Empirical Study of Air Traffic Dynamics Using Coupled Network Modelling and Non-linear Analysis

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ABSTRACT

Air traffic is widely known as a complex, task-critical techno-social system, with numerous interactions between airspace, procedures, aircraft and air traffic controllers. In order to develop and deploy high-level operational concepts and automations scientifically and effectively, it is essential to conduct an in-depth investigation on the intrinsic human-traffic dynamics and characteristics, which is not widely seen in the literature. To fill this gap, we propose a coupled network to model controller and air traffic interactions. Furthermore, a set of analytical metrics including controllers' cognitive complexity, communication load and chaotic metrics are introduced and applied in a case study of Guangzhou terminal airspace. Empirical results show the dynamics and underlying mechanisms of "ATCOs-flow" interactions are revealed and interpreted by adaptive meta-cognition strategies to cope with different phase states based on network analysis. Finally, at the system level, chaos is identified in conflict and communication behavior when system switches to the semi-stable or congested phase. This study offers analytical tools for understanding the complex human-flow interactions at potentially a broad range of air traffic systems, and underpins future developments and automation of intelligent air traffic management systems.

Keywords: Terminal Airspace, Air Traffic Flow, Air Traffic Controller, Chaos

1. INTRODUCTION

Worldwide ATM system is undergoing the process of upgrading and transformation to cope with increasing air traffic demand and congestion especially in high-density airports and surrounding airspaces. Within the strategic planning of ATM systems like SESAR, NextGen and ASBU, numerous advanced operational concepts, e.g. “ATM Network Management”, “User Driven Prioritization Process”, “Flow Contingency Management” and “Complexity Management”, are proposed to enhance the system-wide performance and reduce the propagation of congestion. Air traffic systems are typical examples of complex techno-social systems, the management of which requires a careful understanding of the subtle interplay between technological infrastructure and human behavior (Monechi et al., 2015). In order to develop and deploy high-level operational concepts and automation systems in an effective way, it is essential to conduct an in-depth investigation of the intrinsic air traffic dynamics, by revealing the intrinsic “human” (ATCOs) and “flow” (aircraft) interactions.

There exist a number of studies that attempt to bridge the gap between traffic states and ATCOs’ cognition complexity, by using complexity methods that interpret the “human-flow” dynamics. To this end, a series of traffic flow complexity metrics are developed in the last two decades. Classic metrics include Static Density (Sridhar et al., 1998), Dynamic Density (Laudeman et al., 1998), Tactical Load Smoother (Whiteley, 1999), Input-Output (Lee et al., 2009), Lyapunov exponent of trajectory dynamics (Puechmorel et al., 2009), and Solution space-based metrics (d’Engelbronner et al., 2015). By finding the best match between traffic flow complexity measurements and ATCOs’ workload, the weights of relevant indicators (e.g. traffic density, aircraft type mixture, potential conflict) are calibrated. The weight can be treated as the impact of each traffic scenario on the ATCO’s cognition. Monechi et al. (2015) model a large-scale air transportation system as a complex, dynamic network of flights controlled by humans, and analyze the probability distributions of delay times and potential conflicts. As the development of 4D trajectory operation, Zohrevandi et al. (2016) designed numbers of scenarios to measure how the level of 4D equipped affect controllers’ task load in terminal and en route sectors. Corver et al. (2016) studies how trajectory uncertainties impact controllers’ workload under various traffic density and conflict situations. This line of research, despite the fresh perspective on the relationship between traffic flow and cognitive measures, are inadequate to analyze the evolutionary dynamics of “human-flow” and the mechanisms through which they interact.

As a summary of the literature review above, existing studies focus on the modeling and evaluation of air traffic systems without much effort to understand their inherent ATCO-flow dynamics and rules that govern their co-evolution. There is a lack of quantitative characterization of the complexity of the air traffic system from the perspective of human and aircraft interactions. In order to characterize and interpret the “ATCOs-flow” interaction and co-evolution dynamics systematically, we propose a novel Coupled “ATCOs-Flow” Network (CAFN) approach. The coupled network consists of two sub-layers sharing same vertices: Conflict Situation Network （CSN） and Interventional Communication Network (ICN). In order to underpin such a network, and to reveal internal “ATCOs-flow” dynamics, we develop three classes of analytical metrics: (i) Solution space-based perceived complexity (ii) Communication Load; and (3) chaos metrics for system-level characterization. The main contribution of this paper includes not only the coupled network model, but also the following main findings through an empirical study of a terminal airspace in China.

(1) [ATCOs-flow interactions]. Four phases of air traffic are identified: free, smooth, semi-stable and congested at the sector level. By analyzing the degree distribution and motifs of

CAFN, meta-cognition strategies, pre-activated, inhibition and stress during the transitions of phases are shown to be the underlying mechanisms of ATCOs-flow co-evolution. It provide improved understanding of the ATCOs' adaptive behavioral patterns, and serve as the foundation for customized and intelligent automations with higher acceptance rate by ATCOs.

(2) [Chaotic dynamics at the system level]. Chaos is found in both air traffic and ATCOs' activities by analyzing potential conflict and communication behavior. Moreover, we show that chaos emerges at unstable phases, i.e. semi-stable and congested phases. It enhances system predictability by adopting chaotic prediction methods to forecast air traffic situation in short term.

