The Structure and Dynamics of the Multilayer Air Transport System

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***Abstract*—The field of air traffic management (ATM) has a strong interdisciplinary nature, combining of technological, management, economic and regulatory aspects. The fully understanding of the structure and the dynamics underlying the system continue to be significant challenges in the field. Here we present a novel framework for the study of the structure and dynamics of the air transport system building upon the recent advancement of network science and big data science, as well as taking into account of the unique operation practical, thus bridging the gaps between academic field and operational world. We show that the structure of the air transport system can be captured by four interdependent networks including airlines network, airport networks, air route networks, and air traffic management networks. In particular, we present the initial results on spatial-related dynamics of the system using one-year flight data records. We find that by analyzing flight delay data that (i) airports with similar geographical locations exhibit similar dynamics; (ii) unlike other spatial-embedded complex systems, the propagation of flight delays and failure in the system decay slowly, and the correlations of the failure nodes reaching to 0 when the distance between them approaching to $\sim 1,000km$.**

***Index Terms*—Air traffic management, multilayer network, big data, spatial correlation, cascading failure**

I. Introduction

The last decade has witnessed the improvement of air traffic management (ATM) system in its safety, capacity, and efficiency. Great efforts have been made to enhance the performance of ATM system, ranging from the introduction of new operational concepts, through the deployment of the advanced automation systems, to the long-term research activities. Due to its interdisciplinary nature, the predictability and controllability of such complex social-technical system remain great challenge. Up until now, not much is known about the complete picture of the structure and the dynamics of the system. This is the focus of the present article.

Like much other complex systems, the air transport system is composed of a huge number of interlinked subsystems which operate with their own mechanisms. Network sciences has been significantly advanced our understanding and management of real complex systems since the beginning of last century, ranging from physics, chemistry, through economy, to human social science [1]. It provides a theoretical and algorithmic framework for us to understand the origins and characteristics of complexity of the systems. The available of operating records – data on flight tracks, operational information, and aircraft performance – has created unprecedented opportunities for investigating air transport system, allowing the analyzing of the structure and the dynamics at any scale from various perspectives.

The structure of the air transport is typically studied from complex networks by constructing an aggregate network from flights data, where the nodes represent airports, and a edge will be added between two nodes if there is a direct flight between the two airports. The network can be directed and weighted when considering the directions and the volume of flights or passengers in a given time period. Guimerà et al. have suggested that at a long range scale, the connections of airport network are almost symmetrical, therefore there is no need to consider arc directions[2]. Given the importance of air transport in the propagation of epidemics such as influenza and severe actuary respiratory syndrome, there are considerable number of studies focus on the airport networks structure[3], [4], and their roles in the prediction and predicability of global epidemics[5]. Recent advances towards quantifying delays propagation in the US air transportation system have shed light on the systematic investigation of delays from network perspective [6], [7]. Although the approach of complex networks has been immensely successful, it still has less impact on the ATM field due to the fact that it disregards much important information contained in the operational data. Network researchers have turned their attention on the time-varying and multilayer nature of networks. A recent review on the multilayer network can be found in [8]. As an example of the application of multilayer network theory, the air transport network are commonly considered as the aggregated layers of airlines networks [9], [10]. One of the core component of the air transport system – air traffic management system – is still missing.

The dynamics occurring on the top of the structure of the system preserve enrich information on how system operates. One of the most studied dynamical process in air transport is flight delay. Flight delay can be modeled as the dynamical interaction of a set of flights flying between the connected airports. It is unclear, however, how delay propagate in the air transport network. To date, there have been extensive work looking into the many aspects of flights delay. Many pioneering works on delay propagation use empirical data to explore the the cause for initial and primary delays[11], [12], [13], [14]. The primary delays can trigger a cascade of secondary delays which may spread over the airline networks and airport networks. The delay introduced by the upstream delay are called reactionary delays. A comprehensive study given by Jetzki et al. has analyzed reactionary delays in European airports using the data collected by the Central Office for Delay Analysis [15]. The airline network structure is suggested to play an important role in absorbing delay. Optimizing flight turnaround process by dynamical scheduling buffer time proved to be useful for minimizing delay propagation[12].

