Empirical Analysis of Air Traffic Controller Dynamics

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***Abstract*—This paper addresses an empirical analysis of Air Traffic Controller activities from a human dynamics; complex systems approach. As a matter of fact, workloads metrics have been long well investigated from a cognitive engineering, human factors approach, and have been widely used as an indicator of controller's activity levels. However, the dynamical property of workload is still unknown, which make it difficult to predict workload ahead of time. Recent investigations on human dynamics show several empirical evidences that, different from common belief respecting random-based Poisson distributions, patterns of human activities fit into some power law, heavy tail patterns. Our hypothesis lies upon the question whether or not controller's dynamics obeys the same power law pattern. Our first attempt consists in analyzing the temporal characteristics of controller activities, in term of communication activities. The analysis on ATCOSIM Air Traffic Control Simulation Speech corpus shows that inter-communication times do follow a heavy tail pattern. Over certain thresholds, the distribution of inter-communication times approximates power-law decaying, and the correlations between communication events and traffic activities are influenced by the time-scale selected. However, the meanings of the thresholds are not interpretable due to the lack of available information.**

Keywords- air traffic control; human dynamics; complex systems;

I. INTRODUCTION

Despite the wider and wider range of automation that has been introduced into Air Traffic Management (ATM) systems, scenarios in both SESAR and NextGen concepts still reckon that air traffic controllers (ATCO) continue to constitute the core function of the future system. As the decision-maker and executor of the system, the performance of the controller determines almost entirely the system safety and efficiency. The prediction of ATCO performance with respect to traffic activities is therefore of quantifiable importance.

It has been well known that workload is the main factor measuring controller's performance, and some research efforts have been focusing on measuring and predicting ATCO workload. Earliest work was based on queuing theory and examination of controller routine work. A queuing model was proposed by Schmidt et al. based on the hypothesis of the single-channel of man's information-processing activity, trying to quantify and predict the workload factors affecting controller performance [1-3]. Gawron [4] pointed out that controller workload could not be measured only by observation; data mining technology is also needed in order to calculate workload. The prevalent approach to measure workload is based on the controllers' subjective rating [5]. Controller are asked to report the workload rate that they were experiencing either they are controlling traffic or just afterwards. On-line ratings distracts controller from perceiving and controlling traffic, then could influence the workload results. Whereas for the workload obtained after work, it may fail to capture the essential property of workload as it emerges from the complex interaction of current traffic situation and controller.

Identifying the factors that drive workload is critical if one is trying to predict workload. Many researchers have tried to demonstrate the complexity factors that reduce sector capacity by increasing controller workload. These factors can be categorized into three groups, namely traffic factors, airspace configuration factors and operational constraints[6]. The Dynamic Density (DD) concept attempts to measure control-related workload as a function of both the traffic volume and traffic complexity [7, 8]. Hereafter, different metrics and approaches have been proposed to measure sector complexity [9-13]. A brief summary of some relevant work on cognitive complexity is presented by Hilburn [14]. Although considerable effort has been gone into identifying ATC complexity factors, a great deal of work remains.

Recent investigations showed that workload could be well understood only by considering how controllers use strategies to manage their workload and regulate their workload. Histon et al. [15, 16] showed that a recognized underlying structure could act as the basis for abstractions internal to the controller, which can simplify the controller's working mental model. Standard flow, critical points, grouping, and responsibility are the four common type structure-based abstractions. The reduction of the "order" is the most effective way to mitigate cognitive complexity. Moreover, in the workload modeling and predicting front, useful information can be found in Loft et al. [6], in which the authors pointed out the difficulties and shortcomings of existing studies and concluded with several suggestions, leading us to the study of the dynamics properties of workload incorporated with controller strategies management.

While the progress on the ATC workload analysis has been consequent, much of the available work show difficulties in the predictability of workload level. Given the fact that workload is one of the factors affecting human activities, from a system perspective, it is the human actions that influence the system operation.

