Fluctuations in airport arrival and departure traffic: A network analysis*

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Air traffic is a typical complex system, in which movements of traffic components (pilots, controllers, equipment, and environment), especially airport arrival and departure traffic, form complicated spatial and temporal dynamics. The fluctuations of airport arrival and departure traffic are studied from the point of view of networks as the special correlation between different airports. Our collected flow volume data on the time-dependent activity of US airport arrival and departure traffic indicate that the coupling between the average flux and the fluctuation of an individual airport obeys a certain scaling law with a wide variety of scaling exponents between 1/2 and 1. These scaling phenomena can explain the interaction between the airport internal dynamics (e.g. queuing at airports, a ground delay program and following flying traffic) and a change in the external (network-wide) traffic demand (e.g. an increase in traffic during peak hours every day), allowing us to further understand the mechanisms governing the collective behaviour of the transportation system. We separate internal dynamics from external fluctuations using a scaling law which is helpful for us to systematically determine the origin of fluctuations in airport arrival and departure traffic, uncovering the collective dynamics. Hot spot features are observed in airport traffic data as the dynamical inhomogeneity in the fluxes of individual airports. The intrinsic characteristics of airport arrival and departure traffic under severe weather is discussed as well.

Keywords: air traffic network, fluctuations, scaling law, hot spot

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1. Introduction

Air traffic system is a "man-machine-environment" system, which is complex and dynamic. With the rapid development of the air transport industry, the imbalance between demand and capacity is becoming more and more serious which induces air traffic congestion.[1] Thus, the study of air traffic fluctuations has become a hot spot problem.

Traditional approaches to air traffic fluctuations focus on the long time behaviour of a few dynamical variables, developing models to characterize either the system average behaviour or a single airport (or a sector). Meyn[2] proposed a stochastic model of air traffic demand, which is used to calculate sector demand based on the time and the error distribution function of aircraft arriving and departing the sectors. Chatterji *et al.*[3] established a Gauss distribution model in order to describe the uncertainty of aircrafts' departing sectors. Gilbo and Smith[4] developed a method for the probabilistic prediction of an aggregate 15-min airport demand counts by using the probability distributions of arrival time predictions for individual flights.

As airport is a bottleneck of air traffic management (ATM), it is necessary to study the fluctuations in airport arrival and departure traffic. The methods discussed above are applied to lower traffic volumes. For higher traffic volumes, we must consider the special correlation between different airports which require us to study the fluctuations from the perspective of networks.

How are the dynamics of air traffic networks simultaneously studied? How are the hidden disciplines of air traffic networks uncovered? A framework to investigate the coupling between the average flux and fluctuations, which is actually mean and standard deviation analysis, was developed in Refs. [5]–[10]. It was found that coupling the standard deviation σ_i

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with the average flux $\langle f_i \rangle$ on individual nodes obeys a unique scaling law as

$$\sigma_i \propto \langle f_i \rangle^{\alpha} \tag{1}$$

with

$$\langle f_i \rangle = \sum_{t=1}^{T} f_i^{\Delta t}(t), \tag{2}$$

$$\sigma_i = \sqrt{\sum_{t=1}^{T} (f_i^{\Delta t}(t) - \langle f_i \rangle)^2}, \tag{3}$$

where $f_i^{\Delta t}(t)$ denotes the flux of node i in time interval $(t - \Delta t, t]$.

The dynamical exponent α is in the vicinity of two distinct values, i.e., α=1/2 and α=1. The α=1/2 exponent captures an endogenous behaviour, determined by the system of internal collective fluctuations. In contrast, the $\alpha = 1$ exponent indicates that the fluctuations of individual nodes are driven by time-dependent changes in the external force. The scaling phenomenon has been studied in many systems, such as gene systems,[11] software development,[12] internet systems,[13] precipitation,[14] airline networks,[15] online collaborative writing,[16] and so on.

