Analysis of temporal, spatial dimensions and fluctuation scaling of controller's activities from a human dynamics perspective

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Analysis of Temporal, Spatial Dimensions and Fluctuation Scaling of Controller's Activities from a Human Dynamics Perspective

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ABSTRACT

The automation systems have been prompting the improvement of capability of the Air Traffic Management (ATM) system. However, there remains substantial debate over the role of air traffic controller (ATCO), in particular, controller's activities that are closely related to the operation safety in both current ATM system and future ATM system. As a matter of fact, researchers and operational experts have long been sought the way to measure and predict controllers' activities. With a few exception, most of existing works are incapable of predicting controllers' activities correctly. The difficulty roots in the inadequate knowledge of the dynamics of air traffic controllers. In the context of transforming of the ATM system, there is a need for a generalized description on air traffic controllers' activities.

Recent human dynamics research has unmasked astonishing statistical characteristics in human activities which indicate there might exist a universal law that governs human activities. Building upon the previous research on controllers, this thesis analyzes air traffic controllers' dynamics from human dynamics perspective using a complex system approach.

The first part of this thesis presents the study of temporal behaviors of controllers' communication activities based on two real time simulation datasets and three operational datasets. The analysis based on a two-week real time simulation dataset is performed to examine the interaction between traffic activities and controllers' communication activities. It is, however, found that neither the Dynamic Density nor the Complexity based on Dynamical System Modeling approach has significant influence on the controllers' communications. The use of Detrended Fluctuation Analysis (DFA) found that the inter-communication times of controller are long-rang correlated. Compared to exponential distribution, lognormal distribution, and power law distribution, inverse Gaussian distribution is better to describe the inter-communication times. While taking the fact that it takes **ELEVEN seconds** in average for a successful message transmission into account, a Power law distribution is perfectly fitted to the intervals, with the exponent $\alpha \approx 3.0$. The large exponents suggest the controllers' activities decay much faster than other human activities due to the high pressure and stress.

In the second part, a temporal network approach is proposed to study the "spatial behavior" of controller, aiming at capturing the information propagation process of the controllers. Accounting for the traffic, we transform the controller's communication events that contain both temporal information and flights' information into a network, allowing us to trace the information flow over the flights. (1) In the time aggregated

networks, we found that the degree distribution can be described with the normal distribution which indicate the randomly selection of flights. By leveraging on the community detection algorithm, we found the correlations between traffic and communities sizes (i.e. the number of flights) in the networks. (2) In the temporal networks, we first measure the time dependent degree distribution, and the results show the similar patterns across all the data. We then define three types of motifs, namely chain, loop, and star. A changing point was observed at $\tau_{tw} \approx 150$ seconds where both the percentage of chains and percentage of loops reach at 50%. Chains and loops are identified to be the most frequently occurred topologies in the controller's communication as such topological characteristics being reported in other human communication.

In the third part, we perform the fluctuation scaling analysis of controllers' communications. Empirical results show that the relationship between the average communication activities and its standard deviation can be well described by the Taylor's power law series with $\alpha \approx 0.60$. On the basis of cognitive studies of structure-based abstraction, we build a model to test the grouping behavior that can cause the fluctuation scaling phenomenon. From the simulation results, we draw the conclusion that there were around 10% flights being grouped when the controllers managed the traffic.

The work presented in this dissertation not only provide a fundamental understanding of air traffic controllers' activities, but also may shed light on other human driven system related aspects.

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RÉSUMÉ

0.1 Contexte

L’industrie du transport aérien offre un service de transport pour le grand public dans le but de permettre le commerce, les affaires et les voyages d'agrément. Pour fournir un transport aérien sûr et précis, la gestion du trafic aérien (ATM, *Air Traffic Management*) tend à une gestion dynamique et intégrée de la sécurité de l’espace aérien grâce à la fourniture d'équipements et de services sans couture (*seamless*) en collaboration avec toutes les parties (ICAO 2005). En tant qu’élément clé de l'ATM, le contrôleur du trafic aérien est étroitement lié à la sécurité et à l'efficacité du système. Depuis 1960 (Davis, Danaher et al. 1963), il y a des efforts en cours pour étudier les facteurs humains dans le système ATM, ce qui contribue à notre compréhension des activités de contrôleurs aériens. Cette thèse portera sur l'analyse empirique de la dynamique des contrôleurs aériens d'un point de vue « système complexe » en explorant les caractéristiques temporelles et spatiales de leurs activités de communication ainsi que leurs fluctuations.

0.1.1 Background

Les contrôleurs aériens, appelés simplement « contrôleurs », sont les personnes qui sont responsables de la maintenance et de l’efficacité d’un écoulement sûr et ordonné du trafic aérien. Utilisant les systèmes CNS (*Communication, Navigation and Surveillance*), les contrôleurs dirigent les avions se déplaçant sur le sol et dans l'air. Ils sont tenus de prendre des décisions rapides en réponse aux changements du trafic. La communication vocale était le principal moyen utilisé par les contrôleurs pour contrôler le trafic aérien avant l'émergence de la communication de données numériques entre le contrôleur et les avions. Cependant, c’est encore le seul et principal canal de communication d'informations entre les pilotes et les contrôleurs dans la plupart des centres de contrôle. En fournissant des instructions et des autorisations aux pilotes à travers le système de communication, les contrôleurs dirigent le trafic aérien avec plusieurs objectifs. L'objectif principal est de s'assurer que chaque appareil atteigne sa destination sans risque de collision avec d'autres aéronefs, des phénomènes météorologiques violents, et des zones dangereuses ou des obstacles. En d'autres termes, tous les avions relevant de sa compétence doivent respecter les normes de séparation émises par l'Organisation internationale de l'aviation civile (ICAO, *International Civil Aviation Organization*) ou l'autorité locale des transports. D'autres objectifs tels que l'organisation d'une circulation ordonnée et efficace seront ensuite réalisés.

