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Spatial, Temporal, and Grouping Behaviors in Controller Communication Activities

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***Abstract*— Recent reports on human dynamics have uncovered regular patterns of human communication and other interactive activities that exhibit characteristics of heavy-tailed, power-law distributions instead of ever-belief Poisson-like random distributions. Motivated by these findings, we adopt a similar data-driven approach to investigate controller's communication activities. On three different datasets, we examined the inter-communication events to characterize *temporal behavior* of controller communications. The results showed that controller communications also exhibit a heavy-tailed feature with power-law exponent lying between 2~3. When using a network dynamics approach to characterize *spatial behavior* of controller communications, we found out that the degree of the node (or the number of neighbor flights in the communication process) can be used to quantify the *grouping behavior* in structure-based abstraction for mitigating cognitive complexity. We finally identified a general Poisson distribution that transforms to a power-law distribution when increasing the strength of link connectivity. Also, the analysis of fluctuation scaling phenomena showed that the relationship between the average number of communications and its standard deviation could be well described with a Taylor's series. These exciting results confirm the hypothesis that traditional metrics of controller workload could be replaced by quantifiable measures of controller availability against airspace or sector activities, which is crucial to complex systems modeling approach for ATM.**

Keywords- air traffic control, human dynamics, network dynamics, complex systems, communication activities, human factors

I. INTRODUCTION

Research on human factors in Air Traffic Management (ATM) has emphasized the impact of critical behavior of human beings who are involved on the system safety, such as air traffic controller, and pilot etc. As the system continue to evolve with more advanced technologies and methodologies employed, for example within the framework of NextGen in US, and the SESAR in Europe, the complexities of understanding of operator's and manager's behavior pose a challenge to the research community. Specifically, the performance of the controller, who acts as the decision-maker and executor of the system, is closely interconnected with the system safety and efficiency. The prediction of controller performance with respect to traffic activities is therefore of quantifiable importance.

It is thought that workload, at a microscopic level, is one of the main factors affecting controller's performance. Great efforts have been focusing on measuring and predicting controller workload. Earliest work was based on queuing theory and examination of controller routine work [1-3]. There used to be consensus among research and operational communities that the understanding of the factors that drive workload is essential to measure and to predict workload [4-5]. Examinations on the relationships between workload and task demands were extensively conducted. Metrics derived from traffic data, such as dynamic density to indicate traffic complexity, were proposed as an important input for measuring and predicting workload [6-7]. As stated in [8], the dynamics properties of workload incorporated with controller strategies management should be investigated in order to calculate workload correctly. Notably, methods based on cognitive science have significantly contributed to our understanding of the mechanisms that radar controllers use to mediate cognitive complexity so that simplifying mental workload [9]. Structure-base abstraction summarized the underlying common strategies among controllers. The quantified descriptions of mechanisms, which explain how controller manages system resources are, however, still poorly understood.

Workload is only one factor affecting human activities. From a complex systems perspective, it is the human actions that influence the system operations. Controller is inextricable linked with the system, and the behavior might be depended on the unique sector structure, the dynamical changed traffic, and the individual knowledge and experience. Compared with workload, less is known, at the macroscopic level, on the property of the controller activities.

Since 2005, proposals on human dynamics have suggested that several kinds of universal mechanisms, including priority based queuing processes when human execute tasks, cascading non-homogeneous Poisson process with circadian cycle, the combination of Poisson processes and decision-based queuing processes, may govern human daily activities [10-12]. Heavy-tailed distributions of inter-event times have been widely reporting from various kind of human activities, range from

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correspondence [13], email communication [14], through printing behavior [15], online films rating [16], to human mobility [17]. Instead of randomly occurring, as assumed previously, the temporal patterns of human actions exhibit the bursts of frequent actions separated by long periods of inactivity. Analysis from mobile phone data sets demonstrates that the human trajectories show a high degree of temporal and spatial regularity [17]. Although the studies in human dynamics have been successful in describing human activities, it should be noted that all the examined data are deliberate human activities. Although there is the lack of the evidence from a task-specific activity, as while simple mechanisms may be incapable of capturing the distinct nature of air traffic controller's activity, for example, the dependence on environmental conditions, and urgency or time pressure, the emerging human dynamics studies provide insight into air traffic controller activity.

Here we address the important problem of describing controller activities from both methods and empirical results. We analyze air traffic controller communication activities data from a complex system point of view, to provide an initial demonstration of the physical understanding of the rules by which air traffic controller control the traffic. Specifically, we (i) investigate *temporal behaviors* of controller's communication activities; (ii) demonstrate the use of network dynamics to study *spatial behaviors* in controller communications; (iii) explore the *fluctuation scaling* of communication activities while taking controller as a component of ATM complex system.