Until recently, the temporal characteristic of human actions had been thought to be randomly distributed. The basic assumption of human dynamics models, used from communications to risk assessment, had been that the temporal characteristics of human activities could be approximated by Poisson processes. However, there is increasing evidences showing that the inter-event times, defined by the time difference between two consecutive activities, indeed follow non-Poisson statistical distribution. It can be well characterized by heavy-tailed patterns, with bursts of rapidly occurring events separated by long periods of inactivity. The analysis resulted from large empirical data sets, including human correspondence [17], email communication [18], human printing behavior [19], and online films rating [20], demonstrate that the distribution of inter-activities times can be well approximated by a power-law form with different exponents. Even the human trajectories show a high degree of temporal and spatial regularity [21]. The underlying similarity among human actions indicates that there exists the same law, which governs human activity.

For the first time, a priority queuing model was built by Barabasi to show the bursty nature of human activity rooted from the decision-based queuing process when human execute tasks [22]. Malmgren et al argued that the correspondence patterns are better described by a lognormal distribution rather than a power-law distribution [23]. They also constructed a double-chain Markov model for formulating the cascading non-homogeneous Poisson process, demonstrating that the human correspondence patterns are well described by the circadian cycle, task repetition and changing communication needs [18, 23, 24]. Indeed, it is very difficult to distinguish between power-law distribution and lognormal distribution.

Voice communication was the primary means used by controller to control air traffic before the emerging of digital data communication between controller and aircraft, such as CPDLC. However, it is still the only channel for information flow between pilots and controllers in most control centers. Thus, controller voice communications have direct impact on the whole system evolution. A set of communication activities can be seen as control strategies, which are the result of controller mental and physical efforts after the assessment of current situation according to their experiences. Analysis of communication data has a long history. In the past, communication events were extensively used to measure workload [5, 25-28]. In [5], Manning et al. have examined the relationship between communication events, subjective workload and objective task-load measures. The communication events used in their study were total number of communications, total time spent communicating, average time spent for an individual communication, and communication content. Although some measures of communication events are highly correlated with workload, the analysis does not make a unique contribution to the workload evaluation [5, 29].

It should be noticed that the focus of the above mentioned work is the relationship between communication events and workload, rather than the dynamics of communication activities. In this paper, we are interested in the patterns of communications of controllers; in particular the temporal behaviors of the depicted activities under the assumption that voice communications do reflect the activity level of controllers. We are interested in finding a relationship between controllers' communication dynamics and traffic activities, knowing that traffic complexity is nit necessarily the sole factor that drive ATCO communication events but emergencies and non-nominal events, which are randomly distributed.

The analysis is performed on the ATCOSIM Air Traffic Control Simulation Speech corpus of EUROCONTROL. The particular quantity we focus on is the inter-communication times, defined by the time differences between two consecutive speeches of the same controller. First, we give a general description of data used in this study, and examine the relationship between traffic activities and communication activities in Section II. Then, the statistical results are presented in Section III. Finally, we list several questions and suggestions Section IV, basically why our initial results demonstrate that controller dynamics could not be identified by the only use of current communication data.

II. METHOD

A. ATCOSIM Dataset

The controller communication data used in this study is from 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 communication data, which were recorded during ATC real-time simulations [30, 31]. These simulations were conducted between 20/01/1997 and 14/02/1997, with the aim to evaluate the concept of RVSM (reduced Vertical Separation Minimum) in Europe. For the purpose of ATCOSIM, only controllers' voice was recorded and analyzed. Considering the traffic initialization phase with little speech, the first half-hour of traffic was not recorded. Hence, 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. ATCOSIM dataset also gives information about communication activities, including the speech start time, duration of the speech, and the content of the speech.

Six simulation exercises, which were conducted by four controllers, are considered in our study. The general information of these exercises is given in Table I.

