Twelfth USA/Europe Air Traffic Management Research and Development Seminar (ATM2017)

A case study of non-linear dynamics of "human-flow" behavior in terminal airspace

Lei Yang, Suwan Yin, Minghua Hu
College of Civil Aviation
National Laboratory of Air Traffic Flow Management
Nanjing University of Aeronautics and Astronautics
Nanjing, China

Yan Xu
Department of Telecommunications and Aerospace Engeering
Technical University of Catalonia
Barcelona, Spain

Abstract—**Air traffic is widely known as a complex and task-critical techno-social system mainly composed of airspace, procedures, aircraft and air traffic managers. In order to develop and deploy advanced operational concept and automation system scientifically and effectively, it is essential to take an in-depth research on the intrinsic air traffic dynamics and characteristics which haven't been widely discussed. A systematical empirical study of air traffic operation in Guangzhou terminal airspace is conducted by collecting synchronized flight and air-ground communication data. Three types of metrics are proposed to measure air traffic dynamics from "human-flow" perspective: flow-based metrics, controller-based metrics and chaotic metrics. Empirical results identify synchronized free, smooth, semi-stable and congested phase states from both flow and controllers performance evolutions. Meta-cognition is explained as one of critical underlying mechanisms that drive the phase transitions. Further, by studying data series of potential conflict in "flow system" and communication behaviors in "human system", air traffic system is proved to be a chaotic system, which presents higher short term chaotic predictability, caused by internal instability of semi-stable and congested status. These novel findings will provide theoretical basis for aggregated air traffic flow modeling, decision support system design and tactical flow management.**

Keywords-air traffic; terminal airspace; phase transition; chaotic dynamics

I. INTRODUCTION

Worldwide ATM system is currently in the process of transformation and upgrading to cope with increasing air traffic demand and resulting congestion especially in high-density airports and surrounding airspace. Numerous advanced operation concepts were proposed in world's major long-term strategic planning of ATM system like SESAR (Single European Sky ATM Research), NEXTGEN (Next Generation Air Transportation System) and ASBU (Aviation System Block Upgrades), including "ATM Network Management", "User Driven Prioritization Process", "Flow Contingency Management" and "Complexity Management" etc., in order to enhance the system-wide performance and reduce the propagation of congestion in air traffic system during day-to-day operation[1].

However, air traffic system is always regarded as a "human-in-the-loop", dynamic and non-linear complex system composed of air traffic controllers (ATCOs), aircraft, pilots and airspace, supported by communication/navigation/ surveillance facilities and air traffic management system etc. The interactions of elements in this kind of complex techno-social system will result in a behavior that is often unpredictable [2]. From the microscopic view, air traffic controller, who is responsible for the safety, efficiency and orderliness of air traffic flow by situation perception, comprehension, prediction and decision-making, is the critical element of tactical air traffic operation currently and in future ATM systems [3]. In other words, the feedback interaction between ATCOs and air traffic flow is one of the deterministic factors that impact on air traffic situation evolution. Therefore, in order to understand system predictability, and further to develop and deployment advanced operation concept and automation system scientifically and effectively, it is essential to uncover the intrinsic physics of air traffic system by revealing representative temporal-spatial phase transition pattern of air traffic, explaining its internal mechanism and extracting high-level system emergence under "human" (ATCOs) and "flow" (group aircraft) interactions.

The key to the study of system dynamics is to develop appropriate metrics that represent system behaviors. In air traffic domain, though word "traffic dynamics" are rarely reported, relative researches have been done for decades. Here, we divide current air traffic dynamics studies into three categories: flow dynamics, ATCOs dynamics and system complexity.

Flow dynamics aims at constructing observable and explicit metrics to characterize flow transmission features in local or large-scale airspace. Flight delay is one of the key dynamics metrics depicting air traffic flow operations. Locally, delay is always studied together with throughput or capacity in specified airspace. The classic exponent-shape relationship between throughput and delay presents the basic air traffic flow dynamics and provides the fundamental knowledge in current ATM practice [4]. However, a group of empirical airport traffic demand-supply curves which were similar to Macroscopic Fundamental Diagram [5] proved that departure throughput drops at some critical demand as the continuous increase of departure traffic density on airport surface network [6]. In large-scale or global airport network, novel work emerged focused on delay propagation analysis, modeling and prediction using network approach [7]. Inspired by flow dynamics study of vehicle traffic, lots of flow models were studied in recent years to understand the aggregate delay features of air traffic flow in national airspace system and to support large-scale strategy flow management, mainly including queuing networks, Partial Differential Equation, Cell Transmission Model (CTM)-Large Capacity, Linear Dynamic Systems Model and Cellular Automata [8]. However, the aim of above "flow-centered" models is to establish flow control framework based on modern control theory but to reveal flow dynamics. A CTM-based flow model of terminal airspace was proposed to initially study the flow dynamics by illustrating the relations of "flux-density-velocity" [9]. Nonetheless, according to the principle of CTM, the proposed model is not appropriately applied for being lack of refined fundamental diagram calibration.

Human dynamics studies try to uncover air traffic controllers' general behavioral pattern and self-adaptive mechanism in real-time air traffic control. Reference [10] firstly divided ATCOs' behavioral models into two categories: macroscopic and microscopic. As a macroscopic model, workload is most widely studied as the key metric to evaluate sector capacity. Microscopic modeling of air traffic controllers' behaviors tries to describe the cognition process including attention resource assignment, memory usage, situation awareness, decision making and monitoring, including CT-ATC, MoFL, Apex, etc. [11]. Though the behavioral dynamics of ATCOs' was relatively ideally and intuitively modelled, they provided important tools to refine traditional flow-based air traffic simulation. Since it would be difficult to model every details of ATCOs' mental process, reference [12] proposed an empirical method to study ATCOs' high-level dynamics by analyzing the communication intervals and proved that communication intervals follow Power Law distribution. However, the distribution patterns revealed basic dynamics of controllers' communication behavior, but it would not be straightforward to put into ATM practice.

Complexity methods aim at building bridges between traffic flow situation and ATCOs' cognition complexity and interpreting "human-flow" dynamics in air traffic operation. A series of traffic flow complexity metrics were developed in recent 20 years. Classic metrics include Static Density [13], Dynamic Density [14], Tactical Load Smoother [15], Input-Output [16], Lyapunov exponent of trajectory dynamics [16] and Solution space-based metrics [17]. By finding the best matches between traffic flow complexity measurement and ATCOs workload, the weight of each sub-index was calibrated. The weight can be treated as the impact of each kind of traffic element on ATCOs' cognitions. As the development of complex network, reference [18] modeled the air traffic system as a complex dynamic network of flights controlled by ATCOs who have to solve potentially conflicts and explored congestion phase transitions under various control strategies using real and simulated data.