Pour améliorer la capacité du contrôleur à gérer le trafic, différents outils d'aide à la décision ont été développés et déployés. Malgré l'éventail de plus en plus large de l'automatisation qui a été introduite dans les systèmes ATM, des scénarios à la fois dans les concepts SESAR et NextGen montrent que les contrôleurs de la circulation aérienne continuent de constituer la principale fonction du système de l'avenir. La compréhension de la complexité du comportement de l'opérateur et de son management représente un défi pour la communauté de recherche.

0.1.2 Énoncé du problème et la portée de la recherche

Bien comprendre les comportements des contrôleurs du trafic aérien est d'une importance cruciale pour la sécurité et l'efficacité du système ATM. En raison des interactions non linéaires entre le trafic aérien, l'espace aérien et le contrôleur de la circulation aérienne, les études existantes n'ont pas réussi à saisir la nature instinctive des activités du contrôleur. Les travaux de recherche basés sur la psychologie et les sciences cognitives ont atteint des résultats importants sur la façon dont se comporte le contrôleur quand il contrôle la circulation, en étudiant la charge de travail mental, la complexité cognitive, etc. Cependant, décrire quantitativement les comportements du contrôleur en fonction de la répartition du trafic et des configurations différentes de l'espace aérien, est encore mal compris.

Beaucoup de tâches des contrôleurs se font pendant la communication avec un aéronef ou après la communication avec un aéronef. Pour l'exécution de ses tâches, un contrôleur accepte les données en entrée, les informations sur le processus, il définit les priorités et les actions à réaliser (Rodgers et Drechsler, 1993). La réponse des contrôleurs à ces tâches est toutes les communications qui sont reflétées dans la charge de travail des contrôleurs (Stein, 1985). Bien qu'il existe de nombreux facteurs affectant les activités des contrôleurs, et qui par conséquent influent sur le système, d'un point de vue système cd sont les communications vocales du contrôleur qui influent principalement sur le fonctionnement du système. Par définition, l'activité est un système cohérent de processus internes, de comportements et de motivations externes qui sont combinés pour atteindre des objectifs conscients (Bedny et Meister, 1997). Nous supposons que l'activité de communication vocale du contrôleur encapsule les efforts cognitifs et physiques du contrôleur qui sont nécessaires pour accomplir sa mission principale qui est d'assurer la sécurité et l'efficacité du trafic aérien (voir la figure 0-1).

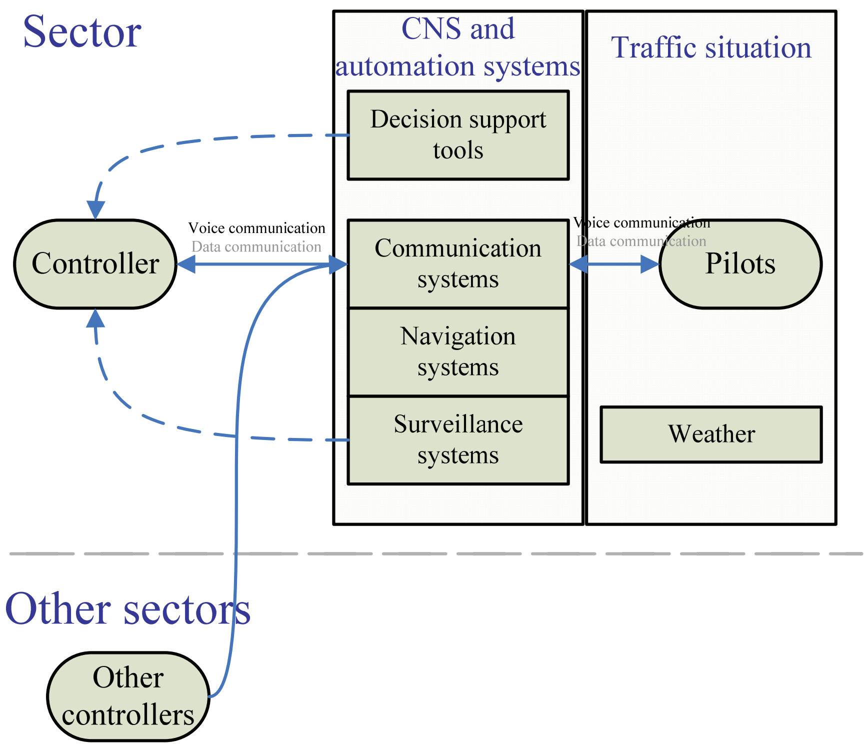


Figure 0- 1 Le rôle de contrôleur de la circulation aérienne

Cette thèse examine la dynamique des communications vocales des contrôleurs aériens. Les données empiriques étudiées dans cette thèse sont les données de communication vocale entre les contrôleurs et les pilotes. Des données à la fois opérationnelles et de simulation ont été enregistrées dans des secteurs d'approche et des secteurs en-route.

0.1.3 Motivation

La science et l'ingénierie ont longtemps étudié les principes de la compréhension des systèmes complexes (Guckenheimer et Ottino2009). Dans notre domaine, l'impulsion pour ces études est motivée par la nécessité de modéliser et de comprendre fondamentalement le système ATM. Le renforcement des bases de connaissances des activités humaines est nécessaire pour atténuer l'occurrence d'événements dangereux. Dans ce système complexe, le contrôleur en tant qu'élément essentiel a une influence directe sur le système qui est en constante évolution. De grands efforts ont été faits pour la mesure et la prédiction de la charge de travail du contrôleur aérien. Ces travaux sont encore insuffisants pour prédire le comportement et les performances du contrôleur en raison de la dynamicité de la charge de travail (Loft, Sanderson et al. 2007).