TABLE I. GENERAL DESCRIPTION OF SIMULATION EXERCISES USED

Exercise ID	ATCO ID	Recording Time	Number of A/C under Control	Number of communication events
zf1_07	zf1	58’15’’	66	211
zf2_07	zf2	64’30’’	65	222
sm1_07	sm1	57’40’’	66	165
sm2_07	sm2	59’16’’	66	235
zf1_08	zf1	47’41’’	61	196
sm2_07	sm2	56’34’’	62	215

B. *Traffic Activities and Communication Activities*

The ATCOSIM dataset does not provide any information about airspace configuration or traffic scenarios, portraying the pictures of traffic situations from a voice communication dataset is not straightforward. The only way to acquire the traffic information is to perform deep analysis from controller’s speech data by identifying aircraft call-signs spelled out by ATCO’s during standard transfer instructions (when aircraft is entering or leaving the sector). In other words, the duration of aircraft flying through the sector can be deduced by means of timing the differences between transfer out and transfer in instructions. Fig. 1 shows an example of communication events in exercise zf1_07. Moreover, instructions to each aircraft can also be enumerated and timed from voice communications. However, *circa* 5.2% of controller messages have not included aircraft call signs. Given the transfer in/out times of each aircraft, the number of aircraft under control within predefined duration can be obtained by iteration. The dynamics on traffic volume and communication events are illustrated as in Fig. 2.