In the present paper, we implement a detailed scaling analysis on the US air traffic network constructed by airports, following the framework mentioned above. From this method we present an overall picture of the statistical dynamics of the air traffic network which has not been studied previously. And then, we use the technique proposed by Menezes and Barabasi[8] to separate the internal and external dynamics, which is used to investigate how traffic volumes in air traffic networks are affected by the changes in the system, such as external (network-wide) patterns and variation of traffic demand, and by the internal queuing dynamics at an individual airport as well as the interactions between airport arrival and departure traffic. This information will help form a deeper understanding of the system behaviour and help to design more efficient air traffic control and air traffic flow management strategies in order to mitigate airport congestion.

2. Scaling law analysis

In order to study the fluctuations in airport traffic from the network point of view, we simplified the air traffic network which is composed of airports. The network structure is shown in Fig. 1.

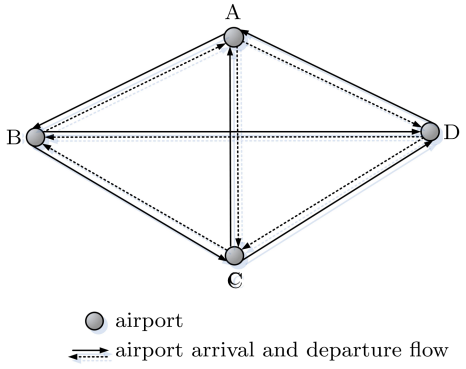


Fig. 1. Structure of the air traffic network composed of airports.

In this study, we collect arrival and departure traffic volume data through different time periods of 72 US airports in order to analyse fluctuations of US airport traffic (The data are obtained from http://www.transtats.bts.gov/Fields.asp?Table_ID=236). The data are obtained between about 6:00 to 24:00 every day from January 1, 2010 to June 31, 2010 as traffic volumes are very small at other times of day. They are recorded in time intervals of one hour. We aggregate the data and carry out the scaling law analysis at different time scales. The average traffic flux $\langle f_i^{\Delta t} \rangle$ and the standard deviation $\sigma_i^{\Delta t}$ are calculated using the method mentioned above. Figure 2 shows the relationship between $\langle f_i^{\Delta t} \rangle$ and $\sigma_i^{\Delta t}$, with time scales of Δt=1 h, 8 h, and 18 h, respectively. Scaling-law between σ and $\langle f \rangle$ can be observed clearly.

We can see that the value of α is between 1/2 and 1, which indicates that the behaviour of air traffic system is affected simultaneously by the internal and the external forces. Moreover, the value of the scaling exponent α increases from $\alpha = 1/2$ (internal driven system) and $\alpha = 1$ (external driven system) as Δt increases, suggesting that the systems may have an inhomogeneous influence as pointed out by Kertesz and Eisler.[17] The reason for this result is that the fluctuations of air traffic are due mainly to macroscopic factors such as the network-wide pattern and variation of traffic demand when Δt is much bigger; on the contrary, the fluctuations of air traffic is due mainly to microscopic factors such as the interaction between arrival and departure traffic of airports when Δt is much smaller.