Depuis 2005, les enquêtes sur les données de différents types de d'activités humaines montrent qu'il y a des schémas similaires d'activités entre les êtres humains. Ces activités vont de la correspondance ordinaire (Barabasi 2005), de la communication par courrier électronique (Malmgren, Hofman et al. 2009), de la communication par messages courts (Wu, Zhouet al. 2010), de l'impression de documents (Harder et Paczuski 2006), de l'évaluation de films en ligne (Zhou, Kiet et al. 2008), à la mobilité humaine (Gonzalez, Hidalgo et al. 2008). Ces résultats indiquent qu'il peut y avoir des lois universelles qui régissent les activités humaines.

Table 0- 1 Comparaison entre les activités des contrôleurs aériens et d'autres activités

	Activité du contrôleur	Activité humaine normale
Caractéristiques	Pression élevée Période de 2 heures	Pression peu élevée Durée longue
Méthodes d'étude	Psychologie Sciences cognitives	Data mining Statistiques
Résultats	Description comportementale en fonction des activités internes	Mesures quantitatives Schémas universels
Inconvénients	Modèle non prédictif Résultats dépendant du trafic, de l'espace aérien et autres facteurs. Echelle trop petite pour être adaptée à l'ATM en entier.	Peu d'études sur les activités dirigées par les tâches Ne peut pas être appliqué simplement à l'ATM.
Le point commun entre les activités du contrôleur et d'autres activités est l'**ADAPTATION**.		

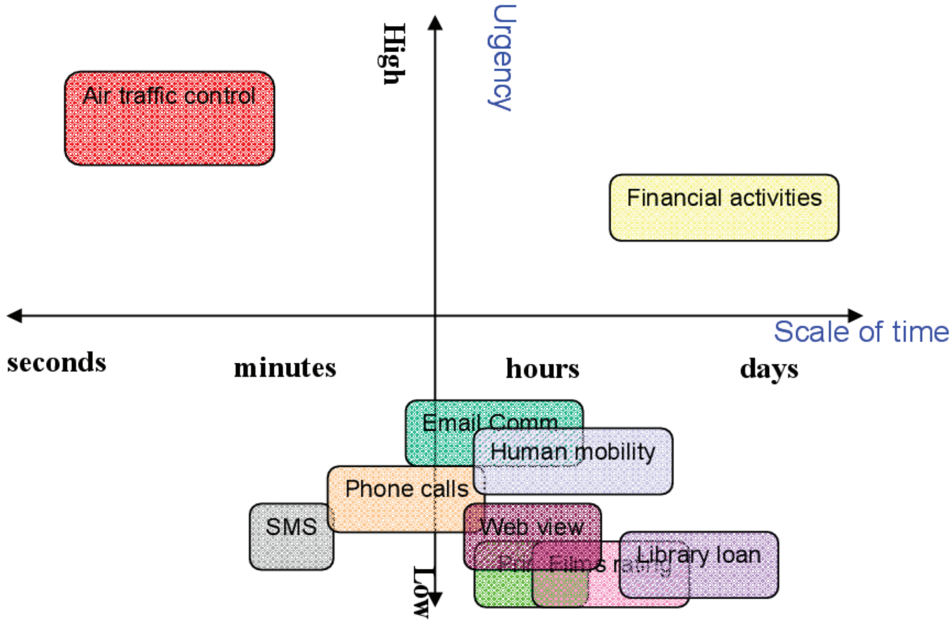


Figure 0- 2 Benchmarking des activités humaines en termes d'urgence et de durée

D'un point de vue système complexe, les humains évoluent en réponse aux besoins liés aux évolutions de l'environnement contextuel grâce à l'adaptation, pour éviter l'échec et pour garantir des performances utiles et fiables à un coût minimal. Les activités qui sont analysées dans la recherche sur la dynamique humaine sont généralement à basse pression et à longues durées. Aucune activité à haute pression telle que le contrôle du trafic aérien n'a été bien étudiée. Une meilleure compréhension des activités humaines sous haute pression facilitera l'évitement des erreurs humaines qui peuvent conduire à une catastrophe système, en particulier pour les systèmes de sécurité concernés, tels que le système ATM ou bien aussi les centrales nucléaires.

0.1.4 Objectif de la recherche

Compte tenu des motivations présentées ci-dessus, l'objectif de cette recherche est d'explorer la dynamique des activités de communication du contrôleur aérien, de fournir une première démonstration de la compréhension physique des règles selon lesquelles le contrôleur aérien contrôle le trafic. Plus précisément, l'objectif est :

(i) d'enquêter sur les comportements temporels des activités de communication des contrôleurs;

(ii) de démontrer l'utilisation de la dynamique des réseaux pour étudier les comportements spatiaux;

(iii) d'étudier les variations d'échelle des fluctuations des activités de communication tout en prenant le contrôleur comme une composante de l'ATM ;

(iv) de modéliser et simuler les mécanismes sous-jacents que les contrôleurs emploient, ce qui pourrait également s'étendre à expliquer et prévoir des activités humaines similaires.

0.1.5 Contributions

La proposition principale de cette thèse est de fournir une compréhension physique des activités de contrôleurs aériens. Sur la base des analyses des activités de communication vocale des contrôleurs aériens, nous fournissons une étude systématique des propriétés statistiques de leurs communications.