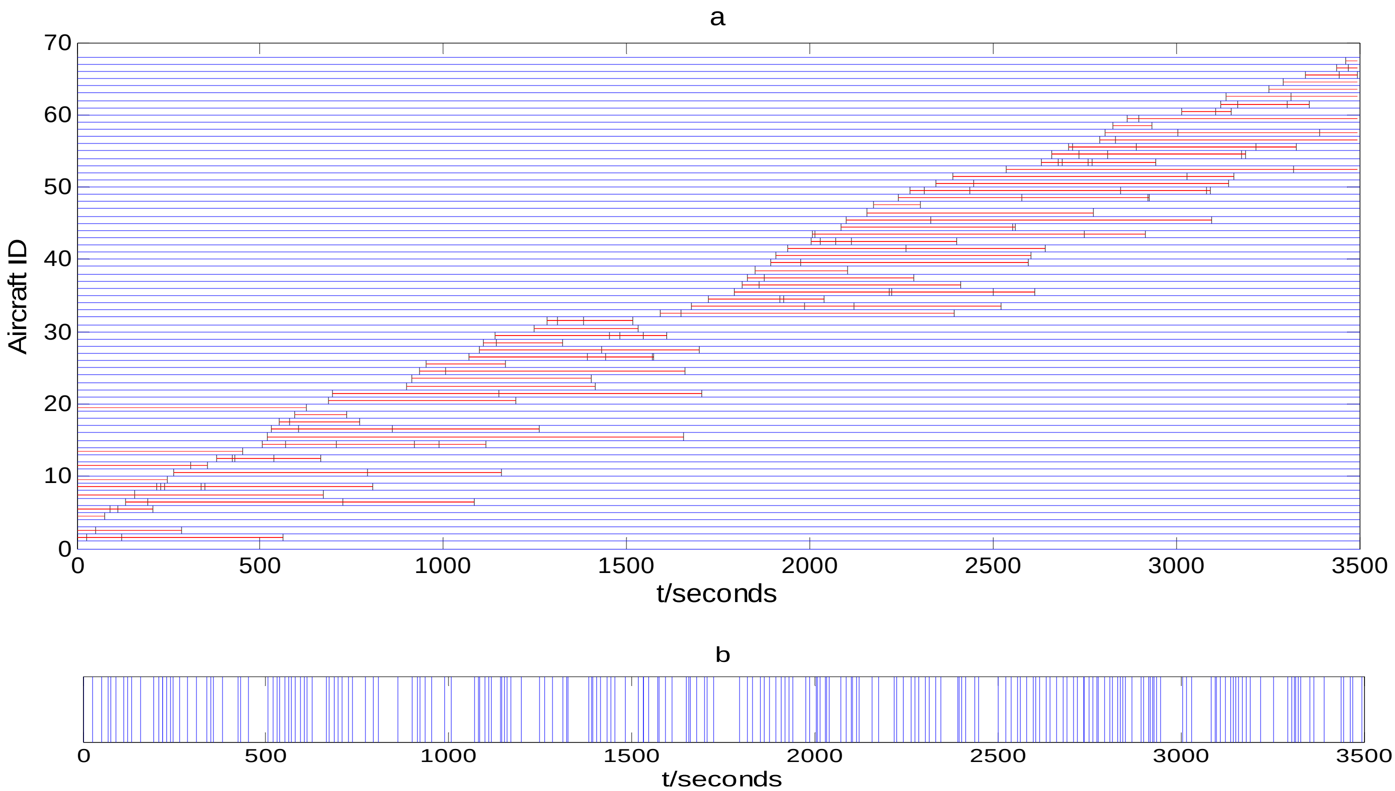

Figure 1. Historical communication activities constructed from controller speeches. a, Display of communication events according to the aircraft. Each horizontal red line stands for a different aircraft, with each vertical black line corresponding to a communication event. The length of red line denotes the duration that aircraft stays in the section during the exercise. b, The succession of communication activities of controller, with each blue vertical line represents a communication event over time.

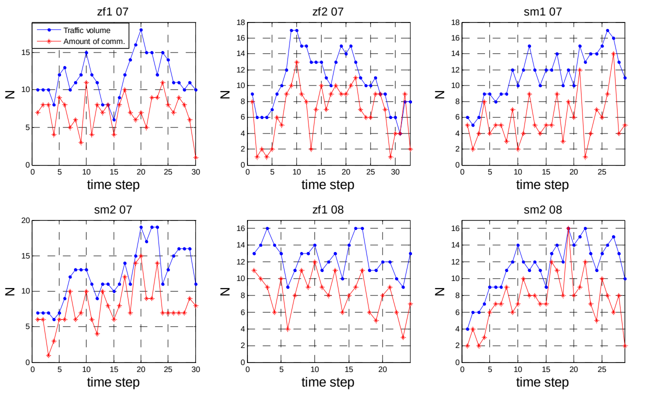

Figure 2. Statistical results on traffic volume and communication activities (time step: 2 minutes). The blue ● markers stand for the number of aircraft in the sector, while the red * denote the number of communication events in each time step.

It can be seen in Fig. 2 that the communication events vary with the change of number of aircraft in the sector. With the obtained number of aircraft and the number of communication events, we calculated the correlations between them. Table II shows these correlations with different time steps. We found that although the total number of aircraft under control is highly correlated with the number of communication events, which is in agreement with previous study [28], the strength of relationships change according to the time steps.

TABLE II. CORRELATIONS BETWEEN TRAFFIC AMOUNT AND COMMUNICATION EVENTS.

Exercise / Time step	zf1_07	zf2_07	sm1_07	sm2_07	zf1_08	sm2_08
1 minute	0.3207	0.6064*	0.4293*	0.5456*	0.5398*	0.5859*
2 minutes	0.3033	0.7520*	0.5849*	0.7162*	0.6840*	0.7586*
3 minutes	0.4863	0.8153*	0.6488	0.7724*	0.6344	0.8311*
5 minutes	0.3638	0.8836*	0.7340	0.8872	0.7676	0.8212*
10 minutes	0.7644	0.9531*	0.7183	0.8834*	0.6601	0.9481