In other instances, further realism has been introduced by the use of queueing theory to analytical study airport delays or enroute delay[16], [17], [18], [19], [20]. Pyrgiotis et al. developed an analytical queuing and network decomposition model called Approximate Network Delays (AND) model to study the delay propagation in the US air transport network [6]. The delay propagation algorithm is to capture the "ripple effect" by tracing individual flight affected by local congestion and updating flight profiles when flights delays occur at the upstream airports. Fleurquin et al. proposed the measures to quantify the macro-scale behavior of the delay dynamics. They examine a variety of graph metrics like degree distribution and coefficients. Interconnected airports are identified to assess the level of ATS system congestion and the importance of network connectivity in the unfolding of the delay spreading mechanism. Ingredients of their model are aircraft rotation, passenger connectivity, and airport congestion. Using data-driven approach, an agent-based model was developed which is able to reproduce the delay patterns captured in the US air transport network [21], [22].

Another aspect that remains little addressed is the cascading failure in air transport system, although much focus are given either to the robustness and vulnerability of the system [23], or to the propagation of flight delays through airlines network. Reports from many fields have demonstrated that small disruptions in the network can trigger unexpected domino-like cascade failure [24]. The very "famous example" is the power grid system blackout in the north eastern U.S. and eastern Canada in 2003[25]. To prevent such cascading failure happening, two questions have been recently risen, are how the failure propagate through the system and how should we build a "safety wall" to stop the propagation?

In this article, we first show that the structure of air transport system can be represented by the four interdependent networks, namely the airline network, airport network, air route network, and air traffic management network (i.e. sector network). We give our attention on the flight delay at the airport level rather than individual flight delay to study the dynamics of air transport system. In particular, we define the failure of airports/route point (sector was not analyzed yet due to limitation of empirical data) according to the aggregated flights delay at the node. Interestingly and surprisingly, it found that the spatial correlations of failure are quite similar in the airport network and air route network. The correlations approach to zeros when the distances between nodes over $1,400km$ and $900km$ for the airport network and air route network respectively. We discuss both the implications of the current results and opening questions left to be answered.

II. The structure of the multilayer air transport system

A. Airport Network

The pioneering work on the study of the structure of air transport system was from statistical physics, focusing on analysis of topological characteristics the system from complex networks theory [26]. The structure of the system was abstracted to a directed/undirected, weighted/unweighted network which normally referred as airport network, with nodes are the airports and edges are determined by the flights. Table I summarizes analytical results of the airport networks worldwide.

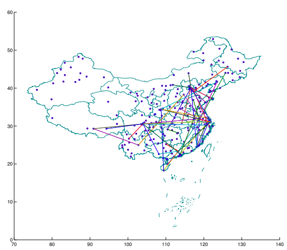
One of the drawbacks of using flights to study air transport system is that much information encoded in the flights data is missing. To overcome this difficulty, the temporal information must be taken into consideration. Topological changes of the network were measured with characteristics that focus on the degree distribution which have been used in prior research on network dynamics. The degree distribution of a graph is defined as a discrete probability distribution that expresses that probability of finding a node with degree k. He et al. studied Chinese airport network in 2004 and concluded that the network is small-world without scale-free property since the degree distribution of nodes is exponential rather than heavy tailed[27]. In a weekly cycle, the Chinese airport network exhibits scale-free properties, and the weekly cumulative degree distribution of nodes follow Pareto law [28]. At a even more small time scale, we could see the transformation of the network in Fig. 1a and Fig. 1b. There are few flights flying in the early morning between 0600 and 0700, while traffic demands increase sharply after 0700AM. To examine the temporal evolution of the networks, we construct the airport networks using every 2 hours flight data. Across the database, there are 396×12 networks generated. The cumulative nodes degree distributions are plotted in Fig. 1c. It is clearly shown that the networks are quite different before and after 0600. Before 0600, the network node degree distributions obey power law decay, while more airports are connected after 0600AM with daily air transport starts. These results agree with previous findings that Chinese airport network is small-world with scale-free properties. Other properties such as community structure are still under investigation.