The rest of the paper is organized as following: Section II presents the methods we use by firstly explaining the use of voice communication activities followed by the dynamic network approach and how to capture fluctuation scaling phenomena. In Section III, we describe three sets of communication data on which we have investigated. Section IV shows the empirical results of the temporal/spatial behaviors, and the ensemble fluctuation scaling in the controller communication activities. The paper ends with conclusion remarks in Section V.

II. METHOD

A. Analysing ATCO Voice Communication Activities

In ATM system, prior to the emerging of digital data communication between controllers and pilots, radio voice communication had been the primary means used by controllers to control air traffic. However, it is still the only channel for information flow between pilots and controllers in most control centers. The use of communication events to measure workload has been extensively investigated [19-21].

In psychology, human activity is defined as a coherent system of internal processes and external behavior and motivation that are combined directed to achieve conscious goals [18]. Thus, we assume that controller voice communication activity encapsulates both cognitive efforts and physical efforts to accomplish the mission of ensuring traffic safety and efficiency.

The point of this paper is, however to investigate the instinct nature of human with the voice communication as a proxy. We believe that human activity will be quickly adapted to the contextual environment while human brain, which drives the external activity, evolves slowly.

Communication activity in this paper is defined as the event that controller press the push-to-talk button and hold in order to send the transmissions to aircraft, disregarding the contents of the transmissions. Particularly, empty transmission is also seen as a complete communication activity. Figure 1 gives an example of the communication activities between a controller and pilots. The start time t_i^s and the end time t_i^e of each activity i have been recorded. The length of activity L_i, which is the time taken to accomplish the activity, is therefore calculated as $L_i = t_i^e - t_i^s$. Two measures widely investigated in human dynamics research are *inter-events times* τ and the *response times* τ_w (or the waiting times). Inter-events time is time interval between two consecutive activities, while the response time is the time difference between the reaction time on an event and the arrival time of the event.

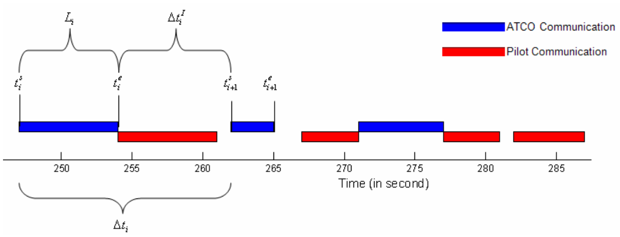


Figure 1. Visualized communication trunks between a controller and pilots.

It is should be pointed out that there are significant differences between controller communication activity and the deliberate activities examined in the above-mentioned studies.

The first and the most notable one is that the length of controller communication activities is sometimes even larger than the inter-communication times, which is not the case in other activities. For example, the time taken to write an email and the inter-arrival times of emails are commonly not in the same magnitude. Therefore, the length of communication might not be disregarded as the other human studies. A common consensus in ATM is that controller will change communication strategies according to different traffic situation. They will shorten each instruction by cut off unimportant information during communication when the traffic increases. The communication with the same length can contain different information. Also, it is difficult to identify all the flight information across the communication data. We therefore, in this article will focus on the inter-communication times $\tau^1 = t_{i+1}^s - t_i^s$ rather than on the response times to the flights. However, it should uncover us more interesting phenomena if we had the flight information of communication.

The second is the fact that controller communications are highly depended on traffic and route structure. There will be no communication if there is no traffic. Hence, the inter-events times that is higher than certain threshold will be disregarded.

To explore how traffic influences communication activities, we examine the fluctuation scaling phenomena and the method will be described in Section IV.C.

The last is the frequently interaction between controller and pilots. Previous studies on ATC communication classify controller communication activities into several types based on the contents of transmissions [22]. Most of controller communications are the interaction with pilots. Normally, controller should give a prompt response to pilot when pilot talk to controller. Communication activities can be classified into two groups: initiative and passive, and each group's communications are the outcome of different mechanisms [12].

B. Network Dynamics to Trace Trajectory of Human Actions

Inspired by the cognitive investigation in [9], grouping is one structure-based abstraction to mitigate cognitive complexity. Our objective here is to quantify the *group behavior* and to capture the *spatial behavior* of controller i.e., how traffic dynamics evolves in controller's mind.

To trace the trajectory that controller selects or has to select a flight communication, we construct a network from the temporal data of the flight information decoded from communication events over time. The assumption is that the physical relationships between flights in the sector are not the same as in controller's mind. If several flights occur simultaneously during a short period in controller communication sequence for a couple of times, then we believe that there are strong relationships among these flights and they were consciously or unconsciously regrouped by controller.

