, 2011.

[44] B. S. Kerner and H. Rehborn, "Experimental properties of phase transitions in traffic flow," *Physical Review Letters*, vol. 79, no. 20, pp. 4030–4033, 1997.