The rest of this paper is organized as follows. Section 2 presents the coupled network model for human-flow interactions. In Section 3, a number of metrics are introduced for the empirical evaluation of air traffic dynamics. Section 4 carries out a case study of Guangzhou terminal airspace to investigate the non-linear and complex dynamics of air traffic. Finally, some conclusions are provided in Section 5.

2. COUPLED "ATCOs-FLOW" NETWORK MODELLING

"Centralized Controllability" is a defining feature of air traffic flow operation, in contrast to other transportation systems. As the core of tactical management of air traffic flow, controllers play vital roles and represent key links in the air traffic networks studied here. In order to uncover the human and flow dynamics in air traffic control, we model the Coupled "ATCO-Flow" Network (CAFN) as a two-layer coupled network $G_{CAFN}(V_{CAFN}, E_{CSN}, E_{ICN}; \tau)$ consisting of sub-networks of (1) conflict situation and (2) air-ground communication, which share the same vertices at the sector level, as shown by Figure 1.

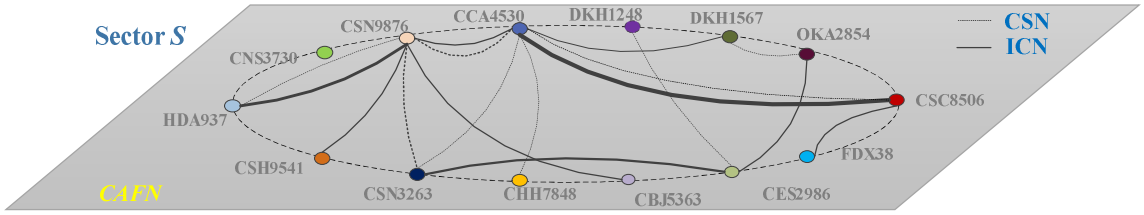


FIGURE 1 Schema of coupled "ATCOs-Flow" network

2.1. First layer: Conflict Situation Network（CSN）

Potential flight conflicts are related to the continuous approaching (i.e. the trends of flights' relative movements) that result in the loss of separation. It should be noted that flight conflicts under "ATCO-centered" terminal airspace operation have their own uniqueness. Firstly, potential conflicts are sector-based, i.e. only conflicts in the same sector are considered. Secondly, the separation between aircraft is determined by not only safety standard but also the required separation at fixes and sector boundaries. As a result, unlike en-route operation, aircraft at different flight levels are often required to maintain a certain horizontal separation in terminal airspaces, especially when they have the same destination. Therefore, we define the potential conflict in terms of the possible violation of expected horizontal separation.

Since conflict is dynamic, interpreted on a spatio-temporal domain, conflict situation is modelled as a time varying network $G^X_{CSN}(V_{CAFN}(\tau), E_{CSN}(\tau))$, where $V_{CAFN}(\tau) = \{f_1, f_2, \dots, f_C\}$ is a finite set of vertices representing existing aircraft during time period τ in the sector X; $|V_{CAFN}(\tau)| = C$ is the total aircraft count; $E_{CSN}(\tau)$ is a finite set of non-directional and unweighted edges. At any time instance t during the window τ, the sets of positions and speeds are respectively $\{\boldsymbol{U}_i = (x_i, y_i): i = 1, \dots, k\} \subset \mathbb{R}^2$ and $\{\boldsymbol{V}_i = (\hat{x}_i, \hat{y}_i\}: i = 1, \dots, k\} \subset \mathbb{R}^2$. Then, the

relative position and speed are $\boldsymbol{U}_{ij} \doteq \boldsymbol{U}_j - \boldsymbol{U}_i, \boldsymbol{V}_{ij} \doteq \boldsymbol{V}_j - \boldsymbol{V}_i$, respectively. We say that i and j have potential conflict if and only if there exists $\Gamma_{ij} \in \mathbb{R}_+$ such that

$$\begin{cases} \left\| \boldsymbol{U}_{ij} + \Gamma_{ij} \cdot \boldsymbol{V}_{ij} \right\| \leq S \\ \Gamma_{ij} \leq \min(t_i, t_j) \end{cases} \quad (1)$$

where S is the expected separation, t_i and t_j are the remaining flight time of aircraft i and j in sector X, respectively. (1) simply says that flights i and j are in potential conflict in sector X if, by the time that either one of them leave the sector X, their relative distance is within the expected separation S.

2.2. Second layer: Interventional Communication Network (ICN)

ICN is a weighted non-directional time-varying network denoted as $G_{ICN}^{\mathrm{X}}(V_{CAFN}, E_{ICN}; \tau)$. The vertices coincide with those of the conflict situation sub-networks, and represent all the flights in the sector X during time window τ. The edges record the frequency of highly related interventional communications. The interventional communication is defined as the Controller-to-Pilot (C-P) commands that aim at adjusting flight status (e.g. speed, altitude and heading) in order to improve flow efficiency or to avoid potential conflicts. The following definition is an adaption of Wang et al. (2016).

Definition 1. (Temporal Distance) Given flights i and j, their temporal distance at time t is defined as $D(i,j;t) = s_j(t) - s_i(t) - l_i(t)$, where $s_i(t)$ denotes the start time of the latest call event for flight i, and $l_i(t)$ is the duration of this call. This is illustrated in FIGURE 2 2.