In order to examine this phenomenon, we propose a novel method for the transform of the temporal activities data into an undirected weighted network. The nodes in the network are the flights traverse the sector, while the link between nodes indicates that there is a temporal relationship between the two flights. First we can obtain the adjacency matrix of the network from the communication data by calculating

$$l_{ij} = \begin{cases} 1, & \text{if flight } i \text{ and flight } j \text{ consecutively receive the message from} \\ & \text{the controller} \\ 0, & \text{else} \end{cases}$$

As such, the network contains much information about the calling trajectory. The temporal information, which is the most important one, is however not included. Our intention is to investigate the relationships between flights rather than building temporal graphs.

It is obvious that the two flights have no relationship if their communication were separated by a long period of time units. In contrary, they should have some kind of relation. Therefore, to determine whether two nodes are connected or disconnect, we firstly calculate the temporal distances d_{ij} between flights. d_{ij} is the time intervals between the communication activities which are related to flight i and j (Figure 2 shows an example). A predefined time window $d_{\min}$ is used to determine the connectivity between the nodes. If d_{ij} is smaller than $d_{\min}$, then we say these two flights are related and a link will be added between the corresponding nodes; otherwise the nodes are not connected directly. The adjacency matrix L of the network can be obtained as

$$l_{ij} = \begin{cases} 1, & d_{ij} \le d_{\min} \\ 0, & \text{otherwise} \end{cases}$$

Especially, we define $L_{ii} = 0$. If $d_{\min}$ is equal or greater than the length of the exercise then we will have a complete network.

Along with the adjacency matrix L, we define a weighted matrix W, in which the integer number w_{ij} is used to record the number of link l_{ij} occurs across the whole data.

Figure 2 illustrates the network generated for the sector OYOT in one exercise.

(a)

	………	………
	8:19:45	AF113ZL
d_{ij}	8:21:45	MCD656
d_{ij}	8:21:50	BZ682ZR
	8:22:00	AF113ZL
	8:23:45	N9325N
	………	………

(b)

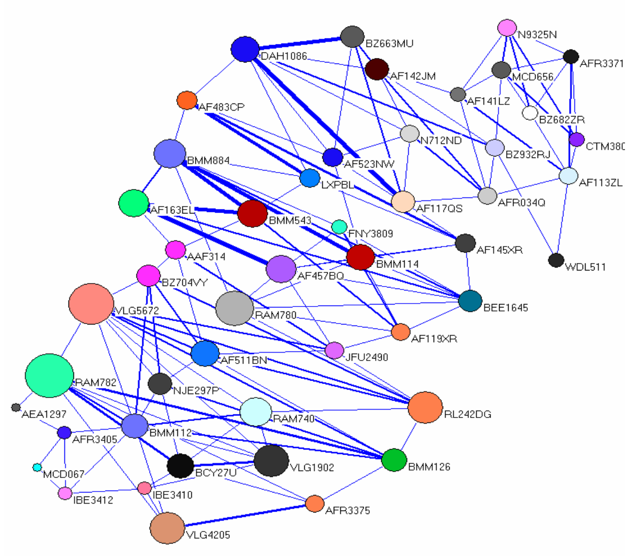


Figure 2. Network representation of the communication activities. (a), the list of flights called by the controller. The flights are arranged according to the order in the communication data. (b), The associate network of the communication events in (a). Each dot corresponds to a flight, and the size of the nodes corresponds to the frequency of communication with controller. The widths of line edges are proportional to the frequency of the communication for the two flights during the time window.

As shown in the calling list (Figure 2(a)), the link between AF113ZL and BZ682ZR can be different according to $d_{\min}$.

$$
\begin{aligned}
&l_{ij}=0, w_{ij}=0,\ if\ \ d_{\min}<5(s)\\
&l_{ij}=1, w_{ij}=1,\ if\ \ 5(s)\le d_{\min}<125(s)\\
&l_{ij}=1, w_{ij}=2,\ otherwise
\end{aligned}
$$

C. Measuring Fluctuation Scaling of Communication Activities

Normally a flight receives at least two messages (hand in and hand off) from the controller when it traverses the sector. The more flights enter the sector, the more communication activities there should be. It is difficult to quantify the correlations between traffic and communication as controller communication activity emerges from the interaction with traffic, airspace, and the human brain.

Instead of looking at how communication grows with respect to traffic increases, we are interested in the fluctuation of communications considering controller as a complex system.

To describe complex systems in characterizing the relationship between fluctuations in the activity of a component and the average activity of the system, Taylor's series (or Taylor's scaling) has been observed in many natural and human-driven systems, ranging from ecology system through stock market to human dynamics [24, 25]. Taylor's power law is named after L. R. Taylor in recognition of his paper in 1961 [23]. The relationship is usually in the following from:

$$Fluctuation \cong constant\ x\ average^{\propto},\ \text{here}\ \ \alpha\in[1/2,1]$$

Based on the data over which the averages are taken, the Taylor's power law can be grouped into two categories: *Temporal Fluctuation Scaling* (TFS) and *Ensemble Fluctuation Scaling* (EFS) [24]. Models for the explanation of the origins of Taylor's power laws can be found in [25].