Nous avons trouvé que les communications des contrôleurs semblent être des processus à mémoire longue par l'utilisation de l'analyse de fluctuations redressées.

Nous avons montré que les communications des contrôleurs présentent des caractéristiques statistiquement du genre *heavy tailed*. Les comportements collectifs des contrôleurs sont caractérisés par une forme en loi de puissance, tandis que les modèles individuels se montrent beaucoup plus hétérogènes.

Une approche à base de réseau temporel a été proposée pour retracer les activités des contrôleurs, ce qui contribue à la quantification des activités humaines.

Nous avons capturé les phénomènes de fluctuation des activités de communication des contrôleurs. De tels phénomènes sont bien expliqués par notre modèle qui décrit le comportement de regroupement des contrôleurs. Les fluctuations d’échelle peuvent nous amener à évaluer la capacité du secteur.

Notez que bien que cette thèse se concentre sur les activités des contrôleurs aériens, il offre aussi des approches et des résultats qui vont au-delà du domaine ATM.

0.2 Les données de testes

Les données opérationnelles et les données de simulation en temps réel ont été recueillies pour étudier les comportements de communication des contrôleurs. Deux ensembles de données de simulation en temps réel, à savoir les données de simulation TMA Pariset et les données de corpus ATCOSIM, viennent du Centre expérimental d'EUROCONTROL, tandis que deux jeux de données réelles ont été enregistrés dans différents centres ATC aux États-Unis d'Amérique et en Chine.

0.2.1 D_1 Dataset

Le premier jeu de données contient des données de simulation TMA Paris, qui ont été enregistrées au cours de deux semaines de simulation en temps réel au Centre Expérimental EUROCONTROL en juin 2010. Le but de cette simulation était de tester la viabilité des améliorations proposées par le français DSNA pour le système ATM desservant Paris-Charles De Gaulle, Paris-Orly et Paris-Le Bourget.

0.2.2 D_2 Dataset

Le deuxième ensemble de données qui a été analysé est l'Air Traffic Control ATCOSIM Simulation Speech Corpus du Centre Expérimental EUROCONTROL. Il se compose de dix heures de données de communication, qui ont été enregistrées au cours de simulations ATC en temps réel qui ont été menées entre les 20/01/1997 et 14/02/1997 (Hering 2001). Seule la voix des contrôleurs a été enregistrée et analysée. Chaque enregistrement se compose d'environ une heure de données de communication. Les données sont composées du signal de parole et de la transcription de l'énoncé, avec l'annotation complète et les métadonnées pour tous les énoncés. Les données de simulation enregistrées ne comprennent pas toutes les informations sur le trafic ou l'espace aérien correspondant aux données de communication.

0.2.3 D_3 Dataset

Pour étudier les effets des autres facteurs sur la communication du contrôleur, comme la culture, nous avons obtenu les données opérationnelles de plusieurs centres de contrôle de la circulation aérienne aux États-Unis d'Amérique. D_3 Dataset est fondés sur les données opérationnelles enregistrées à Kansas City en 1999. Il se compose de 8 échantillons, comprenant quatre secteurs, à savoir le secteur 14, le secteur 30, le secteur 52, et le secteur 54. Au total, il y a 999 événements de communication. En moyenne, chaque échantillon de trafic dispose de 125 événements de communication. Environ 47% de la communication a été faite par le contrôleur radar, 53% a été faite par les pilotes et les autres contrôleurs, voir (Manning, Mills et al. 2002) pour plus de détails.

0.2.4 D_4 Dataset

Les données D_4 Dataset ont été recueillies à partir de 840 heures d'enregistrement des communications contrôleurs-pilotes à Chicago (ZAU) Air Route Traffic Control Center pendant le fonctionnement quotidien. L’analyse de la parole a d'abord été menée afin de récupérer les informations temporelles sur les communications vocales. Par l'utilisation de boîte à outils de segmentation parole, tels que des boîtes à outils Spkdiarization (Peignier et Merlin2010), le silence ou l'activité audio ont été identifiés avec un seuil de 2 secondes. Puis l'heure de début et de fin de chaque événement de communication peut être obtenue. Au total, il y a 59,589 événements de communication contrôleur / pilote dans cet ensemble de données. La *diarisation* de paroles permettant de calculer des données précises sur « qui a parlé et quand » est à l’étude.

0.2.5 D_5 Dataset

Les données D_5 Dataset ont été recueillies au Shanghai Air Traffic Control Centre au début des années 2012. Les activités de communication des contrôleurs ont été enregistrées manuellement sur le site pendant les heures de pointe. Il y a plus de vingt pièces d’enregistrement incluant au total 6,025 activités de communication de contrôleurs.

0.3 Les caractéristiques temporelles des activités de communication des contrôleurs

Les études antérieures sur les communications des contrôleurs mettent l'accent sur les relations entre les événements de communication et la charge de travail mental des contrôleurs plutôt que sur les propriétés dynamiques de la communication. Jusqu'à présent, il y a un manque de compréhension quantitative des mécanismes qui régissent l'activité des contrôleurs.

Les analyses sur différentes gammes de jeux de données des activités humaines ont montré que, à la différente de la croyance commune qu’elles respectent des distributions de Poisson, les schémas des activités humaines ont une distribution en loi de puissance du type *heavy tailed*. Avec le plein essor des preuves empiriques de la dynamique des activités humaines, on a trouvé des motifs similaires, ce qui suggère qu'il existe des mécanismes universels régissant les activités humaines. On pourrait argumenter qu'il existe des différences significatives entre les activités des contrôleurs aériens et les autres activités humaines quotidiennes. Néanmoins, l'apparition de la recherche sur la dynamique des activités humaines fournit les aspects méthodologiques de la compréhension des activités des contrôleurs aériens dont nous discuterons dans cette section.