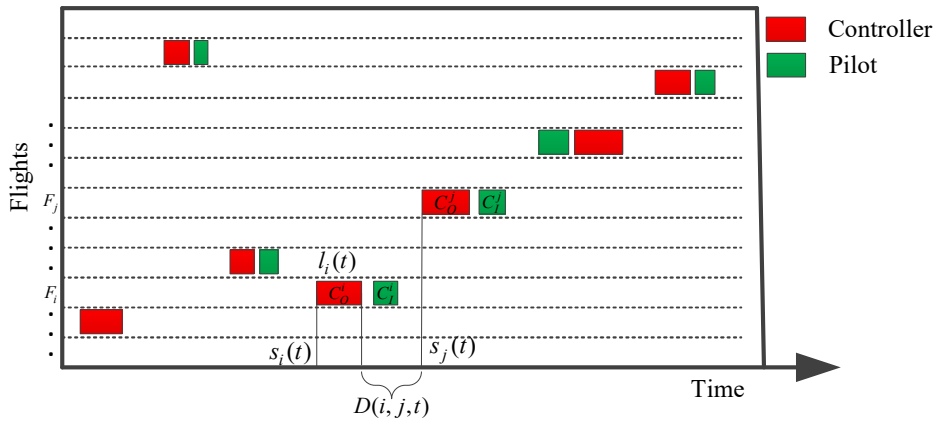


FIGURE 2 Temporal communication activity.

Definition 2. (Connectivity in the Temporal Network) Flights (vertices) i and j are connected at time t if $D(i,j,t) \leq t_{min}$, and the type of command is "Interventional Communication", where t_{min} is the threshold of Temporal Distance.

During time window τ, the weight of an edge in the ICN is the number of times of observed connectivity. The ICN changes from one time windows τ to another. It captures the relationships among flights that are determined by the communication initiated by controllers.

3. ANALYTICAL METRICS

3.1 Solution space-based perceived complexity (SSPC)

Certain horizontal separation should be maintained for aircraft in the terminal airspace. Speed and heading vectoring is the primary means to avoid conflict and keep required headway in controlled

flows. The solution space of potential conflict is defined as the 2-D area of continuous heading-and-speed space (d'Engelbronner et al., 2015). In practice, however, the solution space changes with solution strategy (e.g. sequencing) and restricted by airspace structure and flight procedure (e.g. heading change limitations). In order to reflect such a reality, we propose a complexity metric for conflict situation networks based on modified shadow-based solution space to reflect the urgency and difficulty of potential conflicts.

We assume that aircraft A and B are in potential conflict as shown in Figure 3. Limited by air traffic control regulations and aircraft performance, the heading and speed maneuvering spaces of A at time t_i are $[\theta_{A1}, \theta_{A2}]$ and $\left[v_A^{\min}, v_A^{\max}\right]$ respectively. We define the area of the Total Maneuvering Space (colored by gray in Figure 3 (a)) of aircraft A to be

$$TMS_A(t_i) = 0.5(\theta_{A2} - \theta_{A1})((v_A^{\max})^2 - \left(v_A^{\min}\right)^2). \quad (2)$$

Then, the combined solution spaces of aircraft A under different sequencing strategies are colored by brown as shown in Figure 3.

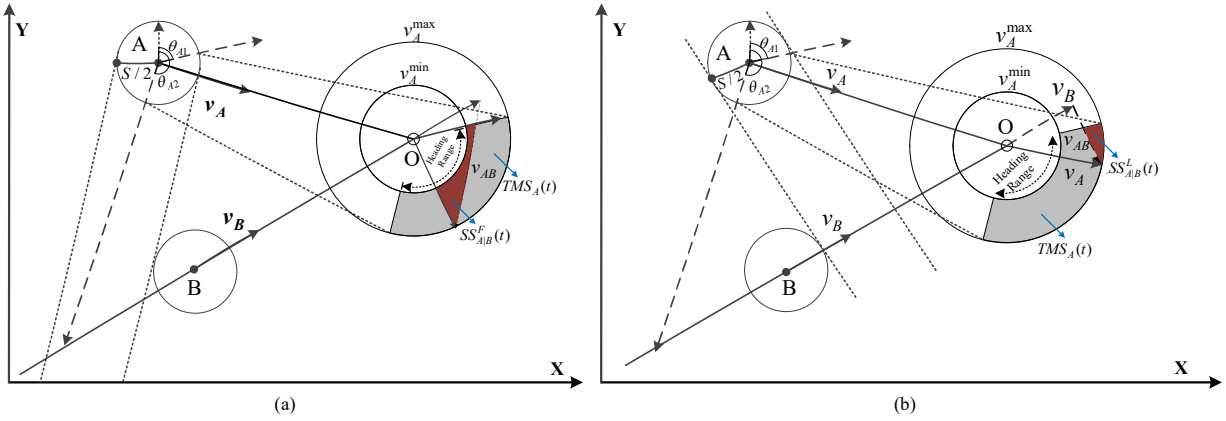


FIGURE 3 Scheme of solution space of aircraft A in potential conflict. (a) Solution space in the condition of aircraft A follows B; (b) Solution space in the condition of aircraft B follows A.