For a sector, we calculate the average of communication $\overline{f}$ and the standard deviation $\overline{\delta}$ according to fixed number of the flights entering the sector. The calculation can be done for sectors of different entering flights. Detailed procedure for capture fluctuation scaling in controller communication can be found in[26].

III. EXPERIMENTAL DATA

Experimental data used in this paper includes ATCOSIM Corpus Data, Paris TMA simulation data, and some operational Data obtained from FAA.

A. Paris TMA Simulation Data

Paris TMA data was recorded during a two weeks real-time simulation at EUROCONTROL Experimental Centre in June 2010. The purpose of this simulation was to test the viability of improvements proposed by French DSNA to the ATM system serving Paris-Charles De Gaulle, Paris-Orly and Paris-Le Bourget airports.

The simulation involved around 100 participants over 2 weeks: 45 controller positions and 35 pilot positions. Thirty sectors were simulated, which includes 11 sectors of the Athis-Mons Control Centre, 13 approach positions, 2 military positions and 4 feeds. The traffic flows between sectors of one exercise are given in Figure. 3.

Traffic samples for simulation were based on the real traffic rate on 29 May, and 12 June, 2009. For each main configuration (facing west and facing east), two samples with heavy traffic were prepared.

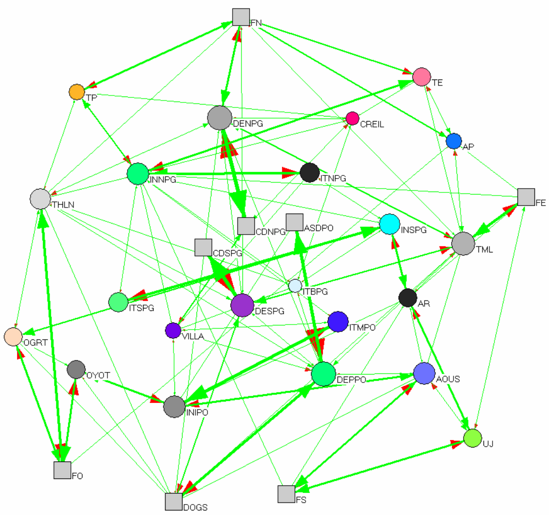


Figure 3. Traffic flow between sectors in Paris TMA simulation. Each node corresponds to a sector. The circle nodes are the sectors recorded for analyzed, while the squire ones are either feeding sectors or the sectors that are not listed in the data. The widths of lines are proportional to the traffic amount between linked sectors, with green arrows standing for outgoing flows and the red ones representing for incoming flows.

There were twenty exercises in total, with an average of one hour and thirty minutes long for each exercise. Among them, fourteen exercises are identified as good exercises that were analyzed in this study. Form the recorded data we pick up three data sets that are necessary for our investigation. For each exercise, data include:

1) ***Radio communication data.*** This one contains the start time and end time of the communication made by controller or pilots. Information on the content of communication is unavailable. There are an average of 300 communication made by controller for each sector in each exercise.
2) ***Pilots manipulating data.*** Pilot data was retrieved from the flight simulator. The simulator recorded every manipulation related to changes of flight motion. Hence, we could find in this dataset all call-signs and the time of pilot's entering instructions to change flight's motion (could be 1~2 seconds differences with the actual entering time due to system delay), as well as the types of instructions. We use these data under the assumption that

the clearances were granted by controller few seconds before.

3) ***Transfer Information.*** Each piece of record contains flight call-sign, transfer time, the sector it is leaving and the sector it will be transferred to. Throughput of the sector varies from 30 to 100 aircraft during the measured period (see Figure 2).

B. *ATCOSIM Data*

The second dataset is the ATCOSIM Air Traffic Control Simulation Speech corpus of EUROCONTROL Experimental Centre. The aim of the ATCOSIM is to provide a speech database of non-prompted and clean ATC operator speech. It consists of ten hours of communication data, which were recorded during ATC real-time simulations that were conducted between 20/01/1997 and 14/02/1997 [27]. Only controllers' voice was recorded and analyzed. Each record consists of *circa* one hour of communication data. Both speech signal data and transcription of the utterance, together with the complete annotation and meta-data for all utterances, can be found in the database. The recorded simulation data does not include information on traffic and airspace corresponding to the communication data.

The general information of the whole fifty exercises is shown in Table 1. The detailed information on each exercise is not given here.