0.3.1 Définitions

Pour examiner les activités des contrôleurs du trafic aérien, nous allons donner les définitions suivantes qui seront utilisés dans la présente section et par la suite.

(1) **Événement de communication (TR).** Il est défini lorsque le contrôleur presse le bouton Push-to-talk et le maintient enfoncé afin d'envoyer le message aux aéronefs. Il est aussi appelé « Transmission » (TR). La transmission vide est également considérée comme un événement de communication complète.

(2) **Transaction (CT).** Une conversation complète entre un aéronef et un contrôleur. Elle est composée de transmissions (TR) séparées qui sont alternativement effectuées par le contrôleur et le pilote. Ceci est défini comme « *Communication Transaction* » (CT) (Hunter et Hsu, 1977). Par exemple, les deux premiers événements de communication bleus sur la Figure 0-3 pourraient être un CT si les quatre premières bandes sont à propos de la conversation entre PL1 et le contrôleur.

Les mesures temporelles qui seront utilisés sont:

(1) L_i : la durée de l'événement de communication i ;

(2) τ_i : le temps inter-arrivée, c'est à dire la différence de temps entre deux événements de communication consécutives i et $i+1$;

(3) τ_w : la longueur de l'intervalle inter-communication. Il est défini comme la longueur de temps entre deux TC consécutives.

La recherche sur les communication des contrôleurs aériens a défini plusieurs mesures de communication pour identifier les relations entre les communications et la charge de travail des contrôleurs dont beaucoup sont liés à une fenêtre de temps t_w (Bruce, Freeberg et al 1993 ; Cardosi 1993 ; Porterfield 1997 ; Morrow et Rodvold ; Corker, Gore et al 2000). Après le travail de (Manning, Mills et al 2002), nous listons deux mesures à l'étude :

C_t^N : le nombre d'événements de communication qui se produisent dans t_w ;

C_t^D : la densité de communication, définie comme $C_t^D = L_t(C_t^N)^\beta$ et β est le paramètre d'équilibre de la fréquence de communication.

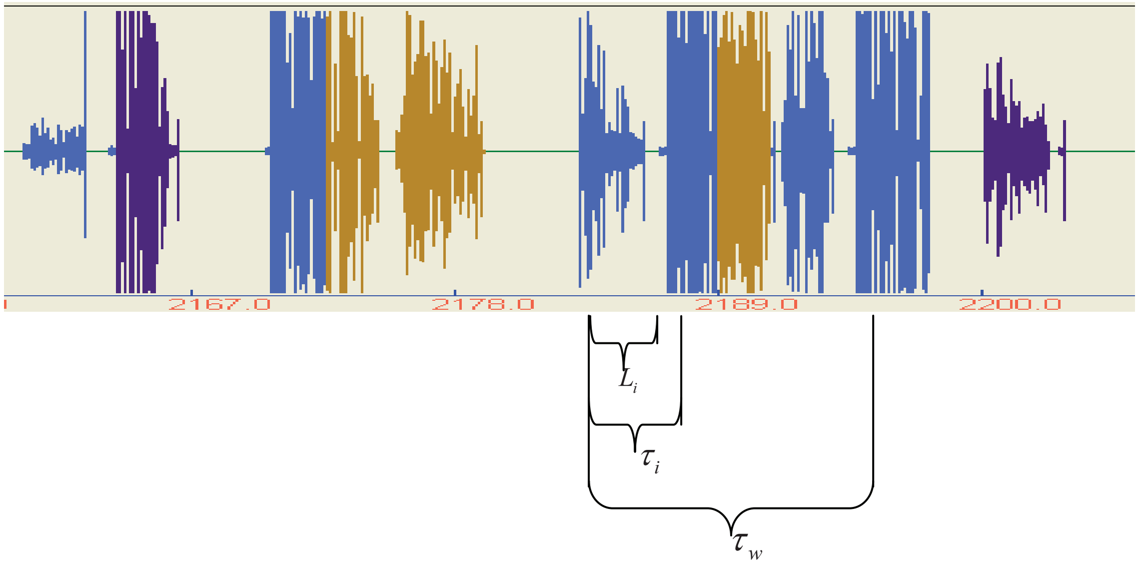


Figure 0- 3 Définitions des activités de communication d'un contrôleur. En bleu sont les communications faites par le contrôleur, en jaune et violet foncé sont les communications faites par les pilotes. Les données ont été enregistrées dans l'ATC Chicago Center.

0.3.2 Les corrélations entre les activités des contrôleurs et la complexité du trafic aérien

Dans cette section, nous présentons les résultats sur les corrélations entre les activités de communication des contrôleurs et des activités de l'espace aérien. L'activité de l'espace aérien est l'activité associée à l'avion et aux conditions météorologiques se déplaçant à travers le secteur. Ici, nous utilisons deux indicateurs de complexité du trafic aérien, à savoir la densité dynamique (DD) et la complexité du trafic aérien basé sur une approche modélisation de système dynamique (C-DSM).

Dans le tableau 0-2, nous présentons les coefficients de corrélation qui montrent les relations entre les activités de communication du contrôleur et les différents facteurs de la circulation aérienne de chaque secteur. La fenêtre de temps t_w et le temps d'échantillonnage en DD sont à 2 minutes tandis que l'exposant β est 2. Les paramètres pondérés pour le calcul DD sont obtenus par les tests de régression.