It is easy to prove that there is no intersection of solution space under these two ordering (sequencing) strategies. So, the total solution space of aircraft A is the sum of solution space in leading and following conditions, denoted as $SS_{A|B}(t_i) = SS_{A|B}^L(t_i) + SS_{A|B}^F(t_i)$. Likewise, the total solution space of aircraft B can be derived similarly. The average solution space area of aircraft A during time period τ is denoted as $SSA_A(\tau) = \sum_{i=1}^{N_A} \Lambda\left(SS_{A|B}(t_i)\right)/N_A$, where N_A is the number of snapshots of aircraft A during time period τ, and function $\Lambda(\cdot)$ is the area operator.

In high-density air traffic operation, multi-aircraft conflicts emerge commonly. Assuming aircraft A is in conflict with more than one aircraft, the urgency index is formulated as $SSA_A(\tau) = \sum_{i=1}^{N_A} \Lambda\left(\cap SS_{A|X}(t_i)\right)/N_A$, where X is the aircraft that have conflict with A; $\cap SS_{A|X}$ is the intersection of solution spaces that can simply be calculated using the method in Figure 3.

The solution space approach not only provides dynamic pictures of microscopic structure of air traffic flow, but also promises novel ATCO's cognition complexity measurements. More intuitively, Solution Space-based Perceived Complexity $SSPC(\tau)$ is modelled as the average difficulty of finding solution space for aircraft in the same sector during time period τ based on the relative area of solution space.

$$SSPC(\tau) = \frac{1}{\mathbb{Q}(\tau)} \sum_{j=1}^{\mathbb{Q}(\tau)} \left(\left(SSA_j(\tau)/TMS_j(\tau)\right)^{-\sigma} - 1\right) \quad (3)$$

where $TMS_j(\tau) = \sum_{i=1}^{N_A} TMS_j(t_i)\ /N_A$ and $\mathbb{Q}(\tau)$ are the average Conflict-free Solution Space of aircraft j and the number of aircraft emerged in the sector during time period τ respectively; σ is a co-efficient, which is simply set as -0.5 here, describing the non-linear impact of solution space on cognition complexity. The value range of *SSPC* value is $[0, +\infty]$. If and only if there is no conflict during some time period, *SSPC* equal to 0.

3.2 Communication load (CL)

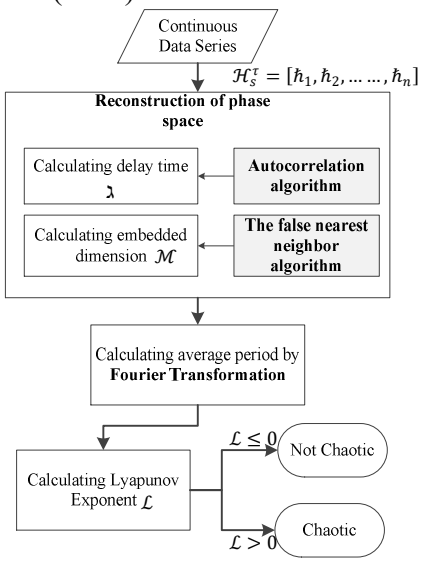
Communication load is the primary composition of ATCOs' workload (Porterfield et al., 1997). Study on the adjustment of communication behavior may reveal controllers' metacognition dynamics to cope with complexity. Communication load is defined as the percentage of air-ground communication channel occupancy in certain time period as shown in formula (4).

$$CL_s(\tau) = \left(\sum_{i=1}^{I} \beth_i^{c \to p} + \sum_{j=1}^{J} \beth_j^{p \to c} \right) \Big/ \tau \tag{4}$$

where $\beth_i^{c \to p}$ and $\beth_j^{p \to c}$ are the duration of the i^{th} controller-pilot and j^{th} pilot-controller communication respectively.

3.3 High-level "ATCOs-flow" non-linear metrics

Chaotic analysis is a modern tool for identifying the high-level characteristics of non-linear dynamic systems (Abarbanel et al., 1993). 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. Shi 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 (Shi, 2001) of air traffic system. Given continuous data series of system variable $\mathcal{H}_s^\tau = [\hbar_1, \hbar_2, \dots\dots, \hbar_n]$, we adopt the largest 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 4. Methods adopted refer to chaotic analysis in Cong et al. (2014).



Step1: Construct continuous data series of air traffic system $\mathcal{H}_s^\tau = [\hbar_1, \hbar_2, \dots\dots, \hbar_n]$, step2 to step4 are applied.

Step2: Using autocorrelation and the false nearest neighbor algorithm to calculate delay time ƛ and embedded dimension $\mathcal{M}$ in purpose of reconstructing phase space $\mathbb{Z}$.

Step3: Fourier transformation of data series is used to derive to average period T.

Step4: Calculating the largest Lyapunov Exponent $\mathcal{L}$ using small-data method. If $\mathcal{L} > 0$, then chaotic features are proved.

FIGURE 4 Process of calculating the largest Lyapunov Exponent

4. EMPIRICAL RESULTS

4.1. Data description

The Guangzhou terminal airspace is mainly responsible for the inbound and outbound traffic of Baiyun International Airport, one of the top three busiest airports in China. In order to explore the dynamic features of the air traffic in the terminal airspace based on the coupled network and analytical metrics, synchronized trajectory data and air-ground communication data on three typical days 15/05/2012, 11/09/2012 and 18/12/2012 are collected. The trajectory data have a time resolution of 15 seconds. The communication data contain records in the radio channel for each sector, including the start and end times of each voice communication.