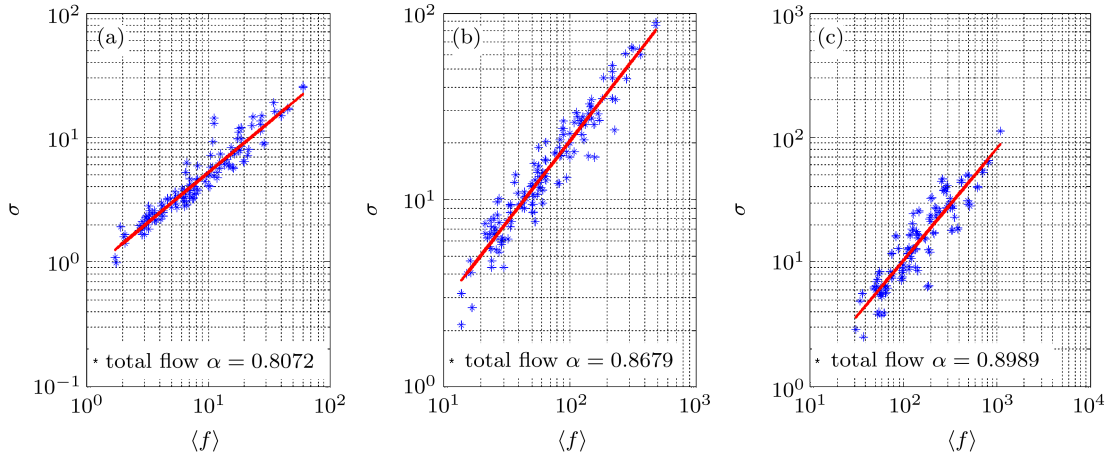


Fig. 2. (colour online) Scaling relations between fluctuations σ and average flux $\langle f\rangle$ at different time scales (a) $\Delta t = 1$ h, (b) $\Delta t = 8$ h, (c) $\Delta t = 1$ d. Each point represents arrival or departure flow data for one airport. The estimated values of scaling exponent α are also indicated.

3. Separating internal and external dynamics

The dynamics of each component are determined by two factors, i.e., (i) interactions between the components, which are governed by some internal dynamical rules that distribute the activity between the various parts of the system, and (ii) global variation in the overall activity of the system.[5]

For the air traffic network, the former factor mainly refers to the local activity of the individual airport (e.g. the interaction of arrival and departure traffic of airport) and the latter one includes the network-wide patterns and variation of traffic demand (e.g. an increase of traffic during peak hours every day). Thus it is impossible to extract the internal dynamics from the externally imposed fluctuations only using the flow information collected at a single airport. To determine the origin of fluctuations, Barabasi *et al.*,[7] and Menezes and Barabasi[8] proposed a method to separate the internal dynamics from the external fluctuations of complex systems as follows. Each time series $\{f_i(t)\}$ of node i reflects the joint contribution from the systems internal dynamics and external fluctuations, so we separate the dynamical variable $f_i(t)$ into two components:

$$f_i(t) = f_i^{\rm int}(t) + f_i^{\rm ext}(t), \tag{4}$$

where $f_i^{\rm ext}(t)$ is the externally driven component, and $f_i^{\rm int}(t)$ represents the contribution from internal dynamics.

To determine $f_i^{\rm ext}(t)$ we assume that the total traffic in the system is distributed in a deterministic manner among all components. In this case node i captures a time-independent fraction A_i of the total traffic, expressed as

$$A_i = \frac{\sum_{t=1}^{T} f_i(t)}{\sum_{i=1}^{N}\sum_{t=1}^{T} f_i(t)}. \tag{5}$$

Thus $f_i^{\rm ext}(t)$ and $f_i^{\rm int}(t)$ can be described as follows:

$$f_i^{\rm ext}(t) = A_i \sum_{i=1}^{N} f_i(t), \tag{6}$$

$$f_i^{\rm int}(t) = f_i(t) - A_i \sum_{i=1}^{N} f_i(t). \tag{7}$$

Further, we can determine whether the fluctuations observed in a system are mainly internally or externally imposed. The ratio between the external and the internal standard deviations for each node is determined as

$$\eta_i = \frac{\sigma_i^{\rm ext}}{\sigma_i^{\rm int}}, \tag{8}$$

where

$$\sigma_i^{\rm ext} = \sqrt{\langle f_i^{\rm ext}(t)^2\rangle - \langle f_i^{\rm ext}(t)\rangle^2}, \tag{9}$$

$$\sigma_i^{\rm int} = \sqrt{\langle f_i^{\rm int}(t)^2\rangle - \langle f_i^{\rm int}(t)\rangle^2}. \tag{10}$$

If $\eta_i \gg 1$, the system dynamics are dominated by external factors, while for $\eta_i \ll 1$, internal dynamics overshadow the externally imposed changes.

In this paper, the above method is applied to the airport arrival and departure traffic data. Similarly to the case of the most complex networks, $f_i^{\rm int}(t)$ exhibits high-frequency fluctuations, while $f_i^{\rm ext}(t)$ exhibits low-frequency fluctuations with periodic patterns (Fig. 3).