Il peut être vu à partir de la table que DD est tout à fait en corrélation avec les événements de communication et la densité de la communication. Alors que le C-DSP montre une relation très faible avec les communications, le C-DSM dans la plupart des secteurs sont en corrélation négative avec le DD. Les deux dernières colonnes présentent les coefficients de corrélation moyenne et l'écart-type associé. Une fois encore, le DD et C-DSM semblent être indépendants les uns des autres.

A partir des résultats obtenus à ce jour, nous tirons la conclusion que la complexité du trafic aérien a peu d'impact sur la dynamique de la communication du contrôleur.

Table 0- 2 Les coefficients de corrélation entre la communication et les facteurs de la circulation. Les valeurs entre parenthèses sont négatives.

	Nbr d'événements de communication				Densité de ommunication				DD VS C-DSM	
	COMM VS DD		COMM VS C-DSM		COMM VS DD		COMM VS C-DSM			
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
AOUS	0.74	0.06	(0.10)	0.08	0.67	0.13	(0.08)	0.03	(0.26)	0.10
AP	0.36	0.19	(0.01)	0.03	0.31	0.19	(0.00)	0.03	0.17	0.20
AR	0.54	0.12	(0.06)	0.10	0.55	0.15	(0.03)	0.03	(0.13)	0.09
CREIL	0.26	0.18	0.00	0.02	0.22	0.21	(0.00)	0.02	0.21	0.16
DENPG	0.57	0.09	(0.01)	0.03	0.53	0.07	(0.02)	0.02	(0.12)	0.08
DEPPO	0.71	0.09	(0.02)	0.04	0.59	0.13	(0.02)	0.03	(0.12)	0.08
DESPG	0.55	0.14	(0.01)	0.03	0.50	0.09	(0.02)	0.02	(0.15)	0.05
INIPO	0.55	0.16	(0.01)	0.05	0.49	0.15	(0.01)	0.03	(0.09)	0.15
INNPG	0.68	0.09	(0.02)	0.02	0.65	0.05	(0.03)	0.02	(0.21)	0.06
INSPG	0.42	0.23	(0.01)	0.03	0.45	0.24	(0.02)	0.03	(0.15)	0.13
ITBPG	0.50	0.14	0.02	0.03	0.33	0.16	0.01	0.03	0.12	0.11
ITMPO	0.26	0.30	(0.04)	0.04	0.20	0.27	(0.03)	0.05	(0.02)	0.17
ITNPG	0.68	0.11	(0.04)	0.04	0.49	0.09	(0.05)	0.03	(0.07)	0.10
ITSPG	0.64	0.13	(0.04)	0.05	0.46	0.13	(0.03)	0.03	(0.09)	0.21
OGRT	0.62	0.07	(0.02)	0.05	0.64	0.04	(0.03)	0.04	(0.11)	0.12
OYOT	0.67	0.21	(0.00)	0.03	0.65	0.14	(0.01)	0.04	(0.10)	0.09
TE	0.65	0.16	(0.01)	0.04	0.64	0.14	(0.02)	0.03	(0.04)	0.20
THLN	0.70	0.20	0.03	0.06	0.57	0.16	0.03	0.07	0.06	0.18
TML	0.62	0.26	(0.01)	0.05	0.50	0.25	(0.01)	0.02	(0.16)	0.07
TP	0.65	0.13	(0.02)	0.09	0.60	0.12	(0.01)	0.05	(0.05)	0.16
UJ	0.62	0.15	(0.05)	0.05	0.56	0.17	(0.02)	0.04	(0.06)	0.14
VILLA	0.26	0.27	0.02	0.05	0.20	0.22	0.04	0.07	(0.04)	0.12

0.3.3 DFA des activités des contrôleurs

Pour examiner la statistique d'auto-affinité des événements inter-communication de chaque ensemble de données, une analyse du deuxième ordre fluctuation redressée (DFA) a été réalisée. DFA a été largement utilisée pour analyser les caractéristiques statistiques de processus stochastiques différents (Peng, Buldyrev et al, 1994 ; Kantelhardt, Zschiegner et al 2002). En bref, la série temporelle $x_t, t \in N$ est d'abord convertie en un processus non borné Y_t par sommation cumulative. Puis la série temporelle convertie est divisée en $N_s = N / s$ observations pour une longueur de fenêtre s. Des tendances locales peuvent être trouvées par la forme linéaire ou polynomiale des données Y_t dans la fenêtre, et la fluctuation $F(s)$ est calculée par l'écart racine carrée moyenne de la tendance (root mean-square deviation). En règle générale, $F(s)$ va augmenter avec la longueur de la fenêtre s. Un tracé log-log de $F(s)$ en fonction de s est construit. Une relation linéaire indique $F(s) \propto s^{\alpha}$ qui permet de dire si la série temporelle semblent être processus à mémoire longue ou un bruit en $1/f$. Généralement, la propriété statistique de la série temporelle sera révélée par l'exposant α de la manière suivante :

- $\alpha < 0.5$: anti-corrélés;
- $\alpha \approx 0.5$: non corrélées, le bruit blanc;
- $\alpha > 0.5$: corrélation;
- $\alpha \approx 1$: le bruit en $1/f$, un bruit rose;
- $\alpha > 1$: non-stationnaire, marche aléatoire, sans limite;
- $\alpha \approx 1.5$: bruit brownien.

Ci-dessous, nous rapportons les résultats utilisant la région $5 \leq s \leq 100$ pour l'estimation d'α .