In summary, previous studies have proposed numerous models and metrics to characterize air traffic performance from different but relatively single aspects. To systematically uncover air traffic dynamics, a case study of Guangzhou terminal airspace is conducted by collecting synchronized operational flight and communication data of each sector, exploring general "human-flow" phase transitions and underlying mechanism, and further revealing chaotic features evolution both in "flow system" and "human system". Novel findings in this paper will provide a brand new perspective on aggregated air traffic flow modeling, decision support system design and system prediction in future ATM upgrade.

The rest of this paper is organized as follows. Section II gives a general description of collected empirical data. Section III uncovers synchronized phase transition patterns and underlying mechanism of "human-flow" at sector level. Section IV further identifies and proves the chaotic feature of "human-flow" system at terminal airspace level and sector level respectively, and provide the initial discussion of the relationship between phase status and chaos. Conclusions and future work are described in Section V.

II. Empirical Data

Guangzhou terminal airspace is mainly responsible for the inbound and outbound traffic of Baiyun airport which is the third busiest airport in China. To analysis the system dynamics of air traffic, synchronized flight plan, trajectory data and air-ground communication data on three typical days 15/05/2014, 11/09/2014 and 18/12/2014 are collected.

Updated Flight plan. This dataset consists of critical attributes of each flight, including flight number, Estimated/Actual Time of Departure, Estimated/Actual Time of Arrival, standard flight routes, pass sectors, and runway in use. This type of data mainly provides reference for further flow analysis together with trajectory data. The airspace configuration and sample traffic flow distribution is shown in Figure 1-2.

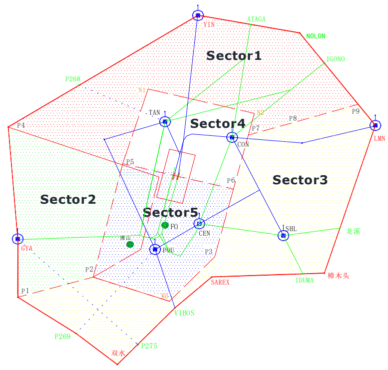

Figure1. Configuration of Guangzhou terminal airspace

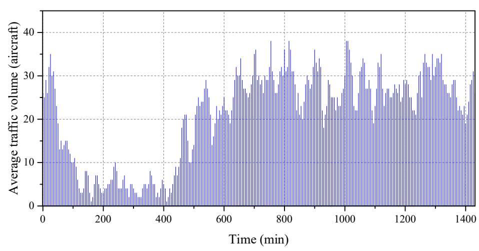

Figure2. Average air traffic volume of 5 minutes interval on 11/09/2014

Trajectory data. A flight trajectory, denoted by Tr, is a time-ordered sequence of 5-tuples (x, y, z, v, t) representing the longitude, latitude, height coordinates and speed of a flight at time t. Let $Tr_i = (p_i^1, p_i^2, \dots\dots, p_i^M)$ denote the trajectory of flight i, where $p_i^m = (x, y, z, v, t)_i^m$ is the mth point of the trajectory Tr_i. The sample radar trajectory data are shown in Figure 3.

Communication data. Data series of air-ground communication in sector s, denoted by $C_s^1 = (c_s^1, c_s^2, \dots\dots, c_s^N)$, records start and end time of each continuous communication, where $c_s^n = (t_s, t_e)_s^n$. It is noted that each continuous communication may initiated by either controller or pilot. Figure 4 shows the sample data of start time and duration of each communication.

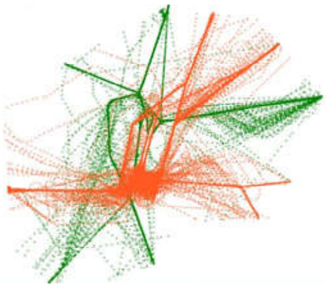

Figure3. Sample arrival and departure radar trajectory in terminal airspace

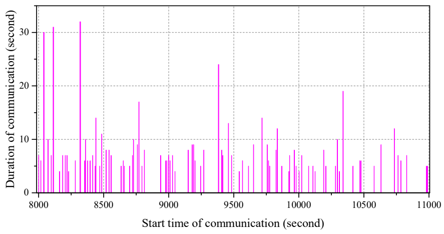

Figure 4. Start time and duration of each air-ground communication

III. General Phase Transitions of Sector Air Traffic

The science of traffic physics is a new field emerging at the boundary of the study of agent-based modeling and statistical physics. The phase is a property of an entire physical system, rather than of any of its particular components [18]. Phase transition in vehicular traffic flow has been studied for years by analyzing the dynamic relations of flow-density-velocity and provided solid theoretical foundations for traffic operations. Since air traffic is widely known as a complex techno-social system mainly characterized by "human-flow" interactions, phase transition in air traffic is regarded as the co-evolution of "human-flow" performance in this paper. To uncover the basic phase transitions of sector air traffic, it is essential to model characteristics metrics for both air traffic flow and air traffic controller's behavior.

A. Metrics for characterization of air traffic operation

1) Flow-based metrics

Inspired by phase transition metrics in vehicular traffic flow, redefined "flow-density-velocity" of air traffic flow is given as follows considering the maneuvering behavior instructed by air traffic controllers.

(1) Flow rate. Each sector is composed of several air routes and has more than one exit point. The flow rate, denoted by $f_s(\tau)$, is defined as the total aircraft flow out of the sector in a certain time period τ.

(2) Average density. At each radar snapshot time, the number of aircraft is calculated as $n_s^\tau(t_i)$, then the average density is defined as follows:

$$\rho_s^\tau = \frac{1}{M}\sum_{i=1}^{M} n_s^\tau(t_i) \tag{1}$$

where M is the total snapshots in a time period.

(3) Average equivalent velocity. As the increase of traffic density and resulting conflicts, controllers normally adopt speed reduction and heading change strategy to avoid conflict. To capture the higher degree of spatial freedom compared to road traffic, and to present the congestion phenomenon, an equivalent average speed is modeled as follows:

$$\overline{v_s^\tau} = \frac{1}{M}\sum_{i=1}^{M} \frac{1}{n_s^\tau(t_i)} \sum_{n=1}^{n_s^\tau(t_i)} \|v_n(t_i)\| \cdot \Im_n^s \tag{2}$$

where $\|v_n(t_i)\|$ is the velocity scalar of aircraft n at snapshot time t_i; $\Im_n^s$ is the Velocity Gain Coefficient (VGC) of aircraft n in sector s defined below. Behaviors like detour, shortcut and holding in congestion situations can be characterized.

Definition 1 (Velocity Gain Coefficient: VGC): VGC is the ratio of standard route length ι_n to actual fly distance in sectors as formulated in (3).

$$\Im_n^s = \iota_n / \sum_{i=1}^{L-1} dist(p_n^i, p_n^{i+1}) \tag{3}$$

where L is the total snapshots of aircraft n in sector s; $dist(p_n^i, p_n^{i+1})$ is the 2-D Euclidean distance of adjacent trajectory points.