Table 1. Information on the 50 exercises in the ATCOSIM database

	TOTAL	AVERAGE
Length of the exercise (hh:mm:ss)	59:18:37	1:11:10
Number of the flights (*complete flights**) identified in the exercise	3121 (1966)	62.42 (40)
Number of the communication events (Unidentified) in the exercise	10078 (1276)	201.56 (26)

**Complete flight* is the flight that receives both *hand-in* message and *handout* message.

C. *FAA Operational Data*

To investigate the other factors effects on the controller communication, such as culture, we obtained data from the Federal Aviation Administration. The data were based on the operational data recorded in the Kansas City in 1999. It consists of 8 samples, including four sectors, namely Sector 14, Sector 30, Sector 52, and Sector 54. In total, there are 999 communication events. On average, each traffic sample has 125 communication events. Around 47% of communication was made by the radar controller, 53% was made by the pilots and the other controllers (see [19] for details).

It was found that each traffic sample is around 15 minutes long with around 10 flights in the sectors. The number of the identified flights in each sample is 15~20, while the flights with both hand in and hand out message is even fewer. Such short period with few flights could not capture the dynamic property of individual controller activity. However, it could be used to test the collective phenomena from human dynamics point of few. Therefore, we complement the temporal part with this data.

IV. EMPIRICAL RESULTS AND DISCUSSION

A. *Temporal Characteristics*

1) *Results*

With the no-traffic-no-communication assumption, we first make a careful examination on the rates of arrival/departure traffic of each sector. Although there were four types of traffic configuration during the simulations, from the empirical cumulative distributions of inter-arrival and inter-departure times we observe that traffic distributions vary slightly in the same sector across all the exercises. However, traffic in different types of sectors (e.g., ACC, APP, and Military sectors) evolves more heterogeneously.

The empirical distribution of the length of communication made by both controller and pilots are also calculated, showing that most communication events last 3~4 seconds, with few events lasting over 6 seconds. Both traffic distribution and length of communication give an overview of the simulation.

Building upon prior research, we investigated the distribution of inter-communication times in each sectors. Results showed that, typically, if the data has a power law distribution $p(\tau) = \tau^{-\alpha}$, then the behavior of complementary cumulative distributions functions (CCDF) in the log-log plot will be a straight line with the slope of $-\alpha$ [28]. In practice, few empirical data obey power laws. For most cases, data with value greater than a minimum threshold can exhibit a form of power law.

Here we use the method described in [29] to test and estimate the parameters of power-law α and $t_{\min}$. Both the probability distribution (PD) and the CCDF of inter-communication times for an exercise over a sector can be plotted on log-log scale. Figure 4 shows the inter-communication times in an exercise of sector AOUS. It can be seen from the probability plot in inset of Figure 4(a) that communication activities exhibit the heavy tailed distribution over 10 seconds.

Almost all exercises have the same distribution shapes with different scales. It suggests that communication data for the same sector are homogenous, allowing us to group the inter-communication times of each sector across all exercises.

The CCDF of the grouped data is plotted in the main plan of Figure 4(a). The solid line in the main figure clearly indicates the power-law fitting of the data. We have examined all involved sectors, and we found that the exponents of power-law fitting $\alpha \in [2.5, 2.9]$, with the cut off at $\tau_{\min} = 12(\pm 5)$.

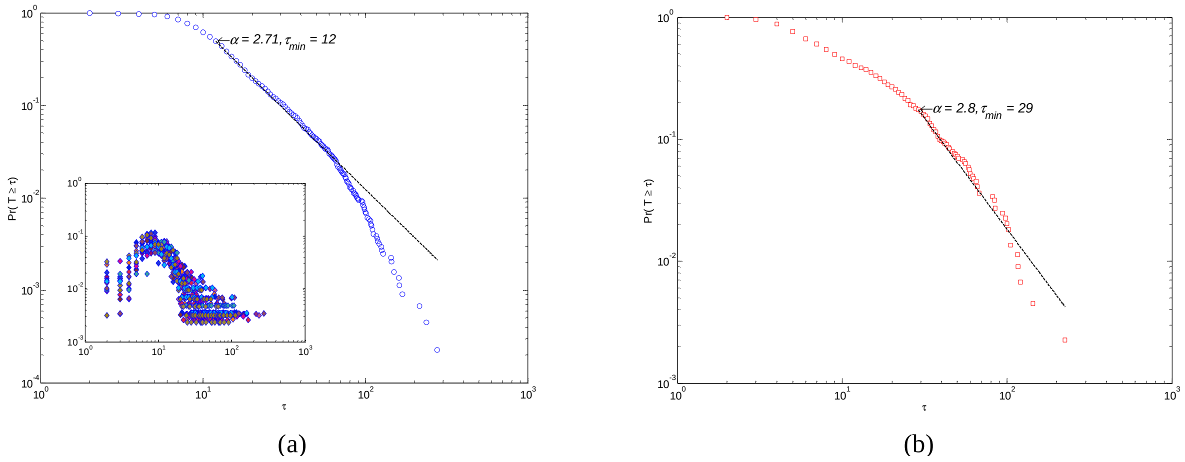


Figure 4. Distributions of inter-communication times. (a), The main figure is the complementary cumulative distributions functions (CCDF) of inter-communication times in sector AOUS across all the exercises. The blue dots correspond to empirical data, while the solid line is the power-law fitting. The inset figure shows the probability of inter times of each exercise of the sector, with different colors of marker stands for different exercises. (b), The CCDF plot of FAA data.