B. The air route network

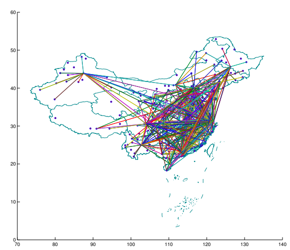
Another widely investigated network in air transport field is the air route network or air navigation route network[29]. Normally, flights will fly along the route structure thus bring the system into life. One may trace the flight back to its origin along the route. In the following section, we will compare the

TABLE I
TOPOLOGY CHARACTERISTICS OF DIFFERENT AIR TRANSPORTATION NETWORK

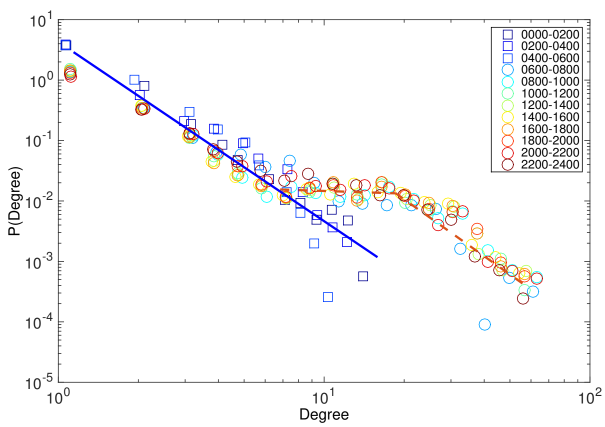
	Network investigated	# Nodes/#Edges	Average path length	Clustering coefficient	Degree distribution
da Rocha et al.	Brazil	142/-	2.34	0.63	power-law distribution
Guida et al.	Italy	42/310	-	0.1	double power law distribution
Bagler	India	79/442	2.26	0.657	power-law distribution
Li-Ping Chi	US	215/-	2.4	0.618	double power law distribution
Barrat et al.	North American	935/-	4	-	power-law distribution
Guimerà	Worldwide	3883/27051	4.4	0.62	double power law distribution



(a) Time: 0600-0700



(b) Time: 0700-0800



(c) Degree distribution of the hourly airport networks.

Fig. 1. **The structures of airport networks in different time periods**. (a) and (b) are the geographical plots of Chinese airport networks, while (c) is the degree distribution of the hourly airport network. Networks are constructed from flights data from operation center of Civil Aviation Administration of China between 1st August 2012 to 31 August 2013.

characteristics of the air route network and airport network. In fact, the optimization of network flow can be done at this layer. The propagations of airspace congestion and flights delay in the air route network requires research effectors.

The recent shift of focus from investigating a single layer network to the multilayer network has also been improving the understanding of air transport system as well. Special attention is given to decompose the airport network into many layers according to different air carriers[9], [10], [30]. Due to lack of knowledge of air traffic control, there is still one important component missing in the previous work, i.e. the air traffic management layer. It is the core structure of the air transport system from the operation point of view. All the air traffic controllers in charge of their own sectors inter-linked form the backbone of the air transport system, working with staff from airports and airline to provide air transport service to customers.

C. The 5 interdependent layers of air transport system

In Fig. 2, we show the interdependent layers of the air transport system. As can be seen from the figure, the basic component of the system is the network formed by the flights operated by a single aircraft. It should be mentioned that air crew should be taken into account when one tries to analyze the propagation of flight delay. It is however out of the scope of current study.

The idea of the decomposition of the structure of the air transport system is inspired from the idea collaborative decision making (CDM). As the three main parties of the CDM are airports, airlines, and air navigation service providers (ANSP), each of them can be represented as one layer of the networks. Zanin et al. and Du et al. have studied the multilayer air transport network with each airline's network as a single layer. The air traffic management layer is disregarded.

Sector is the operation unit of air traffic management, controlled by one or two air traffic controllers. The dynamics of each sector is vital to the whole air transport systems. When there is not enough capacity for handling incoming traffic, traffic flow management initiatives will be issued which results in flight delay. Therefore, the structure of air traffic management layer can be represented by the sector network. The nodes of the network are all the sectors including tower/approach/ground control sectors, approach sectors, and enroute sectors, while the determination of the edges will depend on the letter of agreements (LOA) between different ANSPs or air traffic control units which states detailed information on flights transfer between sectors. There is an edge between two nodes if there is flights transferred between the two sectors. Otherwise, there is no edges between the two sectors even they are physically adjacent. Sector network can be directed and weighted networks when considering the directions of transferring traffic and the volume of traffic flow between them.