2) Controller-based metrics

As the core of tactical management of airspace and traffic flow, air traffic controllers' responsibility is to transit aircraft through sectors in a safe, ordered and efficient way. Therefore, the control behavior which can be regarded as a close-loop decision making that containing process of monitoring, evaluation, plan formulating and command issuing via voice and/or data link, not only plays a vital role in determine the evolution of traffic flow but also shows the cognition strategy to cope with traffic complexity. To study the human dynamics in air traffic control, we divide ATCOs' behaviors into two categories: internal (cognition) complexity and external (communication) activity. ATCOs' cognition complexity is the key attribution that reflects the difficulty in comprehending and predicting air traffic flow situation [19]. Potential aircraft conflict, which is the main index that reflects the degree of flow disorder, is proved to be the most significant factor that influent ATCOs cognition complexity and resulting workload.

As for the external activity, air-ground communication is the integrated output of human internal complexity and strategies.

(1) Solution space based cognition complexity

Potential conflicts are temporal-spatial situations that two or more flights have impending collisions due to continuous loss of separations. It should be noted that flight conflicts in terminal airspace operation have their own specialties. Firstly, due to limitations of human brain, potential conflicts are sector based, i.e. only conflicts in the same sector are considered. The second is the extended concept of conflict. The separation between aircraft is not only determined by safety separation minimum but also by the required separation at fixes or sector boundaries. As a result, aircraft at different flight levels are often required to maintain a certain horizontal separation criterion in terminal airspace especially when they have same destination. So here we define potential conflict as the possible violation of expected horizontal separation.

At any snapshot time, the vector of plane position and speed of aircraft i are denoted by $\boldsymbol{U}_i = [x_i, y_i]$ and $\boldsymbol{V}_i$ respectively. Then the relative position and speed of aircraft i and j are denoted as $\boldsymbol{U}_{ij} = \boldsymbol{U}_j - \boldsymbol{U}_i$ and $\boldsymbol{V}_{ij} = \boldsymbol{V}_j - \boldsymbol{V}_i$. We define that the two aircraft are in potential conflict if and only if solution of Γ_{ij} exists in formula (4).

$$\begin{cases} \left|\boldsymbol{U}_{ij} + \boldsymbol{V}_{ij} \times \Gamma_{ij}\right| \le D \\ \Gamma_{ij} \le \min(t_i, t_j) \end{cases} \tag{4}$$

where D is the expected separation, t_i and t_j is remaining flight time of aircraft i and j in sector s respectively.

Speed and heading vectoring are the major ways to avoid conflict and maintain required headway distance in controlled flows. Solution space of potential conflict defined as the 2D area of continuous heading and speed combination space for conflict resolution is proven to be the key factor that influent ATCO's cognition and air traffic flow ordering theoretically [17]. However, in practice, solution space changes with solution strategy (e.g. sequencing) and is restricted by airspace structure and flight procedure (e.g. heading change limitations). Here, we propose an integrated solution space-based conflict situation index to represent the urgency and difficulty of potential conflicts and ATCOs' cognition complexity.

Without loss of generality, let aircraft A and B be in potential conflict as shown in Figure5. Limited by air traffic control regulations and aircraft performance, available heading and speed solution space of A at time t_i are $\Delta\theta_A = [\theta_{A1}, \theta_{A2}]$ and $|\Delta V_A| = [\min|V_A|, \max|V_A|]$ respectively as colored by gray in Figure 5. We define Available Solution Space Area $A\_SSA_A(t_i) = 0.5(\theta_{A2} - \theta_{A1})(\max|V_A|^2 - \min|V_A|^2)$. Then, the combined solution spaces of aircraft A under different sequencing strategies are colored by brown as shown in Figure5.

Obviously, it is easy to prove that there is no intersection of solution space under these two control strategies. So, the total solution space of aircraft A is the sum of solution space in leading and following conditions, denoted as $SS_{A|B}(t_i) = SS^L_{A|B}(t_i) + SS^F_{A|B}(t_i)$. Likewise, the total solution space of aircraft B can be derived similarly. In high density air traffic operation, multi-aircraft conflict situation emerges commonly. Assuming aircraft A is in conflict with more than one aircraft, the urgency index is formulated as $SSA_A(t_i) = \Lambda(\cap SS_{A|X}(t_i))$, where X is the aircraft that are having conflict with A at snapshot time t_i; $\cap SS_{A|X}$ is the intersections of solution space; function $\Lambda(\cdot)$ is the area operator.

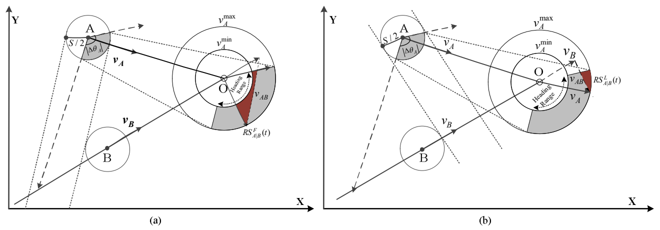

Figure 5. Scheme of solution space of aircraft A in potential conflict. (a) Solution space in the condition of aircraft A follows B; (b) Solution space in the condition of aircraft B follows A

Solution space of potential conflict not only provides dynamic picture of microscopic structure inside air traffic flow, but also give a novel perspective of ATCO's cognition complexity measurement. To make it more intuitionistic, solution space based cognition complexity $SSC(\tau)$ is modelled a weighted sum of solution difficulty during time period τ.

$$SSC(\tau) = \frac{1}{M}\sum_{i=1}^{M}\sum_{n=1}^{n_s^{\tau}(t_i)}\left(\frac{A\_SSA_n(t_i)}{SSA_n(t_i)} - 1\right)^{\sigma} \tag{5}$$

where σ is a co-efficient to model the non-linear impact of solution space on cognition complexity and can be nicely calibrated by human-in-the-loop experiment. Here, we simply set $\sigma = 0.5$. If and only if there is no conflict during some time period, the value of $SSC(\tau)$ equals to 0.

(2) Communication load

Communication load is the primary composition of ATCOs' workload. Study on the adjustment of communication behavior may reveal controllers' internal dynamics to cope with complexity [3]. Communication load here is defined as the percentage of air-ground communication channel occupancy in certain time period as shown in formula (6).

$$CL_s(\tau) = \sum_{i=1}^{I} \beth_s^i \Big/ \tau \tag{6}$$

where $\beth_s^i$ is the duration of the i^{th} continuous communication during time period τ, $\beth_s^i = (t_e - t_s)_s^i$.