4.2. Underlying mechanism of "human-flow" interaction at sector level

A terminal airspace consists of sectors that are collaboratively controlled by ATCs. In the "ATCO-centered" air traffic tactical operation, the initial inflow pattern, output flow expectation and control behavior are the key factors that determine the evolution of air traffic flow inside the sector. In this section, we interpret the underlying mechanism of "human-flow" dynamics in airspace sectors. Here, we set time period $\tau = 15$ min. In each time window, we record average traffic density, sector throughput, and calculate SSPC and CL.

Figure 5 (a) shows all sector throughput obtained with 1-min time resolution. They tend to exhibit significant over-critical traffic, especially for high-demand sectors like 1, 2 and 5, where the average throughput experiences a discernible drop. In order to investigate the detailed dynamics of human-flow evolution, we additionally plot average throughput, CL and SSPC changing with average traffic density for all the 5 sectors, as shown in Figure 5(b)-(f), respectively.

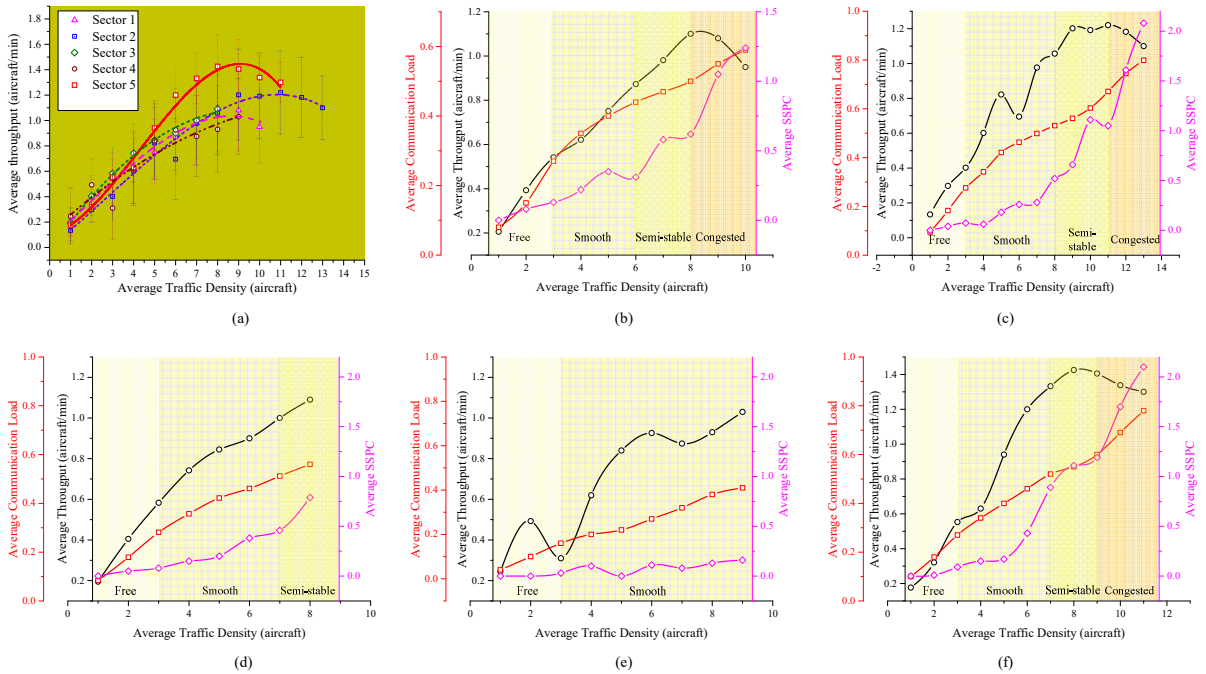


FIGURE 5 "ATCOs-flow" performance in Guangzhou terminal sectors.

Intuitively, increased traffic leads to more conflict, lower flow efficiency and higher workload. Communication load and SSPC show positive correlations with traffic: average Pearson Correlation Coefficient 0.851 and 0.798 respectively, both p-values≈0<0.01. By analyzing the curves' configuration, four phases are divided with the additional help of flight data replay using

SIMMOD simulator: free, smooth, semi-stable and congested. In the following discussion we present some novel findings on ATCOs' performance in each phase state, by uncovering congtroller's metacognition (Flavell, 1979) dynamics. This highlights the "human-flow" interactions through both qualitative and quantitative analyses based on Figure 5 and CAFN. Specifically, we focus on the degree distribution and motifs of CSN and ICN – the two layers of CAFN– in order to uncover patterns of interactions between ATCOs and traffic situation. The motifs are closely related to the conflict structure and control decisions made by ATCOs. We define the following three basic motifs used in the study of social communication (Zhao et al., 2010): chain, loop and star.

We begin with some similarities between "ATCOs-flow" performance and CAFN attributes in each sector as the traffic phases evolves in time.