* Correlation is significant at $p < 0.001$ level

III. RESULTS

We first analyze the number of aircraft as a function of the number of communication events. The aircraft without transfer in or transfer out instructions are discarded. As Fig. 3 shows, a large number of aircraft received less than 4 messages, while a small fraction of aircraft tends to get more. On average, less than 20% aircraft are communicated over 4 times (31% for sm2_07). After this initial drop however, few aircraft received 7 messages. Aircraft with more than 8 messages are supposed to have been in abnormal situations. We note that the discreetness and sparseness of the data does not allow us to prove the number of aircraft decay follows a power-law, though the shapes of curves look familiar. However, the graphical analysis of Fig 3 can be considered for further investigations. The differences of maximum number of aircraft between exercises could be interpreted with the different types of sectors. For example, the sectors in the exercises sm1_07 may be the en-route sector, whereas the sector in sm2_07 is an approach sectors with few flights flying- over.

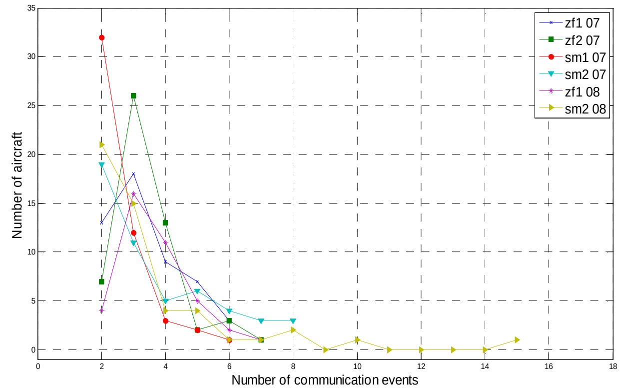

Figure 3. Number of aircraft distribution as a function of the number of messages it received.

To determine the temporal characteristics of communication activities, we investigated the distribution of inter-communication times in each exercise.

The inter-communication time in exercise j is measured as

$$t_i^j = T_{i+1}^j - (T_i^j + L_i^j) \qquad (1)$$

where T_i^j is the i^{th} communication event starts time, and L_i^j is the length of the i^{th} message.

Intervals less than one second are neglected. 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 α [32].

Here we use the method described in[33] to test and estimate the parameters of power-law, α and $t_{\min}$. The result is shown in Table III.

TABLE III. ESTIMATED PARAMETERS FOR POWER-LAW DISTRIBUTION

	zf107	zf207	sm107	sm207	zf108	sm208
α	2.8027	2.2104	2.0097	2.4286	3.6602	2.6093
$t_{\min}$ (in seconds)	12.491	7.0141	7.2485	8.1673	19.215	15.703
proportion	0.4029	0.5213	0.6474	0.4363	0.1907	0.2513

While $t_{\min}$ specifies a lower bound of the observed data over which the data shows power-law behavior, and the proportion of each exercise describe the amount of intervals which are greater than $t_{\min}$. However, the lack of available data to complement communication records has limited the explanation of the meaning of $t_{\min}$.

The CCDF of intervals in each exercise are plotted in a logarithmic picture (Fig. 4). Different marker stands for the different simulation data, while the solid line is the corresponding power-law fit form. Although the behaviors of intervals in each exercise are similar, especially zf2_07, sm1_07 and sm2_07, we cannot conclude that the distribution of inter-communication times follows a power-law distribution from the obtained results. More investigations on operational data should be established.

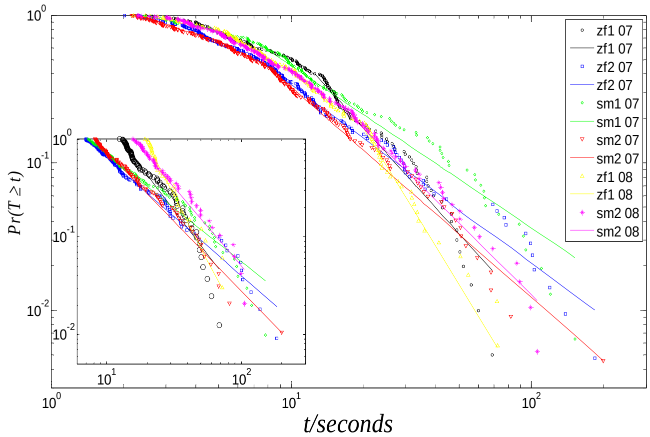

Figure 4. Distribution of inter-communication times of each exercise. The inset figure is the intervals greater than $t_{\min}$.