B. Phase transitions of "human-flow" evolution

In this section, metrics are deployed by loading empirical data. We try to explore general phase transition pattern and uncover its underlying mechanism of "human-flow" evolution implied in sector air traffic. Here, we set time period $\tau = 5$ minutes to have a detailed and closer look into empirical data.

1) MFD based flow dynamics

MFDs [5] characterize the aggregate behavior of traffic network in term of occupancy and throughput, in a parsimonious way yet capable of capturing the key demand-supply relationship. Sector based MFDs are modeled as the relationship between Flow Rate and Average Density.

Figure 6 (a) shows the average flow rate change with traffic density. Quadratic or cubic polynomial curves are best fitted to generate sector-based MFDs. The average R-square of fitting is 0.922 with average relative standard deviation of 28.5%. Interestingly, a critical density is uncovered which contradicts with traditional assumptions that as the increase of demand, throughput will reaches and maintain the maximum. However, critical density proves that when demand climbs to a certain level, the flow rate (throughput) starts decreasing. Similar conclusion are drawn that runway departure throughput drops when taxi-out demand at airport surface over a certain point [6]. It is also noted that critical density is not observed in all the sectors simply due to the uneven temporal-spatial distribution of traffic flow. Following reasons can be used to interpret the novel findings.

- Network congestion. Throughput is the integrated system output generated by aggregate behavior of aircraft in airspace network. As the increase of traffic density, average flow speed present continuous drop due to rising conflicts as shown by the blue curve in Figure 6 (b)-(f). Since spatial separation is adopted as a control reference in current air traffic operation, reduced speed enlarges the temporal distance and lead to the decline of flow rate (throughput) in congested situation.
- Stress status of controllers. In high density traffic situation, more instructions of speed adjustments, heading changes, or even holding strategies are issued by controllers to avoid conflicts and result in less thinking time. However, due to the regulation of maneuvering (e.g. speed adjustment should be an integral multiple of 10nm/h) and unprecise calculation of human brain, the spatial distance of aircraft flying out of sector normally larger than the expected separation for higher safety vigilance in congested situation.

2) Phase transitions of "human-flow" performance

To further understand the "human-flow" interactions, we plot above flow-based and controller-based metrics for each sectors to explore the underlying mechanism of phase transitions as shown in Figure 6 (b)-(f). Each curve presents the average value changes with flow density.

Intuitively, increased traffic leads to lower flow efficiency, higher workload and cognition complexity. Correlation analysis shows that EAS has a negative correlation with traffic density: average Pearson Correlation Coefficient -0.811 and two-tailed probability 0, while communication load and cognition complexity index show positive correlations with density: average Pearson Correlation Coefficient 0.851 and 0.798 respectively, two-tailed probability are both 0. By analyzing the curve configuration and replay of radar data, four phase states are identified empirically.

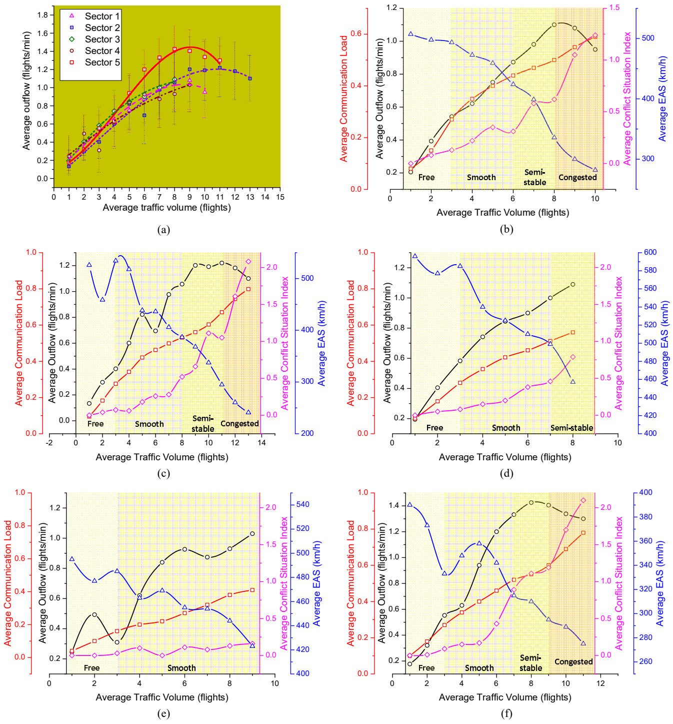

Figure 6. "human-flow" performance in Guangzhou terminal sectors.

(1) Free Phase. Extremely low density results in large spatial headways and little conflict among aircraft. Shortcut is most commonly used by ATCOs during this phase as shown in Figure 7 (a) which is the temporal-spatial diagram of flight trajectory along merged routes GYA-AGVOS and TAN-AGVOS in sector 2. Shortcut is the presentation of internal meta-cognition dynamics named "pre-activation" in low workload and cognition complexity. It is regarded as a strategy of mental preparations for better adaption to sudden rise of traffic by speeding up the flow and increasing the complexity intentionally. As a result, the ATCOs' communication loads climb quickly though only occasional even no conflict occurs.

(2) Smooth Phase. In this status, flow efficiency is still well maintained though conflicts come up more frequently. Interestingly, cognition complexity index increases more sharply than communication as shown in Figure5. This is one of the most important strategies of ATCOs' meta-cognition dynamics called "cognition complexity inhibition" which is similar to a proved traffic control strategy-"standard flow" [20]. As a result, aircraft are lined up in standard flight route with approximately equal flight distance observed in Figure 7 (b) to form a stable and familiar traffic picture.

(3) Semi-stable Phase. Most of the aircraft are still flying along standard routes with closer and more uniform spatial headways as shown in Figure7(c). Flow rate slowly approaches to the maximum at some critical density while a noticeable decline of flow velocity appears due to significant increase of conflict and cognition complexity. However, driven by metacognition dynamics, strategy of "cognition complexity inhibition" in smooth phase is applied by "critical points", which means ATCOs use certain navigation fixes or

intermediate points along standard routes to ease the traffic picture when issuing radar vectoring command [20]. The average growth rate of communication load is just slightly higher than that in smooth phase. Normally, sector capacity which is defined as the maximum throughput or the threshold of ATCO's workload will be achieved in this phase. Since airspace resource is in its full usage condition, the traffic state is not stable and phase transition may easily occur when disturbance merges.

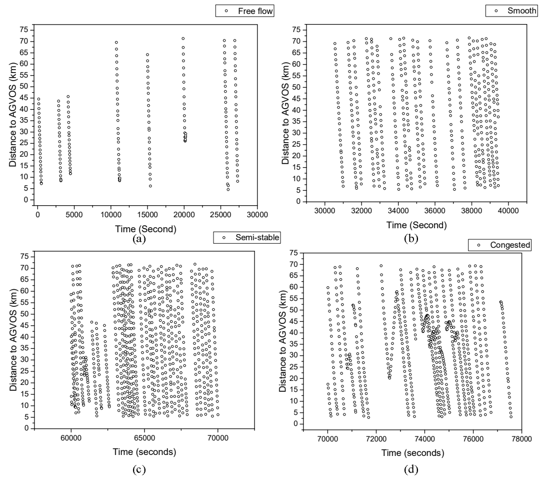

Figure 7. Temporal-spatial diagram of air traffic flow along merged routes GYA-AGVOS and TAN-AGVOS.