- With the increase of traffic density, CL and SSPC rise simultaneously and non-linearly as shown by the fluctuant average increase rate in T. Generally, CL increased much more slowly than SSPC except in the free phase due to meta-cognition dynamics explained later. Particularly, extreme low SSPCs in sector 4 are due to its simple diverging route structure with few conflicts.
- The empirical degree distributions of ICN (denoted p_I) and CSN (denoted p_C) vary by the traffic phases. As t_{min} increases p_I becomes less left-skewed, and its expectation increases as well. This is evident across all four phases and coincides with intuition.
- We observe positive correlations with moderate significance between the degrees of vertices shared by CSN and ICN except in the free phase (Figure 6 (b)). The fact that degrees of vertices of two layers in CAFN present higher correlation in busier traffic situation implies that as the increase of congestion, interventional communications are mainly triggered passively by potential conflicts rather than pro-actively (e.g. trajectory adjustment) in light traffic situations.
- Chains and stars are the most common motifs in CSN, while chains and loops appear mostly in ICN. Noted that more motifs of loops in ICN emerge as the increase of traffic load and star-like motifs in CSN. It implies that controllers issue circulatory commands to aircraft one by one to ensure the safety separations among aircraft in complex conflict situation.

TABLE 1 Average increase rate of CL and SSPC during each phase in sectors.

Sector	Performance Index	Free	Smooth	Semi-stable	Congested
Sector1	CL	0.085	0.040	0.047	0.057
	SSPC	0.065	0.107	0.135	0.26
Sector2	CL	0.091	0.051	0.059	0.064
	SSPC	0.037	0.089	0.095	0.515
Sector3	CL	0.098	0.051	0.068	×
	SSPC	0.040	0.103	0.330	×
Sector4	CL	0.060	0.042	×	×
	SSPC	0.021	0.025	×	×
Sector5	CL	0.085	0.042	0.049	0.090
	SSPC	0.045	0.160	0.171	0.456

In the following, the distinct features are discussed to demonstrate and prove the underlying dynamics of "ATCOs-flow" interaction.

In the free phase, there is a discernible increase in the ATCOs' communication loads (see Figure 5) with little to no conflict, as is evident from the heavily left-skewed distribution p_C and the motifs in TABLE 2. Besides, extremely low correlations between the degrees of vertices shared

by CSN and ICN is observed for different t_{min} as shown in Figure 6 (b). Moreover, motifs analysis shows that as t_{min} increases, the cumulative proportion of three motifs is getting close to 100% even though the conflict situation is quite simple. Based on these results, we define one of the metacognition dynamics as "pre-activation" of cognition complexity in low workload for the preparation for unexpected traffic situations, by increasing the traffic complexity intentionally. Driven by "pre-activation", the communication load is not generated by conflict but by issuing interventional commands like shortcut, approach with high speed, and descent delay, etc.

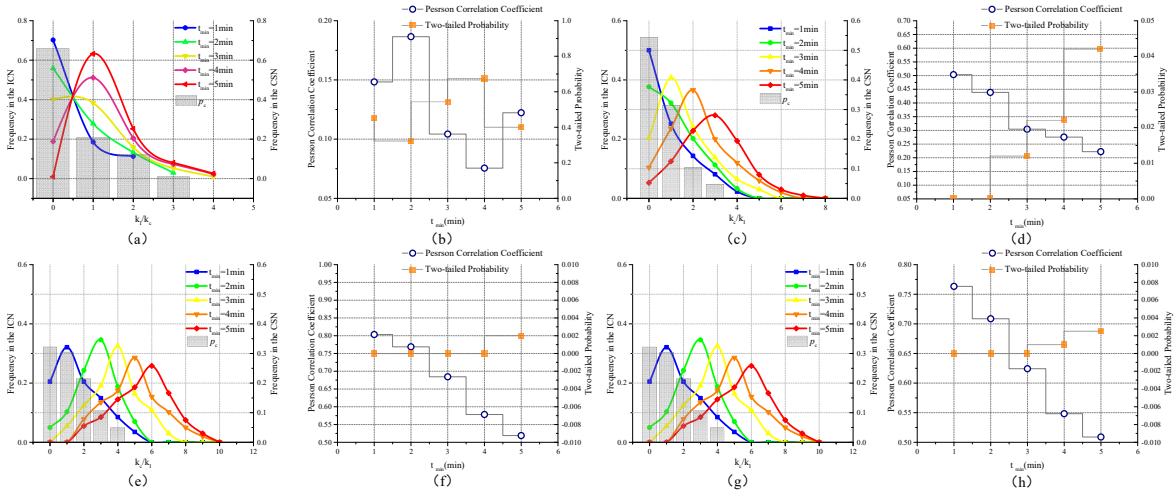


FIGURE 6. Degree distributions of CSN and ICN and Degree Correlation for vetices shared by CSN and ICN. (a)-(b): free phase; (c)-(d): smooth phase;(e)-(f): semi-stable phase;(g)-(h):congested phase.

In the smooth phase, traffic efficiency is still well maintained though conflicts occur more frequently. Interestingly, the workload of ATCOs increases with a slower rate as shown in Figure 5 and T. This is one of the most important features of ATCOs' meta-cognition, called "cognition complexity inhibition", which is similar to a proven traffic control strategy "standard flow" (Histon et al., 2002). ATCOs reduce their workload by simplifying the traffic picture by assigning standard routes to aircraft to form a stable and familiar traffic structure to reduce the controllers' cognition workload. More importantly, in-trailed following of aircraft by speed adjustment makes it much easier to avoid conflicts and reduce communication. Figure 6 (c) shows the dominance of degree 1 in the CSN, suggesting that most conflicts involve only two aircraft. Regarding the degrees of vertices shared by the two networks, their correlations are more significant than the free phase; see Figure 6 (d). The prevailing motifs are chains and loops in the ICN due to the "cognition complexity inhibition" strategy, which is employed in dealing with chain-like or star-like conflicts; see inTable 2.