IV. DISCUSSION

The use of the underlying mechanisms that govern system evolution is a basic way to modeling, predicting and controlling system. While there is a great deal of expectation that the dynamics of controllers can be characterized by sole activities, our initial results demonstrate that it could not be identified by the only use of current communication data.

One of the possible reasons could be fact that the communication actions are not performed independently. For example, the sending of a next instruction may depend on the pilot's response to a previous one. Also as previous mentioned, the combination of several communication instructions might be related to control strategy.

Other reasons could be that the controllers were unfamiliar with the operation procedures when they did simulations. Meanwhile we didn't investigate the distribution of different types of communications according to their contents, as certain type of instructions, such as transfer-in and transfer-out, must be sent at certain time.

To fully understand the complex system, not only the network theory is required to capture the emergence and structural evolution of the skeleton of the system, but also the incorporated dynamical processes that are taking place on the mentioned network[34].

This paper presents the results of our first attempt on controller dynamics from a human dynamics approach. We reckoned that on top of human dynamics, network dynamics, i.e. interconnectivities between human activities overtime, would better illustrate the mechanism underlying current traffic situation. Therefore, network dynamics constitutes the core of the next steps of our investigations.

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REFERENCES

[1] D. K. Schmidt, "On modeling ATC work load and sector capacity," *Journal of Aircraft,* vol. 13, no. 7, pp. 531-537, 1976.

[2] D. K. Schmidt, "A queuing analysis of the air traffic controller's work load," *IEEE Transactions on Systems, Man and Cybernetics,* vol. 8, pp. 492-498, 1978.

[3] A. Robertson, M. Grossberg, and J. Richards, *Validation of air traffic controller workload models,* Transportation systems center, Cambridge, MA, 1979.

[4] V. Gawron, J. Ball, T. Slater *et al.*, "Intercorrelations among physiological and subjective measures of workload." pp. 755-760.

[5] C. Manning, S. H. Mills, C. M. Fox *et al.*, *Using air traffic control taskload measures and communication events to predict subjective workload,* DOT/FAA/AM-02/4, Federal Aviation Administration, Oklahoma City, 2002.

[6] S. Loft, P. Sanderson, A. Neal *et al.*, "Modeling and predicting mental workload in en route air traffic control: Critical review and broader implications," *Human Factors,* vol. 49, no. 3, pp. 376-399, 2007.

[7] I. V. Laudeman, S. Shelden, R. Branstrom *et al.*, *Dynamic density: An air traffic management metric,* NASA/TM—1998-112226, National Aeronautics and Space Administration, Ames Research Center;, 1998.

[8] B. Sridhar, K. S. Sheth, and S. Grabbe, "Airspace complexity and its application in air traffic management."

[9] A. J. Masalonis, M. B. Callaham, and C. R. Wanke, "Dynamic density and complexity metrics for realtime traffic flow management." pp. 23-28.

[10] G. B. Chatterji, and B. Sridhar, "Measures for air traffic controller workload prediction." pp. 16-18.

[11] S. Athenes, P. Averty, S. Puechmorel *et al.*, "ATC complexity and controller workload: Trying to bridge the gap." pp. 56-60.

[12] H. G. Busing, and R. J. Hansman, *Air traffic control operating modes and the management of complexity*, 2006.

[13] P. Kopardekar, J. Rhodes, A. Schwartz *et al.*, "Relationship of maximum manageable air traffic control complexity and sector capacity."

[14] B. Hilburn, *"Cognitive complexity in air traffic control –a literature review,"* EEC Note No.04/04, EUROCONTROL, Brétigny-sur-Orge, France, 2004.