Four approach sectors (DENPG, DESPG, INNPG, and ITBPG), and one ACC sector (THLN) have the exponents higher than 3. Figure 4(b) shows the inter-communication times of FAA data, which also indicates a power-law decays.

2) *Discussion*

A recent report of human dynamics [12] has shown both empirical evidences and simulation results for the bimodal distribution rather than the single form of power-law distribution in human communications. A significant difference from the Barabasi's model [10] is that, aside from the priority-based queuing for decision-making, the random Poisson processes as well as the interaction among individuals contribute to the heavy-tailed feature of human dynamics.

Controller communication shows a heavy tailed behavior, and it is not the bimodal distribution uncovered in short message-sending activities [12], therefore the cut-off and heavy-tail here should be interpreted with caution. The major factors are the inter-dependence of communication and the dependence on the pilots' communication. We hypothesize that the priority-based queuing process (that will be well explain the priority of strategies management process, together with the Markov process which take the effect of dependence of communication and interaction into account) could explain the complex communication phenomena.

B. *Spatial Characteristics*

1) *Results*

Along with the patterns of temporal behavior, we measured the *spatial behavior* of controller by reconstructing the communication trajectories. The network of temporal events of communication can capture the relationships of flights in controller's mind.

Topological changes were measured with characteristics that focus on the nodes' connectivity and degree distribution and that have been used in prior research on network dynamics. The connectivity may has less meaning than degree distribution, as degree distribution shows the number of neighbor flights which were grouped by controller.

We have tested the effects of different $d_{\min}$ and $w_{\min}$ on the network properties. The degree (d_i) of the flight i is the number of the neighbors in the network, which indicates how many flights that flight i has been involved with. Hence, we have

$$d_i = \sum_j L_{ij}$$

Note that a pair of flights can been linked because they occurred in the predetermined time window only once. However, there could be the result of random selection. Communicating with the second flight may have nothing to do with controller strategy. In contrast, if this pair of flights occurred several times during communication, this clearly suggests that either because of physical relationship between flights, or because of the group abstraction to mitigate cognitive complexity, controller communicate with the two flights alternately. Following this logic, we measure the number of neighbors of each flight under different weight of link by calculation as:

$$d_i = \sum_{j, w_{ij} \geq w_{\min}} w_{ij}$$

To our surprise, the degree distributions have quite similar shapes across all the sectors. With $d_{\min}$ fixed and $w_{\min} \leq 3$, instead of a random distribution, most of data can be described as a Poisson distribution or Normal distribution (see Figure 5). Such trends appear commonly in the random network studied by Erdos and Renyi [30] and each edge is present or absent with equal probability.

This suggests that the pairs of flights are uniformly selected. With $w_{\min}$ increases, the distribution moves towards left which means there are fewer flights have large degree while most flights have few neighbor flights, and the average of degree for all flights decreases. A different type of distribution possibly emerges when w_{min} exceed 4. Most flights have a small degree, while few flights still have more neighbors.

Due to limited size of the network, we cannot give a positive fitting the data with power-law distribution although the data exhibits such trends. The change on degree distribution suggests a transformation of the network. Reasonable explanation could be the “preferential attachment” proposed by Barabasi for the explanation of power-law distribution of degree in complex network [10]. We can see that controller keeps few “important flights” in their call list, and the other flights are attached to these flights with higher probability.

In addition, we can see that the maximum probability of the degree is correlated to the number of adjacent sectors (see Figure 6). Interpretably, the more adjacent sectors a sector has, the climax of the degree will be. For instance, sector AOUS, THLN and TML.