TABLE 2 Motifs within CSN and ICN in the each phase.

Phase state	Motifs	Conflict Situation Network (*CSN*)	Interventional Communication Network (*ICN*)				
			$t_{min}=1$	$t_{min}=2$	$t_{min}=3$	$t_{min}=4$	$t_{min}=5$
Free phase	Chain	28.4%	28.5%	42.2%	53.5%	62.1%	77.9%
	Star	0%	0%	0%	1.3%	4.7%	14.2%
	Loop	0%	0%	0%	3.6%	6.2%	7.6%
Smooth phase	Chain	33.5%	50.5%	52.2%	55.1%	42.3%	35%
	Star	12.5%	0%	0%	2.5%	9.8%	16.9%
	Loop	0%	0%	9.1%	12.6%	36.2%	42.6%
Semi-stable	Chain	38.4%	74.5%	70.2%	59.1%	42.3%	30.2%

phase	Star	20.6%	0%	6.5%	8.3%	11.5%	18.5%
	Loop	10.7%	4.8%	17.1%	32.6%	46.2%	51.3%
Congested	Chain	44.4%	60.5%	50.2%	39.1%	29.4%	20.6%
	Star	25.6%	15.8%	22.3%	28.4%	34.2%	38.1%
	Loop	14.7%	23.7%	27.5%	32.5%	36.4%	41.3%

In semi-stable phase, the Average Outflow Rate approaches maximum. Sector capacity, defined as the maximum throughput or the threshold of ATCO's workload, is achieved in this phase. As the traffic volume and conflicts significantly increase, the average growth rate of CL is slightly higher than that in the smooth phase due to heading changes adopted to avoid conflicts, which need more interventions than speed adjustment. It implies that driven by metacognition dynamics, the strategy of "cognition complexity inhibition" is inherited from the smooth phase and is applied using "critical points" (e.g. merging points or navigation fixes) along standard routes to ease the traffic picture and workload when issuing radar vectoring commands (Histon et al., 2002). As shown in Figure 6 (e)-(f) and Table 2, in the semi-stable phase, as the multi-aircraft conflict grows (see p_C), interventional communication is more passive and conflict-oriented, as indicated by the higher degree correlations of shared vertices in each layer. More importantly, facing the increasing complexity of conflict pattern, controllers are still able to solve the problems in an efficient and ordered way (i.e. dominated chain and loop-like motifs of communication network) driven by metacognition dynamics.

In the congested phase, the average throughput drops due to highly complex conflict situations. In order to avoid conflict with tight physical constraints, ATCOs widely adopt heading changes to keep safe separation and maintain flow efficiency. Holding is another standard flow control strategy in congested phases, and reduces the efficiency of air traffic flow due to fixed holding pattern and position. Driven by metacognition dynamics, controllers tend to focus on the safety rather than efficiency in a stressing, or even chaotic, work environment. Figure 6 (g)-(h) shows that the degree correlation of shared vertices in the networks are as significant as in the semi-stable phase. Moreover, the increasing complexity of conflict leads to more star motifs in the ICN. Both continuous growth of degree and motifs of CAFN prove the lower efficiency of traffic operation and the consistency of conflict and communication pattern in congested phase.

In summary, by analyzing the sector throughput, communication load and network characteristics of CAFN at a sector level, the co-evolution of air traffic situation and ATCOs' performance is quantitatively and qualitatively described. The underlying mechanism of "human-flow" interaction can be reasonably explained as the adaptive cognition management strategy "metacognition dynamics" of air traffic controllers to cope with traffic flow complexity. In the next section, chaotic properties of the "human-flow" system are explored.

4.3. High-level non-linear dynamics of terminal air traffic system

Air traffic system operation is a complex chaotic problem (Shi, 2001). However, non-chaotic feature of air traffic flow was proven in terminal airspace by analyzing the time series of traffic volume (Cong et al., 2014). Nonetheless, intuitively, the dynamic evolution of air traffic flow (in all phases) is the integrated output of adaptive human control activities dealing with increasing traffic conflicts, which exhibits non-linear characteristics such as uncertainty, burstiness and diffusivity. 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 secondary conflict in other area). With these in mind, two hypotheses are made as follows.

Hypothesis 1: The system under investigation is chaotic, and the chaotic phenomenon can be observed in both ATCOs and air traffic flow behavior.

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

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, additional data of ATCO's behavior is studied by adopting method in Section 3.3, together with time series of potential conflicts in specific sectors. Inspired by previous research on ATCOs' communication dynamics (Wang et al., 2013) and chaos analysis of vehicle headway evolution at a fixed observing spot (Zhang et al., 2009), silence period of radio channel (a.k.a. communication interval), which characterizes temporal dynamics of controllers, is used as a representative behavior of "human system". Here, both communication types of intervention and nonintervention are included. For simplicity, the series of silence period and potential conflict of Sector 2 on 11/09/2012 are shown in Figure 7 (a)-(b). Result shows that the largest Lyapunov exponents of silence period series and potential conflict time series of Sector 2 are 0.00131 and 0.00173 respectively as shown in Figure 7F (c)-(d).