In Fig. 3, we show the degree distributions of the three main networks of Chinese air transport system, airport network, air route network, and sectors network. The statistical information on the 3 networks are given in table II. As it can be seen from the figure and the table, sector network and air route network demonstrate similar characteristics which are significantly differing from airport network. Although the number of nodes in air route networks or sector network is much more than the total nodes in the airport network, both the average degree of the nodes and the maximum degree are quite smaller than that in the airport network. The airport network can be characterized with small network properties and scale free feature while the other two are not. This could be the main reason that study of airport network from complex networks has little impact in the air transport field.

Here we have just present our view on the structure of airport system, opening a new avenue for the study of the fundamental structure of air transport system. Still, there are great work to be done in order to uncover the properties of the multilayer of the air transport system.

III. The dynamics of the air transport system

The advancement of big data science together with the availability of large operational datasets allow us to unreal the hidden dynamics of air transport system. The occurrence of flight delay suggests that there are disruptions happening in the system. Our interest is to study the dynamics occurring on top of the networks that are described in Section II by the analysis of flight delay. One big question here is that how flight delays spatially distributed in the network? It is directly related to the resilience and vulnerability of air transport system [26]. In the following, we show our initial analytical results on the spatial correlations of flight delay in airport network and the cascading failure behavior of both airport network and air route network.

A. The correlations on flight delay between airports.

Pearson correlation coefficient is used to capture the correlations between flight delays in different airports. To make the time series data sets comparable, we use 15mins as the sampling rate to calculate departure flight delays at each airport. Let $X_i(t)$ represents the departure delay at i^{th} airport at t^{th} time slot, while T is the number of time slots that are observed in a traffic scenario.

To compute the correlation ρ_{ij} between i^{th} airport and j^{th} airport, one can use the following equation

$$\rho_{ij} = \frac{E(X_i X_j) - E(X_i)E(X_j)}{\sqrt{E({X_i}^2) - E^2(X_i)}\sqrt{E({X_j}^2) - E^2(X_j)}}, \qquad (1)$$

where $\rho \in [-1, 1]$.

To study the correlation of the flight delays in airport network, we calculate the cross-correlation matrix C of airport delays series data according to eq 1. It is very interesting to find that the most correlated airports in both two countries have quite similar characteristics. Fig. 4 plots the most correlated airport pairs in the two air transport systems.

Newark airport, LaGuardia airport and Kennedy airport are all located in New York metroplex area, while Boston Logan airport and Philadelphia airport have close relationships with these three airports. Due to similar operational environments and geographical locations, flight delays in these airports also show similar characteristics. Likewise, Baltimore airport and Washington National airport are located in the Washington area, Fort Lauderdale airport, Orlando airport and Tampa airport are located in the Miami area. The other six airports with a high correlative degree are located in the western coast. In China, the correlation coefficients of airports between Guangzhou and Shenzhen, Shanghai Pudong and Shanghai Hongqiao, Changchun and Harbin, are much larger than the other airport pairs. It indicates that geographical locations as the external factors have huge impact on dynamics of air transport system.

B. Cascading failure behavior of the air transport system

The understanding of the temporal-spatial characteristics of the cascading failure of the network systems has been recognized as an important step to predict and minimize the cascading failure. A very small failure in one of system may lead to catastrophic consequences[31]. Similar to other spatial-embedded system, we try to understand how far the "failure" can propagate in the system so that we may be able to set up a "safety wall" to prevent the failure.

First, the aggregated average flight delay at each airport at a given time window $[t_1, t_2]$ is calculated. Then, we decide the failure of node i. $x_i = 1$ if the average flight delay is higher than predefined threshold (α in minutes per flight). Otherwise, $x_i = 0$. The concept of spatial correlations, $C(r)$ is introduced to quantify the relation between failures separated at a distance r. $C(r)$ is calculated as

$$C(r) = \frac{1}{\delta^2}\frac{\sum_{ij,i\in F}(x_i - \bar{x})(x_j - \bar{x})\delta(r_{ij} - r)}{\sum_{ij,iinF}(r_{ij} - r)} \qquad (2)$$

where $\delta()$ is a selecting function to select the nodes whose Euclidean distance to the failure node is r (or within a range). Positive values of $C(r)$ means positive correlations between nodes suggesting the tendency of failures to be close to each other, while negative values indicate anti-correlations.