Comme le montre la figure 0-4, quatre exposants sur cinq sont autour de 0,65, indiquant que les ensembles de données sont corrélés à long terme. Notez que D_3 Dataset a été construit à partir de huit de longs échantillons de 15 minutes et il y a moins de 470 communications de contrôleurs. Le peu de données dans D_3 Dataset pourrait être la raison principale pour laquelle les communications des contrôleurs ne sont pas corrélées. En revanche, les quatre autres ensembles de données présentent une forme en loi de puissance plus lente que la décroissance exponentielle. Il suggère que les comportements en communication des contrôleurs sont dépendants du long terme. Les exposants de chaque secteur de chaque exercice de D_1 sont donnés dans le tableau 0-3.

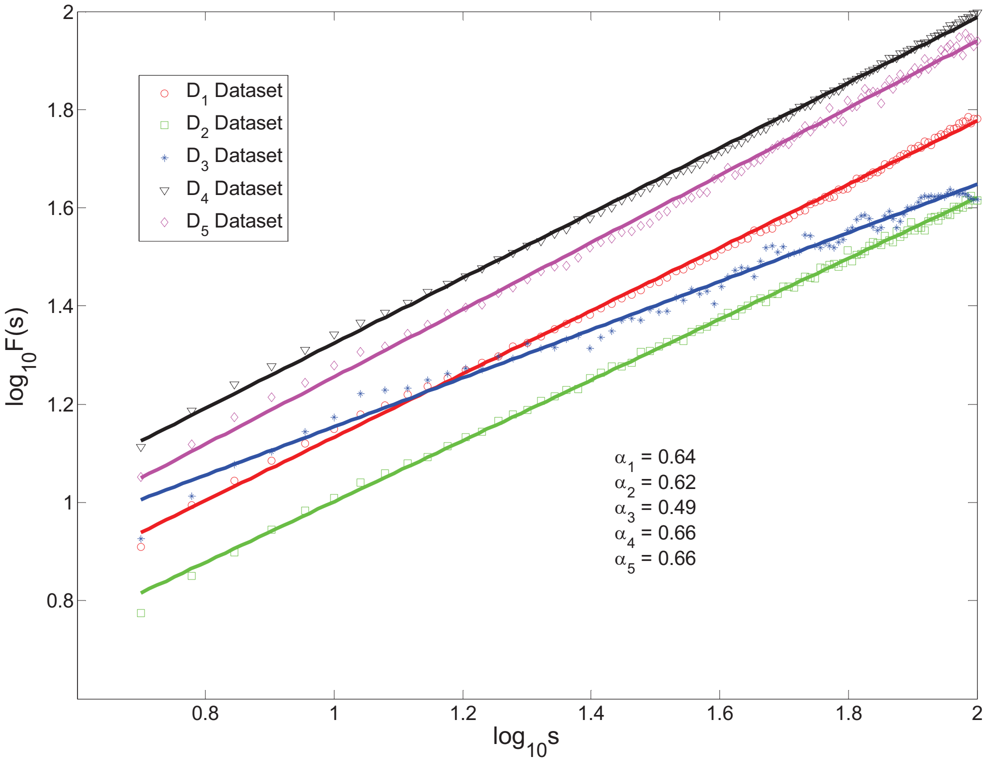


Figure 0- 4 DFA 2 fonction $\log_{10} F(s)$ par rapport à l'échelle de temps $\log_{10} s$

Table 0- 3 Exposants d'échelle DFA de chaque secteur de chaque exercice

	100607B	100610A	100610B	100611A	100611B	100614B	100615A	100615B	100616A	100616B	100617A	100617B	100618A	100618B	Mean	Std
AOUS	0.47	0.50	0.49	0.44	0.54	0.49	0.73	0.50	0.57	0.51	0.54	0.47	0.57	0.51	0.52	0.07
AP	0.45	–	–	0.56	0.61	0.61	0.56	0.41	0.62	0.59	0.84	0.69	0.62	0.58	0.60	0.11
AR	0.62	0.51	0.46	0.61	0.44	0.64	0.60	0.61	0.44	0.63	0.57	0.46	0.70	0.37	0.55	0.10
CREIL	0.75	0.56	0.97	0.42	0.37	0.54	0.78	0.45	0.60	0.62	0.60	0.59	0.76	0.75	0.62	0.16
DENPG	0.69	0.50	0.57	0.68	0.49	0.61	0.59	0.55	0.72	0.43	0.62	0.64	0.66	0.61	0.60	0.08
DEPPO	0.67	0.54	0.60	0.47	0.62	0.75	0.71	0.66	0.56	0.47	0.65	0.64	0.48	0.54	0.60	0.09
DESPG	0.53	0.56	0.65	0.53	0.56	0.49	0.65	0.62	0.62	0.45	0.66	0.53	0.59	0.53	0.57	0.07
INIPO	0.61	0.53	0.47	0.53	0.65	0.54	0.67	0.74	0.54	0.68	0.68	0.50	0.60	0.46	0.59	0.09
INNPG	0.67	0.63	0.66	0.61	0.79	0.63	0.55	0.57	0.59	0.72	0.48	0.53	0.62	0.67	0.62	0.08
INSPG	0.53	0.47	0.60	0.56	0.54	0.61	0.65	0.61	0.55	0.49	0.52	0.59	0.59	0.42	0.55	0.06
ITBPG	0.60	0.58	0.49	0.78	0.74	0.76	0.77	0.71	0.90	0.55	0.71	0.59	0.65	0.54	0.67	0.12
ITMPO	0.61	0.61	0.58	0.61	0.46	0.62	0.73	0.57	0.68	0.65	0.62	0.57	0.70	0.54	0.61	0.07
ITNPG	0.56	0.57	0.55	0.62	0.57	0.53	0.54	0.63	0.61	0.71	0.49	0.61	0.63	0.68	0.59	0.06
ITSPG	0.53	0.64	0.48	0.56	0.56	0.49	0.61	0.59	0.55	0.51	0.56	0.56	0.58	0.49	0.55	0.05
OGRT	0.58	0.60	0.49	0.74	0.93	0.46	0.70	0.52	0.59	0.46	0.58	0.56	0.68	0.43	0.60	0.14
OYOT	0.73	0.63	0.71	0.72	0.43	0.54	0.52	0.53	0.63	0.60	0.58	0.64	0.59	0.64	0.61	0.09
TE	0.74	0.73	0.49	0.50	0.42	0.69	0.70	0.54	0.67	0.61	0.82	0.57	0.64	0.58	0.62	0.11
THLN	0.61	0.71	0.82	0.48	0.73	0.69	0.55	0.53	0.74	0.58	0.49	0.66	0.58	0.57	0.62	0.10
TML	0.74	0.66	0.61	0.45	0.43	0.48	0.70	0.65	0.46	0.26	0.69	0.59	0.63	0.35	0.55	0.15
TP	0.61	0.51	0.56	0.56	0.61	0.69	0.36	0.62	0.56	0.56	0.53	0.38	0.76	0.43	0.55	0.11
UJ	0.57	0.64	0.63	0.58	0.49	0.53	0.61	0.70	0.65	0.47	0.48	0.58	0.48	0.63	0.57	0.07
VILLA	0.74	0.62	0.60	0.83	0.64	0.76	0.57	0.77	0.76	0.18	0.71	0.72	0.69	0.38	0.64	0.17
Mean	0.62	0.58	0.59	0.58	0.57	0.60	0.63	0.59	0.62	0.53	0.61	0.57	0.63	0.53		
Std	0.09	0.07	0.12	0.11	0.14	0.10	0.10	0.09	0.10	0.13	0.10	0.08	0.07	0.11		