[15] J. M. Histon, R. J. Hansman, B. Gottlieb *et al.*, "Structural considerations and cognitive complexity in air traffic control."

[16] J. M. Histon, and R. J. Hansman Jr, *Mitigating complexity in air traffic control: the role of structure-based abstractions,* ICAT-2008-05, ICAT, Cambridge, 2008.

[17] J. G. Oliveira, and A.-L. Barabasi, "Human dynamics: darwin and einstein correspondence patterns," *Nature,* vol. 437, no. 7063, pp. 1251-1251, 2005.

[18] R. D. Malmgren, J. M. Hofman, L. A. N. Amaral *et al.*, "Characterizing individual communication patterns," in Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, Paris, France, 2009, pp. 607-616.

[19] U. Harder, and M. Paczuski, “Correlated dynamics in human printing behavior,” *Physica A: Statistical Mechanics and its Applications,* vol. 361, no. 1, pp. 329-336, 2006.
[20] T. Zhou, H. Kiet, J. B. Kim *et al.*, “Role of activity in human dynamics,” *EPL,* vol. 82, no. 28002, 2008.
[21] M. C. Gonzalez, C. A. Hidalgo, and A.-L. Barabasi, “Understanding individual human mobility patterns,” *Nature,* vol. 453, no. 7196, pp. 779-782, 2008.
[22] A.-L. Barabasi, “The origin of bursts and heavy tails in human dynamics,” *Nature,* vol. 435, no. 7039, pp. 207-211, 2005.
[23] R. D. Malmgren, B. D. Stouffer, A. S. L. O. Campanharo *et al.*, “On universality in human correspondence activity,” *Science,* vol. 325, no. 5948, pp. 1696 - 1700, 2009.
[24] R. D. Malmgren, D. B. Stouffer, A. E. Motter *et al.*, “A poissonian explanation for heavy tails in e-mail communication,” *Proceedings of the National Academy of Sciences,* vol. 105, no. 47, pp. 18153-18158, November 25, 2008, 2008.
[25] K. Cardosi, “Time required for transmission of time-critical air traffic control messages in an en route environment,” *International Journal of Aviation Psychology,* vol. 7, pp. 171 - 182, 1993.
[26] K. Corker, B. F. Gore, K. Fleming *et al.*, "Free flight and the context of control: Experiments and modeling to determine the impact of distributed air-ground air traffic management on safety and procedure."
[27] D. Morrow, and M. Rodvold, "Communication issues in air traffic control," *Human factors in air traffic control,* M. Smolensky and E. S. Stein, eds., pp. 421 - 456, San Diego, CA, 1998.
[28] C. Manning, C. Fox, and E. Pfleiderer, “Relationships between measures of air traffic controller voice communications, taskload, and traffic compleixty,” in The 5th USA/Europe ATM R&D Seminar, Budapest, Hungary, 2003.
[29] C. Manning, and E. Pfleiderer, *Relationship of sector activity and sector complexity to air traffic controller taskload*, 2006.
[30] K. Hofbauer, S. Petrik, and H. Hering, "The ATCOSIM corpus of non-prompted clean air traffic control speech."
[31] H. Hering, *Technical analysis of ATC controller to pilot voice communication with regard to automatic speech recognition system,* EEC Note N. 01/2001, EUROCONTROL Experimental Centre, Paris, France, 2001.
[32] M. Mitzenmacher, “A brief history of generative models for power law and lognormal distributions,” *Internet Mathematics,* vol. 1, no. 2, pp. 226 - 251, 2004.
[33] A. Clauset, C. R. Shalizi, and M. E. J. Newman, “Power-law distributions in empirical data,” *SIAM Review,* vol. 51, no. 4, pp. 661 - 703, 2009.
[34] A. L. Barabasi, “The architecture of complexity,” *Control Systems Magazine, IEEE,* vol. 27, no. 4, pp. 33-42, 2007.