We calculate the daily spatial correlations based on the hourly delay at the airport as the function of r. Fig. 5a and 5b are the averaged correlation results over one year for the airport network and air route network respectively. The time period $[t_1, t_2]$ seems to be no effects on trend of correlation results since all the curves of $C(r)$ exhibit similar shapes as shown in the figures. These results are significant different from the other complex systems, such as power grid system and road traffic system. Instead of decaying in the form of power-law, $C(r)$ decrease dramatically at the initial few steps. It is in agreement with the findings in previous section that airports with similar geographical locations show similar behavior. However, in airport network, $C(r)$ fluctuates around 0.03 before it drops blow 0 when $r > 1,350km$. In the air route network, $C(r)$ decreases almost linearly with the increasement of r.

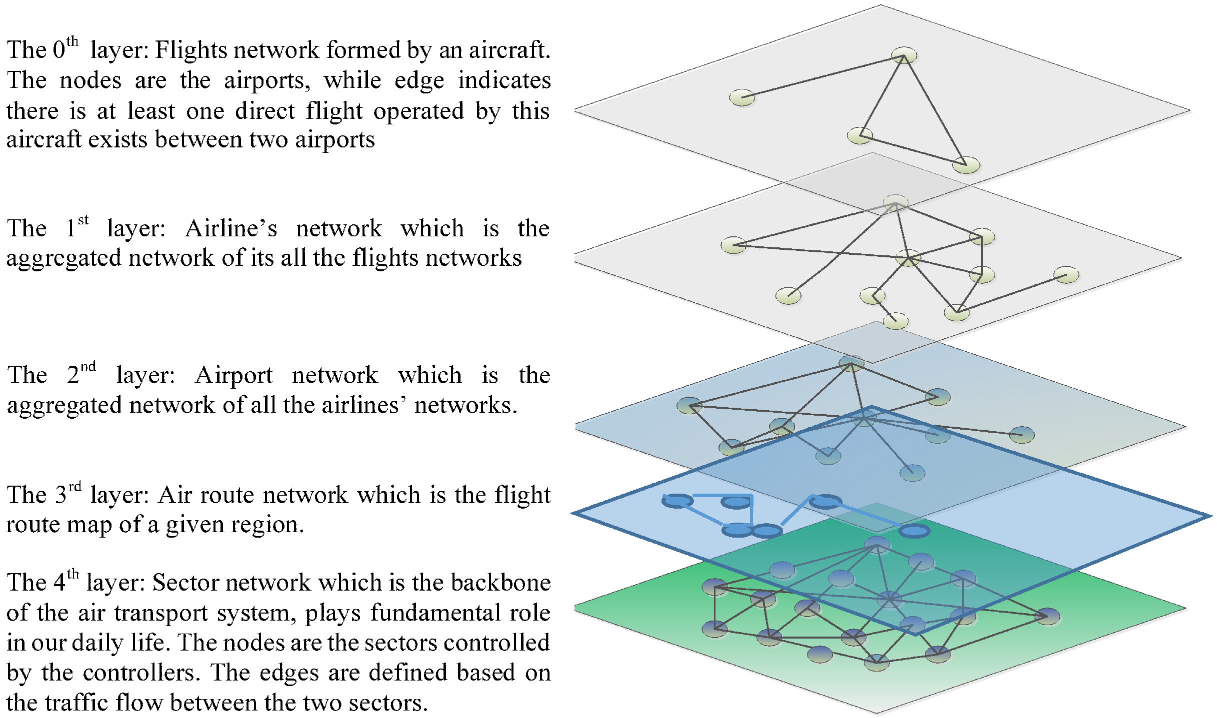
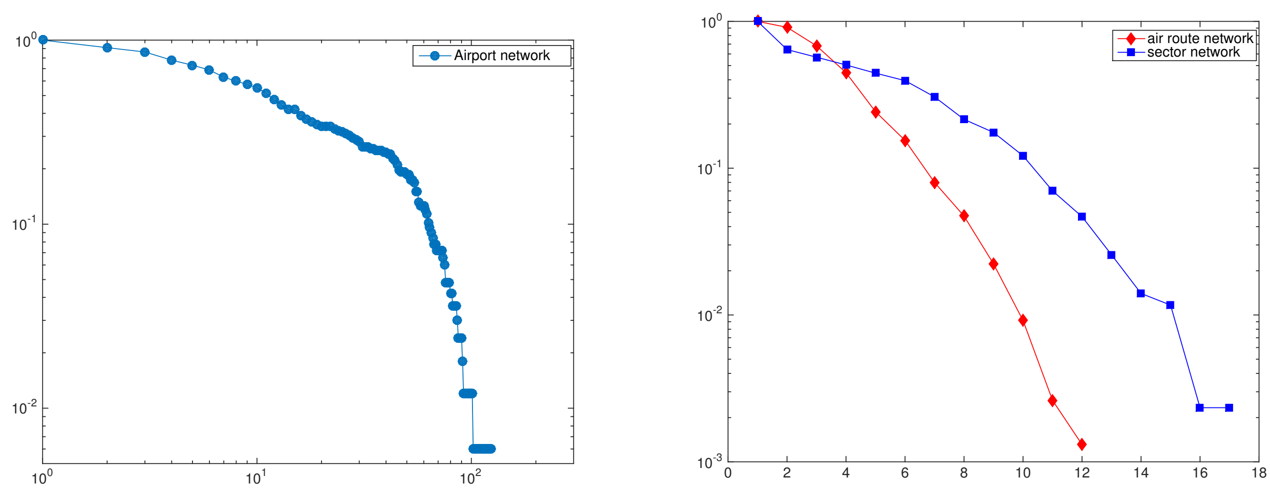