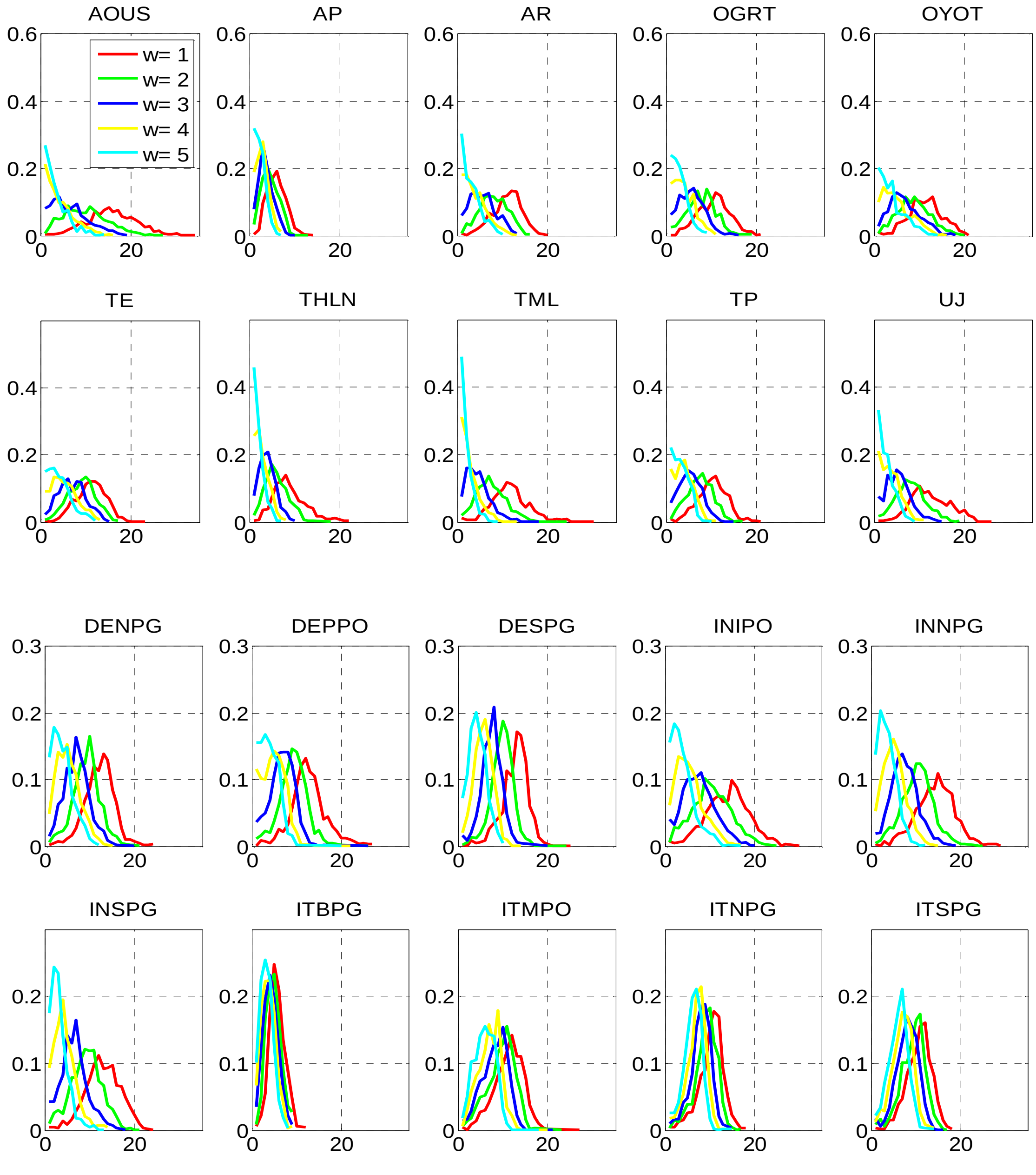


Figure 5. Degree distributions of spatial networks in ACC sectors (the first two rows) and in APP sectors (the last two rows), both with the min distance between flight is 60 seconds. The horizontal-axis is the degree, while the vertical-axis is the percentage of nodes (flights).

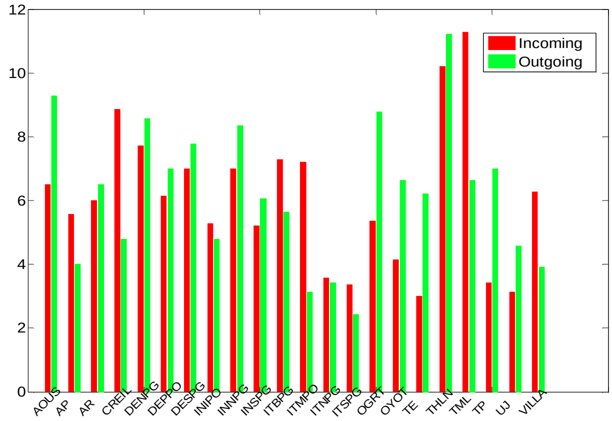


Figure 6. Number of adjacent sectors. For each simulation exercise, the number of adjacent sectors of a sector can be obtained by examining the traffic transfer information. Because of different simulation configurations, there are slightly differences across all exercises with the standard deviation around 1.