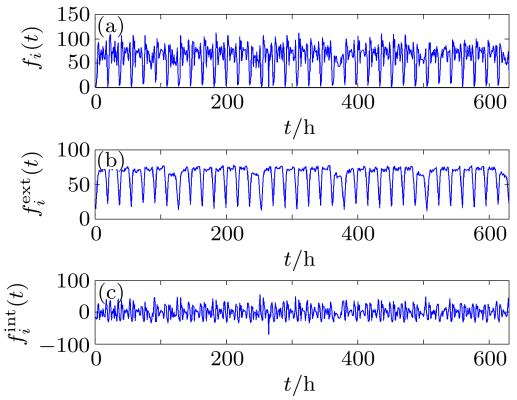


Fig. 3. (colour online) A typical result of separating the original flow into its external and internal contributions of ATL (Atlanta) departure traffic data. (a) The original flow series. (b) The external contribution given by Eq. (6), which recovers the period patterns. (c) The internal contribution given by Eq. (7).

The scaling-law is also observed in internal and external fluctuations as shown in $\sigma^{\rm ext} - \langle f\rangle$ and $\sigma^{\rm int} - \langle f\rangle$ plots (Fig. 4). For internal components, the values of exponent $\alpha_{\rm ext}$ for the external components are constant. For internal components, points in the $\sigma^{\rm int} - \langle f\rangle$ plot become dispersed at the large time scale, and the deviations are significantly larger than those of total flows as shown in Fig. 3, which indicates that there is a weaker existence of the scaling law. Moreover, $\alpha_{\rm int}^{\Delta t}$ decreases with Δt, because the external factors play a more and more important role with the increase of Δt in the system, which thus results in the increase of α for the total flow in Fig. 3.

As claimed in many papers,[18–20] it is useful to remove the data from regular period patterns, so that we can gain an insight into the random part of the external influence (e.g. occurrence of severe weather) from time series $f_i^{\rm int}(t)$ as $f_i^{\rm ext}(t)$ can be taken as periodic components.

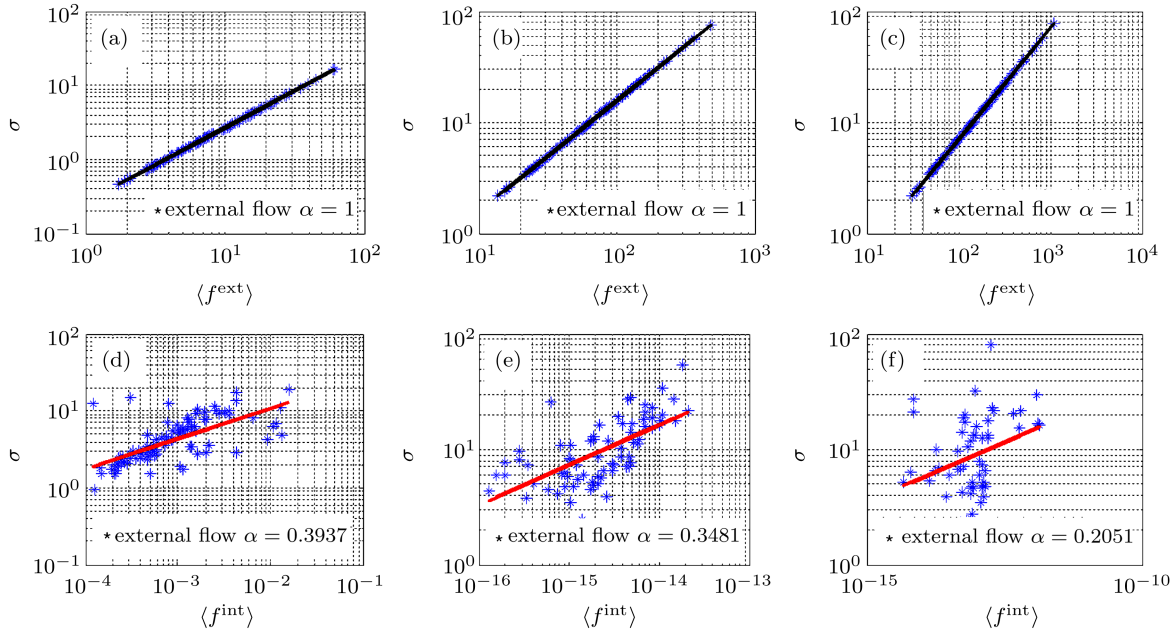


Fig. 4. (colour online) Scaling relations between external/internal fluctuations σ and average flux $\langle f\rangle$ at different time scales (a) and (d) $\Delta t = 1$ h, (b) and (e) $\Delta t = 8$ h, (c) and (f) $\Delta t = 1$ d. The values of fitted scaling exponent α for these two components are also indicated.