Fig. 2. **The 5 interdependent layers of the air transport system.**



(a) (b)

Fig. 3. **The complementary cumulative density functions of 3 networks.** Note that scale for airport network is logarithmic, while the scale for air route network and sector network is semi logarithimic.

TABLE II
THE STATISTICAL CHARACTERISTICS OF THREE NETWORKS

	Airport Network	Air Route Network	Sector Network
Number of Nodes	167	763	428
Number of Edges	1900	1415	973
Network Density	0.14	0.005	0.01
Average Degree	22.75	3.60	4.55
Maximum Degree	124	12	17
Average Shortest Path Length	2.07	9.84	6.55
Network Diameter	4	28	16
Assortativity	-0.36	0.02	0.05
Average Clustering Coefficient	0.70	0.15	0.21
Average Betweeness	0.006	0.01	0.01

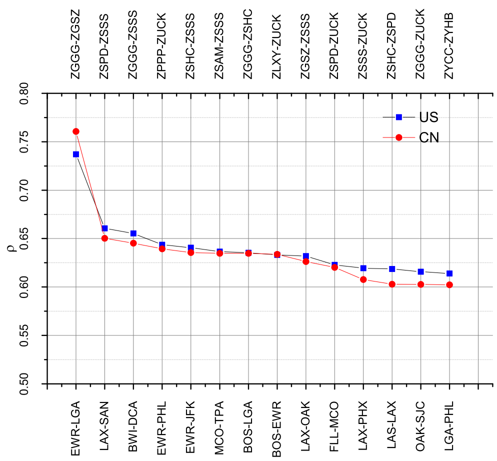


Fig. 4. **The correlation coefficients of airport pairs.** Flights data was obtained from operationa and management center of CAAC and Bureau of Transport Statics.

The effect of α is examined through the whole dataset. The three main patterns are plotted in Fig. 5c, 5d, and 5e. In the morning, α and r have coupling effect on the correlation results; while in the afternoon, α seems has little influence on the yresults when $r > 1,900km$. In the evening, there will be more anti-correlated nodes when α is small while r is large.

Although the approach used here is simple, it still can capture the instinct dynamics of air transport system. The determination of failure of the node should be more realistic by considering the capability of the node. To validate this findings, a theoretical model is going to be developed in our future work.