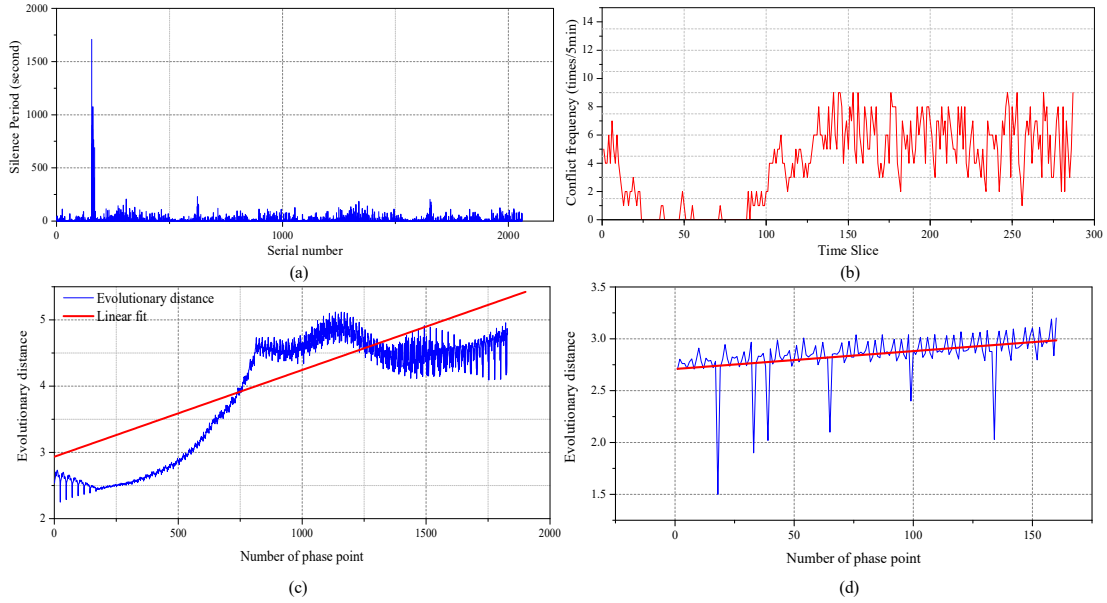


FIGURE 7 Selected input and output of chaotic analysis in Sector 2. (a) Silence period series; (b) Conflict time series; (c) The largest Lyapunov exponent of silence period series; (d) The largest Lyapunov exponent of potential conflict series.

The same method is applied to identify the chaos features in the 4 other sectors respectively. Table 3 shows the result of delay time, embedded dimension and the largest Lyapunov exponent of all 5 sectors on the day of 11/09/2012. Interestingly, chaos in "human system" and "flow-system" emerges asynchronously: flow chaos emerges in sectors 1, 2, 3 and 5 where semi-stable or/and congested phases are observed, while human chaos is absent in sector 3, where there is no congested phase. Based on the discussions on underlying mechanism of "human-flow" interactions in Section 4.2, conclusions of asynchronism can be simply supported by ATCOs metacognition of avoiding chaos as the increase of traffic. It is noted that the same conclusion of asynchronous chaos of "human system" and "flow-system" are drawn by analyzing the data on the other two days.

TABLE 3 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 terminal and sector levels, we conclude that chaos exists in terminal airspace, and emerges when traffic becomes (nearly) saturated; it is intrinsic to the dynamics of the co-evolution of "flow system" and "human-system". Due to the highly congested airspace systems in China, European and the U.S., it is expected that chaotic dynamics may be prevalent and provide new tools and insights for the prediction and control of air traffic system evolution.

5. CONCLUSION

The study of complex air traffic dynamics is essential for understanding the nature of air traffic system and uncovering technical potentials for advancing air traffic management. Among a variety of analytical approaches, network analysis is an effective and intuitive way to understand multi-agent behavior at varying granularities. In order to characterize air traffic physics and interpret underlying mechanism of "ATCOs-flow" interactions, a COUPLED network is constructed to integrate and present potential conflicts and ATCOs' interventions activities. To further represent the dynamics of "human-flow" interaction, as well as system nonlinearity, a series of analytical metrics are introduced (e.g. ATCOs' cognitive complexity, communication load and chaos).

Systematic analyses are conducted based on the proposed network as well as analytical metrics using a case study of Guangzhou terminal airspace; the main subjects of investigation include

1. Underlying mechanism of "ATCOs-flow" interactions: Four phases of air traffic are identified: free, smooth, semi-stable and congested at the sector level. Meta-cognition strategies of controllers are interpreted as the mechanism of "ATCOs-flow" performance co-evolution including "pre-activation", "inhibition" and "stress".
2. Chaos identification: at the system level, chaos is identified in both flow and human dynamics, when air traffic is characterized as semi-stable or congested.

This study represents an empirical exploration of the Guangzhou terminal airspace by employing a generic methodology. As a future study, it is essential to test the generality of our findings and identify critical features that are responsible for qualitatively different system behaviors. Real-time human-in-the-loop simulation is considered an effective way to supplement addition of ATCO-related data in various scenarios.

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