2) *Discussion*

The currently results were based on the pilot manipulating data related to flight motion change which were recorded by the flight simulator. Although there may be few seconds of delay between the controller sending the clearance to change flight heading, speed, or altitude, these data reflects the willing or the intention of controller about how he/she wants traffic to evolve. The fact is that controller dynamically changes the strategies according to the traffic. Spatial behavior captures the patterns of selecting flights to some extent. The link of the temporal behavior and spatial behavior may lead to a better understanding of controller's activities. Therefore it will likely shed light on other human factors related problems.

C. *Fluctuation Scaling*

1) *Results*

We regroup the data of each sector to examine the relations between the amount of traffic and that of communication.

Results show that both the average and the standard deviation of the communication activities grow quickly as the number of flights increases. Because of the limited number of exercises (14 exercises) for each sector, we observed stronger fluctuations at the beginning of the tests.

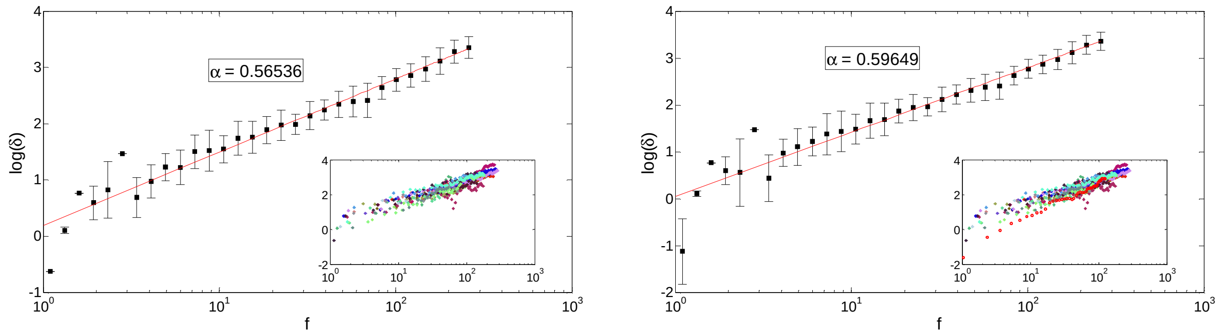
When we plotted the standard deviation according to the average of the communication activities, as shown in Figure 7 (a), we observe linear fit of the empirical data in the log-log plot (solid red line). Hence, the standard deviation of the activities and the average activities do exhibit a clear Taylor's power-law relationship with $\alpha = 0.56536$.

After adding the ATCOSIM data, the slope changed slightly, while the whole dataset still can be described with a power-law form with $\alpha = 0.59649$

2) *Discussion*

The detection of fluctuation scaling was particularly noteworthy. On one hand, it captures the interesting adaptive phenomena of controller activity with respect to incoming traffic. Together with the temporal characteristics of communication, it may provide a way to understand the general properties of the controller's activities across different incoming traffic.

On the other hand, it may reveal the inherent nature of the system with the controller as an important element in the system. With the system continues to evolve; such complex phenomena are critical to our understanding of the dynamical aspects of the evolution.



(a) (b)

Figure 7. Fluctuation scaling for communication activities. (a) results from Paris TMA data, and in (b) we add the ATCOSIM data (the red dots in the inset figure) to compare the fitting forms. The fitted exponents are shown with error ± 0.04 due to logarithmically binning data. Points were logarithmically binned and log sigma was averaged for better visibility, the error bars represent the standard deviations inside the bins. The inset shows the same axis range, but without binning.

V. CONCLUSIONS

Investigations on historical data have been uncovering the striking statistical properties of human activities, leading us to a quantitative understanding of the rules governing human actions. The present work shows that controller inter-communication does exhibit the heavy-tailed feature similar to other daily human interactive activities.

However, such results should be interpreted with caution because the decaying functions may vary according to traffic and sectors.

In addition, we have demonstrated that network dynamics-based approach can capture the underlying patterns of controller communication activity. The proposed approach has complementary role in the study of controller workload and cognitive complexity.

The fluctuation scaling of communication suggests that controller, as a complex system, his/her activities can be well characterized by a complex system approach.

Our results must be considered in light of several limitations of the present study. First, our empirical data were mainly based on Paris TMA simulation data containing around twenty-one hours' busy traffic and communication activity data for each sector. Although the results show quite similar general patterns among different exercise data, it still needs to be tested with other different data.

Also the homogeneous and heterogeneous properties should be examined. The spatial network is able to reconstruct the activity trajectory, so that it is easier to analyze the data by the use of network dynamics approaches. We note that the group-based abstraction is a dynamic strategy rather than static one. More systematic exploration of the influence of traffic and airspace factors on controller activities is needed.

We anticipate that with the knowledge of previous work on workload and cognitive complexity, the use of data-driven approach will further advance the understanding of the dynamics of the ATM system as a human-driven system. Future work should focus on using existing models, such as random walk, priority-based queuing, and preferential attachment for modeling the human controller system.

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