(4) Congested Phase. Flow rate and velocity continuously drop while conflicts and cognition complexity soar. To deal with such complex traffic situation, driven by "stressed" metacognition dynamics, controllers mainly focus on the safety rather than efficiency by instinct reactions with less motivations of traffic optimization. Chaos and conditioned reflexes are the primary nature of mental status of controllers in congested phase. As a result, from microscopic view, the resolution of conflict turns from speed strategy to radar vectoring even holding as shown in Figure7(d); from macroscopic view, the streamlines of traffic change from structured linear into disseminative planar configuration. The air traffic picture falls into chaos and disordering.

In all, metacognition dynamics of air traffic controllers can be reasonably explained as an adaptive cognition management strategy to cope with traffic complexity and a primary driving force that leads to the "human-flow" phase transitions together with traffic demand as shown in Figure 8. Observable evolution of air traffic flow and ATCOs' performance are the quantified and integrated outputs of abstract "human-flow" interactions in air traffic operations. However, it is still not clear about the high-level intrinsic nature of air traffic system which is essential for future air traffic management upgrade. In next section, chaotic properties of "human-flow" system are initially studied.

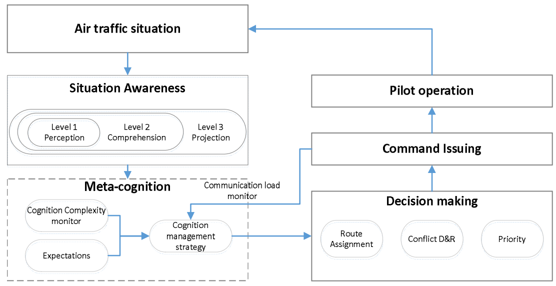

Figure 8. Brief schema of "human-flow" interactions

IV. High-level Chaotic Dynamics of Air traffic System

Chaotic analysis is a modern tool for identifying the high-level characteristics of non-linear dynamic systems. The dynamics of "human-flow" interacted air traffic system is always regarded as complex and nonlinear, and can't be described using a group of functions. Reference [21] pointed out that the first-line task of fully achieving automated air traffic management is to figure out the complex chaotic problems fall in between randomness and certainty in air traffic system. However, non-chaotic feature of air traffic flow was proved in terminal airspace by analyzing the time series of traffic volume [22]. Nonetheless, intuitively, as discussed above, dynamic evolution of air traffic flow from free to congestion is the integrated output of adaptive human control activities dealing with increasing traffic and resulting potential conflicts which possess of non-linear characteristics like uncertainty, burstiness and diffusivity, etc. Besides, potential conflicts can be regarded not only as the dynamics of air traffic demand but also the system emergence triggered by "human-flow" and "human-human" interactions during multi-sectors operation (e.g. local conflict resolution in one sector or one route will lead to secondary conflict in other area). Considering above system features, two hypotheses are given as follows.

Hypothesis 1: air traffic system is a chaos system, and the chaotic phenomenon can be observed in terminal level and sector level.

Hypothesis 2: Chaos is highly related to the phase state of air traffic flow.

A. Brief description of chaos identification method

Given continuous data series of system variable $\mathcal{H}_s^\tau = [\hbar_1, \hbar_2, \dots\dots, \hbar_n]$, we adopt Lyapunov Exponent metric to capture the chaos characteristics based on reconstruction of system phase space. These metrics were widely used in identifying chaos of natural, social, and sociotechnical systems. Here, only brief descriptions of the process are provided as shown in Figure 9. Methods adopted refer to chaotic analysis in [22].

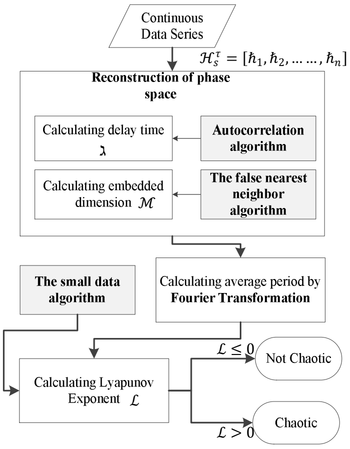

Figure 9. Process of calculating Lyapunov Exponent

B. Data series

Based on the hypotheses stated above, two type of data series are gathered based on initial empirical data and potential conflict calculated in section IV.

1) Communication interval. Previous researches proved that communication intervals fit power law distribution which was characterized as behavioral dynamics of controllers. This type of data is also known as the silence duration in radio channel denoted by $T_M = (\Delta t_1, \Delta t_2, \dots\dots \Delta t_M)$, where Δt_m is the duration of the *m*th silence.

2) Potential conflict. Conflict emerges in pairs. In each time period, the number of potential conflicts is denoted as $\mathcal{H}_s^\tau = [\hbar_1, \hbar_2, \dots\dots, \hbar_n]$, where $\hbar_i$ is the number of potential conflict pairs in time period τ_i.

C. Conflict chaos at terminal airspace level

To avoid lengthy descriptions, continuous time series of potential conflict on 11/09/2014 is taken as an example to show the intermediate results of chaos identification at terminal level. To be consistent with the temporal scale used in basic "human-flow" dynamics analysis in Section IV, we set $\tau = 5$min.

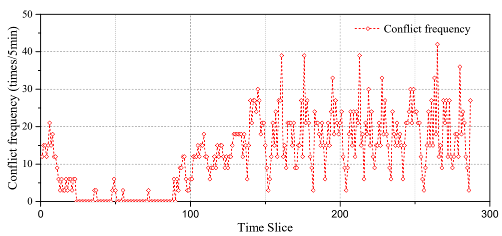

Figure10. Time series of potential conflict frequency on 11/09/2014 in terminal airspace

Phase space which is a basic data process of complex system that cannot be completely modelled is reconstructed by calculating delay time and embedded dimension to acquire primary features of system. By adopting autocorrelative function, the delay time $\lambda_{\mathcal{H}} = 23$ is obtained when function value reaches to the minimum for the first time as shown in Figure 11 (a). Meanwhile, false nearest neighbor algorithm is used to calculate the embedded dimension $\mathcal{M}_{\mathcal{H}}$. When the proportion of false nearest neighbor points stops decreasing or decrease rate less than 0.001 with dimension, attractors are regarded as unfolded. Figure11 (b) shows the evolution curve of proportion of false nearest neighbor points, the embedded dimension of the time series $\mathcal{H}_s^\tau$ is $\mathcal{M}_{\mathcal{H}} = 7$. Then, the largest Lyapunov exponent which is a classic metric of quantificational assess the system's sensitivity to initial conditions is calculated as the slope of the linear regression function in Figure11(c). The value of the largest Lyapunov exponent is $\lambda = 0.00193$. It is noted that same conclusions are drawn by using traffic data on 15/05/2014 and 18/12/2014 with the largest Lyapunov exponent is 0.00174 and 0.00202 respectively.