The $P(\eta_i)$ distribution is plotted in Fig. 5. The mean of η_i increases significantly with Δt increasing, indicating an increase in the relative strength of the external force, which is in correspondence with the increasing of α values in Fig. 3. When $\eta_i > 1$ with larger Δt, it means that the external and internal dynamics are comparable in magnitude for air traffic networks in which the dynamics of the system are dominated mainly by external factors. On the contrary, the internal forces play an important role in shaping the dynamical behaviours of systems. In particular, the $P(\eta_i)$ distribution is closer to a Gaussian distribution.

4. Spatial inhomogeneity and hot spots

Complex networks with inhomogeneous topology are very fragile against the intentional attacks on the "hot spots".[21] It is very important to find out the

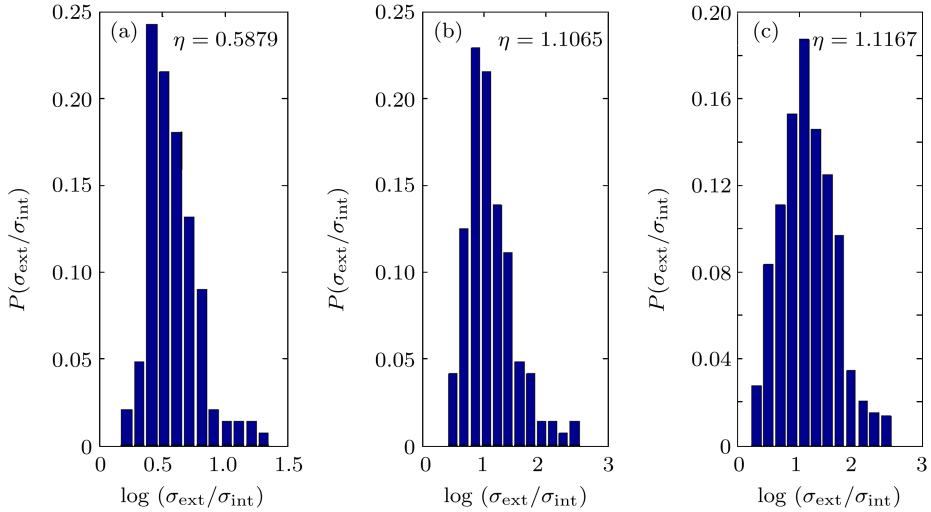


Fig. 5. (colour online) Empirical distributions of η at different time scales $\Delta t = 1$ h (a), $\Delta t = 8$ h (b), $\Delta t = 1$ d (c). The values of mean η_i are also displayed.

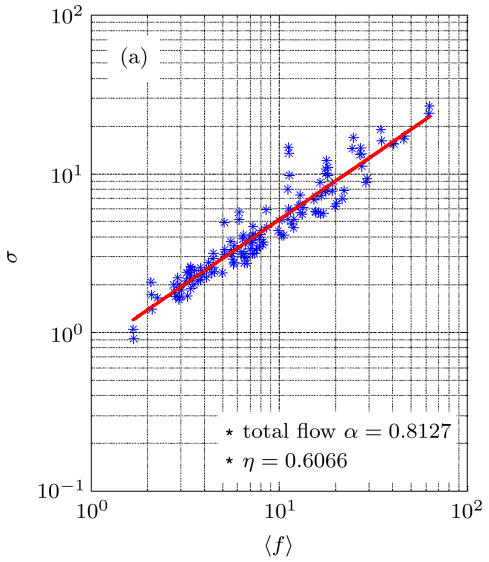
"hot spots" which carry an overwhelming fraction of the network activity. As high fluctuations may lead to bottlenecks and congestion, the finding of these "hot spots" is useful for prediction and prevention of failure. The wide range of $\langle f_i \rangle$ indicates that while most airports have relatively small fluxes, there exist groups of airports for which $\langle f_i \rangle$ takes a relatively large value. These "hot spots" are responsible for a considerable fraction of the system activity: the top 20% of the airports carry 49.79% of total traffic, and the top 10% of the airports carry 32.77% of total traffic.