IV. Discussions

The filed of air traffic management has a strong interdisciplinary nature, combining of technological, economic and regulatory aspects. A great number of contributions have emerged from the interactions between scientists trained in different fields, ranging from computer science, through mathematics, to psychology. Researchers and operation experts have contributed to the improvement of the capability and efficiency of the system. However, there are still emerged unanswered questions. To ensure the safety of the system, one must have the ability to predict and control the air transport system. Thus, the knowledge on the structure and dynamics of the system is a significant issues for practical control of air transport system.

The recent surge of physicists into the realms of social science and other scientific fields has been fuelled largely by the availability of huge empirical data. The combination of the statistical mechanics theory and the observations of system behavior have arisen in part to fulfil the particular need of quantitative illustration of system structure and dynamics. In this work, we have investigated the structure and dynamis of air transport system from the operation point of view, providing a framework allowing the applications of theoretical findings into real world systems.

V. Acknowledgements

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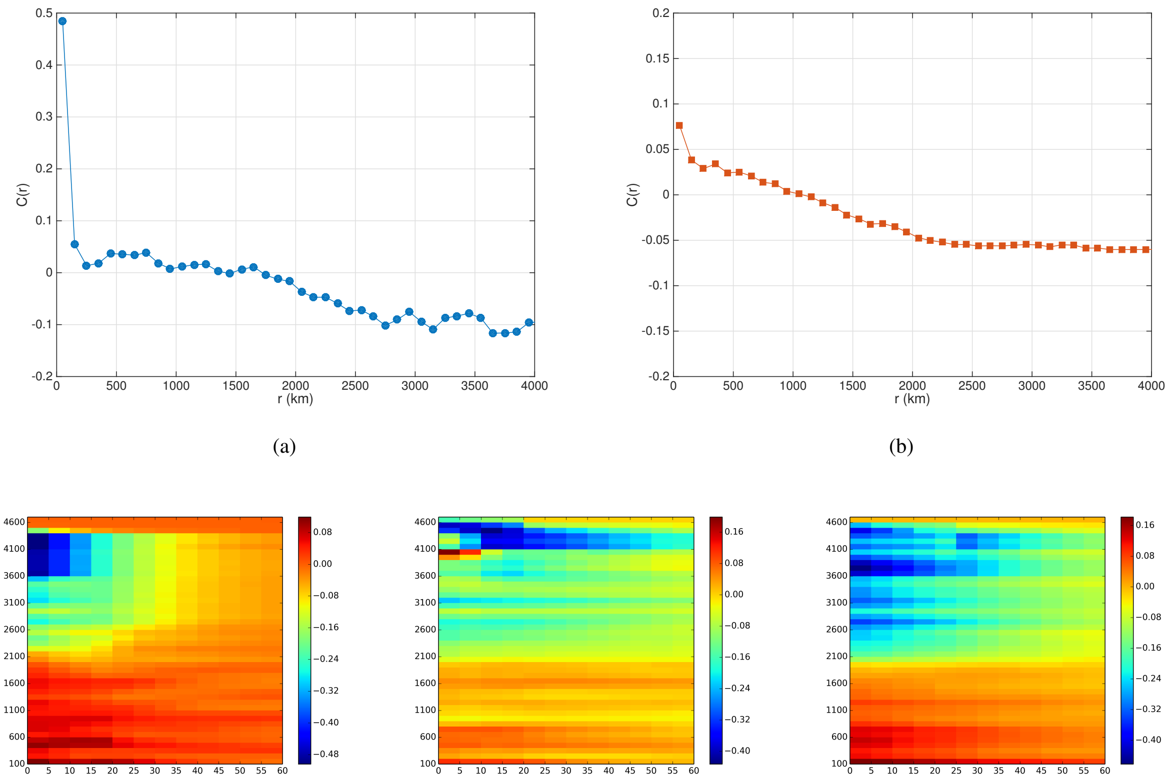

(a) (b)

(c) (d) (e)

Fig. 5. **Spatial correlations of cascading failures in the air transport system.** (a), Spatial correlations in airport network and in air route network (b). X-axis is the distance r in km. (c) and (d) are the effects of physical distance and the strength of resilience of the nodes, with x-axis is α and y-axis is the distance r in km.

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