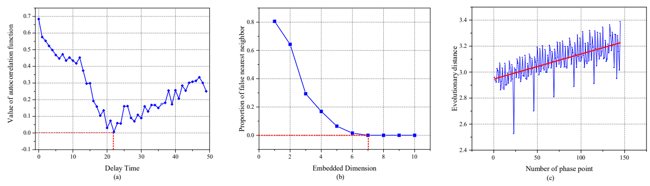

Figure 11. Result of chaotic analysis. (a) Delay time calculation. (b) Embedded dimension measurement.(c) The largest Lyapunov exponent.

It is proved that chaos is the intrinsic feature of air traffic system emerged under autonomous interactions of multi-aircraft and multi-sector controllers. Potential conflict chaotic prediction provides vital basis for air traffic management modernization. To further reveal the chaotic evolution with traffic volume, we calculate the largest Lyapunov exponent each 4 hours in the three days as shown in Figure 12. It implies that chaos in air traffic system is induced by high traffic and resulting intensive potential conflicts which would create more random elements under multi-sector interactions.

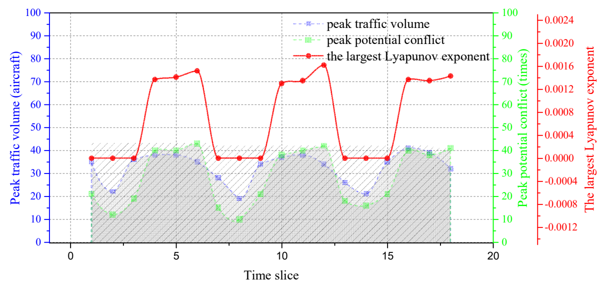

Figure12. Chaotic evolution with traffic volume and potential conflict

D. Chaotic analysis of "human-flow" system at sector level

Since air traffic system can be simply divided into "flow system" and "human-system", to further understand the chaotic features of this artificial system under "human-flow" interactions, same methods are adopted to identify chaos in potential conflict and communication interval at sector level. Likewise, to avoid lengthy description, only potential conflict and communication interval data series of sector 2 on 11/09/2014 are detailed in Figure13.

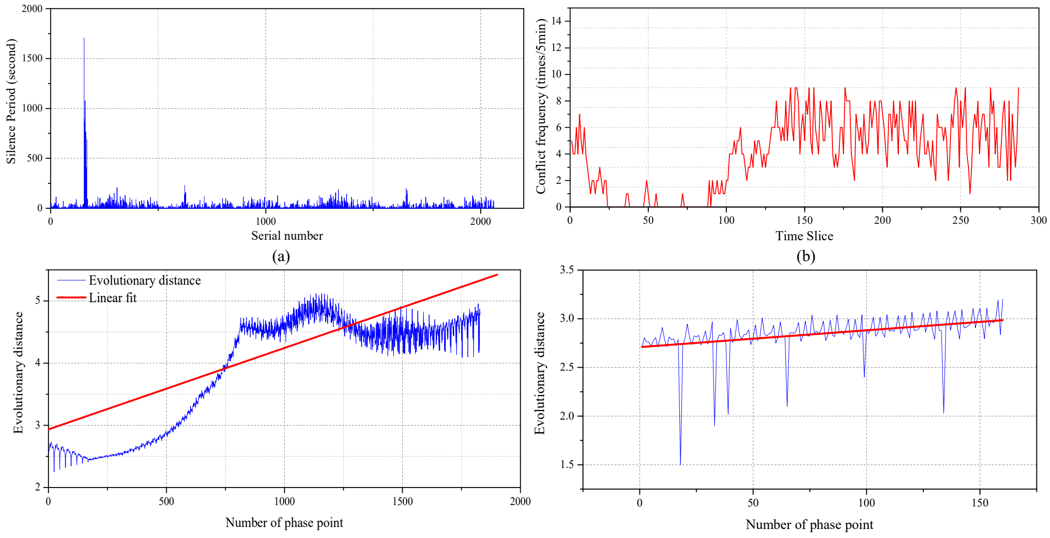

Figure 13. Selected input and output of chaotic analysis in Sector 2. (a) Data series of silence period; (b) Data series of conflict; (c) The largest Lyapunov exponent of silence period series; (d) The largest Lyapunov exponent of potential conflict series

Table I shows the result of delay time, embedded dimension and the largest Lyapunov exponent of all 5 sectors on day of 11/09/2014. Interestingly, chaos in "human system" and "flow-system" emerges asynchronously: flow chaos emerges in Sector 1, 2, 3 and 5 where semi-stable or/and congested phases are observed, while human chaos emerges only in Sector 1, 2 and 5 where congested phases appear. According to the analysis of phase transitions in Section III, meta-cognitions of ATCOs are the key factors that prevent themselves from falling into chaos. It is noted that same conclusions are drawn by analyzing the data on another two days.

TABLE I. CHAOTIC RESULTS OF "HUMAN-FLOW" SYSTEM IN AIRSPACE SECTORS

	Sector 1		Sector 2		Sector 3		Sector 4		Sector 5	
	Flow	ATCO	Flow	ATCO	Flow	ATCO	Flow	ATCO	Flow	ATCO
Delay time	21	20	22	24	17	9	8	5	23	22
Embedded dimension	7	9	8	10	6	6	2	3	9	11
The largest Lyapunov exponent	0.00155	0.00129	0.00173	0.00131	0.00101	0	0	0	0.00149	0.00127

By analyzing the chaotic dynamics at both terminal and sector level, we can infer that chaos is not an intrinsic nature of air traffic system in terminal airspace, but emerges when air traffic system is unstable. Chaotic dynamics provides new insight into air traffic prediction and control.