For driven system ($\alpha = 1/2$), the network can offer reasonable bounds on the maximum capacity, potentially avoiding bottlenecks. In contrast, for driven system ($\alpha = 1$) the relative fluctuation, $\omega = \sigma/\langle f \rangle$ is independent of flux, i.e., fluctuations on the hot spots increase linearly with the flux increasing. Thus we can draw the conclusion that the air traffic networks are closer to the $\alpha = 1$ case, which thus requires more attention in order to avoid congestions and breakdowns in critical airports.

5. Weather and dynamics

Air traffic demand and capacity will be imbalanced by the occurrence of severe weather as it reduces the air traffic capacity. Thus, the air traffic flow during severe weather conditions usually exhibits significantly different behaviour. It is important to find out the mechanisms governing such different dynamic behaviours.

We analyse the dynamics of traffic data collected in April and June. The relationship between the average traffic flux and standard deviation is given in Fig. 6 from which we can see that traffic in April has a larger scaling exponent. This can be explained as follows: for traffic in June, the internal effects derived from local activities such as queuing and traffic following induced by severe weather are much stronger with an average delay of 0.5891. However, in April, the internal effects are negligible and thus external factors become dominant as the weather is much better with an average delay of 0.2303. Furthermore, $\bar{\eta}_i$ of traffic in June is 0.5411 while $\bar{\eta}_i$ of traffic in April is 0.6066, which indicates that the internal dynamics of traffic in June is much higher than that of traffic in April. For example, at ATL airport the departure traffic fluctuation in June is much bigger than that in April as their standard deviations are 13.75 and 13.61, respectively.



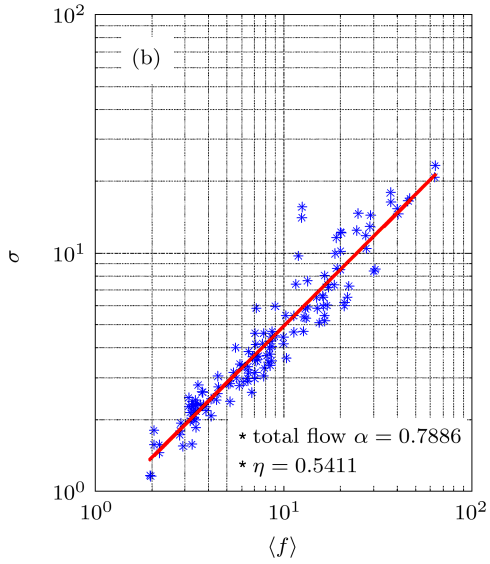


Fig. 6. (colour online) Scaling relationship between fluctuations σ and average flux $\langle f \rangle$ for April (a) and June (b) data. The fitted scaling exponents α and the mean of η_i are also indicated.

6. Conclusions

Airport congestion caused by the contradiction of airport demand and capacity require us to analyse the fluctuations of airport arrival and departure traffic. In this paper, we studied the fluctuations from the point of view of networks consisting of airports. To quantify the flow dynamics, we collected and analysed the traffic flows at 72 US airports and identified the existence of a certain scaling law. The estimated scaling exponents are different from the universal class 1/2 and 1, and heavily depend on parameters such as time scale, internal/external components, and severe weather/non-severe weather flows. Such scaling phenomena reveal the complex competition between the internal queuing dynamics at each airport and the changes in the external (network-wide) forces of the system. These findings allow us to gain an insight into the intrinsic characteristics of airport arrival and departure flows, and provide a foundation for the further analysis of the mechanisms governing the air traffic system collective dynamics.

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