E. Predictability of chaotic "human-flow" system

Chaotic dynamics uncovers the air traffic system evolution patterns between certainty and randomness. Predictability illustrates the non-linear dynamics of chaotic system from another side. Currently, it's not easy to predict chaotic system accurately using general method e.g. Neural Network, Supporting vector Machine, etc. without considering its chaotic dynamics. Lyapunov exponent is proved as an excellent predictable parameter which depicts the geometrical feature of phase space. The largest Lyapunov exponent based forecasting method proposed by Wolf et al. is to find the similar points in historical data series, and further to formulate predict models according to the evolution behaviors of the similar points and physical meaning of the largest Lyapunov exponent [23]. We take chaotic data series of potential conflict $\mathcal{H}_s^\tau = [\hbar_1, \hbar_2, \dots\dots, \hbar_n]$ as an example. The phase space is reconstructed based on delay time τ and embedded dimension m. Each phase point is formulated as

$$H_i = [h(t_i), h(t_i+\tau), \dots\dots, h(t_i+(m-1)\tau)], i \in [1, M]$$

i.e.

$$H = \begin{bmatrix} h(t_1) & \cdots & h(t_M) \\ \vdots & \ddots & \vdots \\ h(t_1+(m-1)\tau) & \cdots & h(t_M+(m-1)\tau) \end{bmatrix} \quad (7)$$

where M is the number of phase point in m-dimensional phase space, $M = n-(m-1)\tau$.

Brief descriptions of chaotic prediction is stated as follows:

Step1: Find the nearest phase point H_{Ub} of H_U, and calculate the Euclidean Distance $d = \|H_U - H_{Ub}\|$.

Step2: Phase point H_U and H_{Ub} further evolve into H_{U+1} and H_{Ub+1} respectively in next time step. Based on the physical meaning of the largest Lyapunov exponent, $\|H_{U+1} - H_{Ub+1}\| = \|H_U - H_{Ub}\| e^{\lambda} = de^{\lambda}$.

Step3: Potential conflict $\hat{\hbar}_{u+1}$ which is the mth component of H_{U+1} can be estimated by formula (8), where the selection of "$\pm$" depends on the intersection angle in the phase space and practical constraints [24].

$$\hat{h}_{u+1} = H_{U+1}(m) = H_{Ub+1}(m) \pm \sqrt{\sum_{i=1}^{m-1} [H_{U+1}(i) - H_{Ub+1}(i)]^2 - (de^{\lambda})^2} \quad (8)$$

Proposed chaotic forecasting method is adopted to illustrate the predictability of "human-flow" system in short term (next 15min for conflict forecast and next 10 data points for communication forecast). Figure 14 shows the potential conflict prediction in last 88 time period on 11/09/2014 in sector 2. The largest Lyapunov exponent calculated based on first 200 data point is 0.00186. The average relative error of prediction is 4.3%. Figure15 shows the communication interval forecast based on first 1000 data point on 11/09/2014 in sector 2. The largest Lyapunov exponent is 0.00125. The average relative error of prediction is 6.3%.

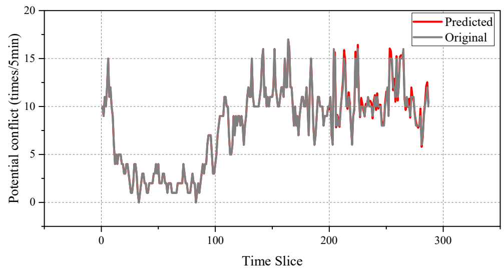

Figure14. Predictability of chaotic potential conflict system based on the largest Lyapunov exponent

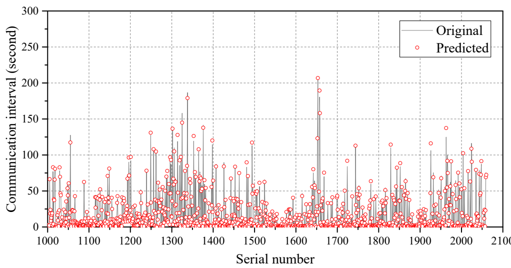

Figure15. Predictability of chaotic communication behavior based on the largest Lyapunov exponent

SVM-based prediction [25] is used for comparison. We assume that forecasting value is determined by historical data, i.e. $x_{i+1} = f(X_i)$, where $X_i = (x_{i-n+1}, x_{i-n+2}, \ldots \ldots, x_i) \in R^n$. Radial Basis Function (RBF) is adopted as the kernel function [26]. Here, same data set on 11/09/2014 in sector 2 is used. For potential conflict forecast, we set $n_1 = 5$, forecast period is 15min, size of training data is 200; and for communication interval forecast, we set $n_2 = 30$, forecast period is 10 data points, size of training data is 1000. Result shows that average relative error of prediction is 15.5% and 20.9% for conflict and communication prediction respectively as shown in Figure16 and 17.

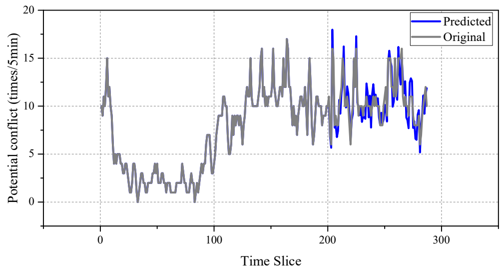

Figure16. Predictability of chaotic potential conflict system based on SVM

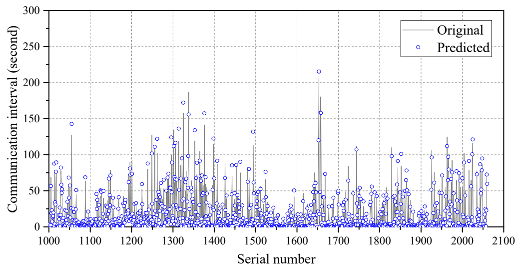

Figure17. Predictability of chaotic communication behavior based on SVM

It is known that the accuracy of prediction performance is sensitive to the size of training data and forecast period. The trend of average relative error is shown in Figure 18 -19. It is proved that, by identifying chaotic feature of system, the non-linear predictability performance is stably enhanced and is less sensitive to subjective factors. It is noted that similar conclusions are drawn using data sets of other sectors on other days.

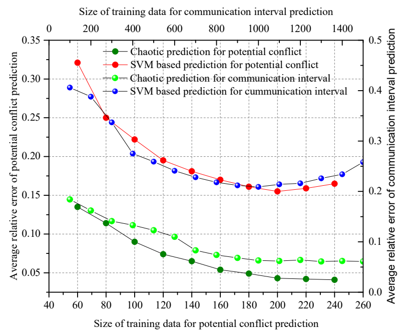

Figure18. Prediction performance evolution with different size of training data

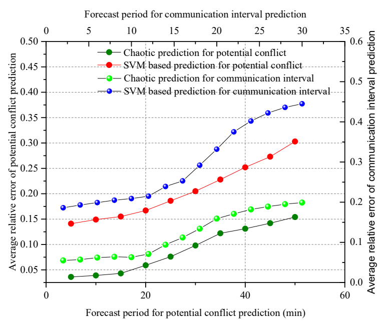

Figure18. Prediction performance evolution with different forecasting period

V. CONCLUSIONS

Non-linear dynamics in the "human-in-the-loop" air traffic system are emergent behaviors result from interactions between the constituent elements and the operating environment. For terminal airspace system, the elements are mainly composed of human operators, working procedures, airspace configurations, and even weather conditions. To develop and deploy advance operational concepts and systems, it's vital to understand the intrinsic characteristics of air traffic operation at system level.

In this paper, we studied the evolution of both ATCOs and traffic flow by modeling and analyzing dynamics performance using empirical data of Guangzhou terminal airspace in China. Underlying mechanism of "human-flow" phase transitions from free, smooth, semi-stable to congested status were interpreted by metacognition. Besides, since air traffic system can be intuitively divided into "flow system" and "human system", chaotic features were identified in both systems and proved a strong relation with unstable phase status of system by adopting classic chaos analysis and prediction methods. This novel findings will bring new perspective to understand the characteristics of air traffic system and provided references to aggregated air traffic flow modeling and tactical management. To solve the difficulty of collecting synchronized air traffic data and controllers' behavior data in further studies, real-time simulation in the "human-in-the-loop" environment seems to be a better and feasible solution to generate air traffic operational data close to reality and draw more generalized conclusions. Moreover, system sensitivity to the selection of time interval needs to be further explored to discuss the appropriate time horizon of tactical air traffic management strategy.

ACKNOWLEDGMENT

This work was supported by Chinese Scholarship Council (CSC).

REFERENCES

[1] H. Zhang, L. Yang, Y. Bie, and S. Yin, "Research on generalized following behavior modeling and complex phase-Transition law of approaching traffic flow in terminal airspace," Acta Aeronautica Et Astronautica Sinica, vol. 36, pp. 949-961, 2015.

[2] A. Vespignani, "Predicting the behavior of Techno-Social systems," Science, vol. 325, pp.425-428, 2009.

[3] Y. Wang, J. Bu, K. Han, R. Sun, M. Hu, and C. Zhu, "A novel network approach to study communication activities of air traffic controllers," Transportation Research Part C: Emerging Technologies, vol. 68, pp. 369-388, 2016.

[4] G. Newell, "Airport capacity and delays," Transportation Science, vol. 13, pp. 201-241, 1979.

[5] C. Daganzo, "The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory," Transportation Research Part B, vol. 28, pp. 269-287, 1994.

[6] I. Simaiakis, H. Khadilkar, H. Balakrishnan, G. Tom, R. Reynolds, and J. Hansman, "Demonstration of reduced airport congestion through pushback rate control," Transportation Research Part A, vol. 66, pp. 251-267, 2014.

[7] N. Kafle, and B. Zou, "Modeling flight delay propagation: A new analytical-econometric approach," Transportation Research Part B: Methodological, vol. 93, pp. 520-542, 2016.

[8] C. Gwiggner, and S. Nagaoka, "Recent models in the analysis of air traffic flow," Proc. Aeron. Space Sci., vol. 57/666, pp. 210-216, 2009.

[9] H. Zhang, Y. Xu, and L. Yang, "Macroscopic model and simulation analysis of air traffic flow in airport terminal area," Discrete Dynamics in Nature and Society, vol. 2014, pp. 1-15, 2014.

[10] A. Odoni, J. Bowman, and D. Delahaye, "Existing and required modeling capabilities for evaluating ATM systems and concepts," Technical Report, NASA-CR-204978, 1997.

[11] J. de Prins, RG. Ledesma, M. Mulder, and MM Van Paassen, "Literature review of air traffic controller modeling for traffic simulation," Digital Avionics System Conference, 2.C.3-1-2.C.3-11, 2008.

[12] Y. Wang, V. Frizo, M. Hu, and V. Duong, "Empirical analysis of air traffic controller dynamics," Transportation Research Part C: Emerging Technologies, vol. 33, pp. 203-213, 2013.

[13] B. Sridhar, K. Sheth, and S. Grabbe, "Airspace complexity and its application in air traffic management," 2nd USA/European Air Traffic Management R&D Seminar, Orlando, US, 1998.

[14] I. Laudeman, S. Shelden, and R. Branstrom, "Dynamic density: an air traffic management metric", Technical Report, NASA/TM-1998-112226, 1998.

[15] M. Whiteley, "PHARE advanced tools tactical load smoother," Technical Report, European Organisation for the Safety of Air Navigation, 1999.

[16] K. Lee, E. Feron and A. Pritchet, "Describing airspace complexity: airspace response to disturbance," Journal of Guidance, Control and Dynamics, vol. 32, pp. 210-222, 2009.

[17] S. Puechmorel, and D. Delahaye, "New trend in air traffic complexity," In proceedings of EIWAC, Tokyo, Japan, 2009.

[18] J. d'Engelbronner, C. Borst, J. Ellerbroek, MM. van Paassen, and M. Mulder, "Solution-space-based analysis of dynamic air traffic controller workload," Journal of Aircraft, vol. 52, pp. 1146-1160, 2015.

[19] B. Hilburn, "Cognitive complexity in air traffic control: A literature review," Technical report. Center for Human Performance Research, 2004.

[20] J. Histon, R. Hansman, and G. Aigoin, "Introducing structural considerations into complexity metrics," ATC Quarterly, vol. 10, pp. 115-130, 2002.

[21] H. Shi, "New theory of air traffic management," Book published by Xiamen University publishing House, 2001.

[22] W. Cong, and M. Hu, "Chaotic characteristics analysis of air traffic system," Transactions of Nanjing University of Aeronautics and Astronautics, vol. 31,pp. 636-642, 2014.

[23] A. Wolf, J. Swift, and H. Swinney, "Determine Lyapunov exponent from a time series," Physica D, vol. 16, pp. 285-317, 1985.

[24] S. Li, "Research on indentification and prediction methods of air traffic congestion," Doctoral dissertation, Tianjing University, Tianjing, 2013.

[25] B. Yao, P. Hu, M. Zhang, and M. Jin. "A Support Vector Machine with the Tabu Search Algorithm For Freeway Incident Detection," International Journal of Applied Mathematics and Computer Science, vol. 24, pp. 397-404, 2014.

[26] H. Zhang, C. Jiang, and L. Yang, "Forecasting traffic congestion status in terminal areas based on support vector machinec," Advances in Mechanical Engineering, vol. 8, 2016.

AUTHOR BIOGRAPHY

Lei Yang received a Master degree in 2012, and now is a PhD candidate at Nanjing University of Aeronautics and Astronautics jointly trained with TU Delft. His research interests are oriented in air traffic dynamics and network optimization.

Suwan Yin received a Master degree in 2014, and now is a PhD candidate at Nanjing University of Aeronautics and Astronautics. Her research interests are oriented in airport operation and optimization.

Minghua Hu received a Master degree in 1987, and now is a professor at Nanjing University of Aeronautics and Astronautics. His research interests are oriented in intelligent air traffic management and system design.

Yan Xu received a Master degree in 2015, and now is a PhD candidate at Technical University of Catalonia. His research interests are oriented in 4D air traffic flow optimization.