0.3.4 Les temps inter-communication

Dans ce qui suit, nous avons examiné les données empiriques inter-communication en utilisant *Maximum Likelihood Estimation* (MLE) pour estimer quatre types de distribution, de la distribution exponentielle, à savoir la distribution log-normale, la distribution loi de puissance, et la distribution Gaussienne inverse.

0.3.4.1 Temps inter-arrivée

Comme le montre le tableau 0-4, le meilleur modèle diffère selon les ensembles de données. La Gaussienne inverse est le meilleur modèle pour ajuster les données obtenues à partir des bases de données D_3 et D_4 , alors qu'il a échoué à capturer les moments d'inter-arrivée de moins de 15 secondes (voir la figure 0-5 à $\tau \approx 10^{1.2}$ seconde) des ensembles de D_1 et D_2 . La distribution en loi de puissance est beaucoup mieux pour décrire tous les temps inter-arrivée dans les jeux de données D_1 de D_2 et, avec un seuil minimum à 12 secondes et 13.3 secondes, respectivement. La diversité de la répartition des temps d'inter-arrivée pourrait résider dans les modèles de trafic qui ont été évoqués ci-dessus. Par rapport aux données opérationnelles dans des ensembles de données D_3 et D_4 , les communications faites par les contrôleurs des deux premiers ensembles de données sont exploitées pendant les heures de pointe. Les accords en loi de puissance pour les deux premiers ensembles de données nécessitent des temps minimum inter-arrivée supérieurs à 11 secondes. Il peut être vu dans la Figure 0-6 que les intervalles inter-communication qui sont à plus de 11 secondes présentent la décroissance sont la loi de puissance. Les formes en loi de puissance avec des exposants 2,64 et 2,71 semblent capturer les comportements collectifs des contrôleurs, ce qui suggère que les processus de décision sous-jacentes des contrôleurs sont les mêmes que ceux expliqués par les modèles de la dynamique humaine. Que les contrôleurs suivent individuellement la même règle n'est pas établi. Pour tester cette hypothèse, nous analysons les longueurs des écarts inter-communication des contrôleurs calculés à partir des ensembles de données D_1 et D_2 .

Table 0- 4 Probabilités d'accord pour les données empiriques (en-TR)

Nom	PDF	Paramètres	D_1	D_2	D_3	D_4	D_5
Exponentielle	$\lambda e^{-\lambda x}$	λ	19.1842	17.0713	17.9953	39.6385	25.6036
		LR	-314251	-37863.6	-1657.19	-250009	-25307
		AIC	628504	75729.2	3316.38	500020	50616
Log normale	$\frac{1}{x\sqrt{2\pi\sigma^2}}\exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right]$	μ	2.59313	2.56279	2.38417	3.36411	2.70115
		σ	0.756983	0.686706	0.946182	0.779025	0.977448
		LR	-296732	-35578.7	-1596.06	-242184	-24661
		AIC	593468	71161.4	3196.12	484372	49326
Loi de puissance	$x^{-\alpha}$	α	2.42	2.7078	2.8	4.4108	3.9468
		$x_{\min}$	**12**	**13.3387**	29	133.3269	97
		LR	-155460	-15598	-332.322	-7706.4	-1039.2
		AIC	**310924**	**31200**	668.644	15416.8	2082
		$Prop$	46.62%	43.41%	**17.61**	**2.91%**	**3.49%**
Gaussienne inverse	$\left[\frac{\lambda}{2\pi x^3}\right]^{1/2}\exp\frac{-\lambda(x-\mu)^2}{2\mu^2}x$	μ	19.1842	17.0713	17.9953	39.6385	24.6435
		λ	23.5348	27.5143	13.1099	48.5121	15.9193
		LR	-223361	-26511	-1188.36	-192603	-19067.9
		AIC	446726	53026	**2380.72**	**385210**	**39219.8**

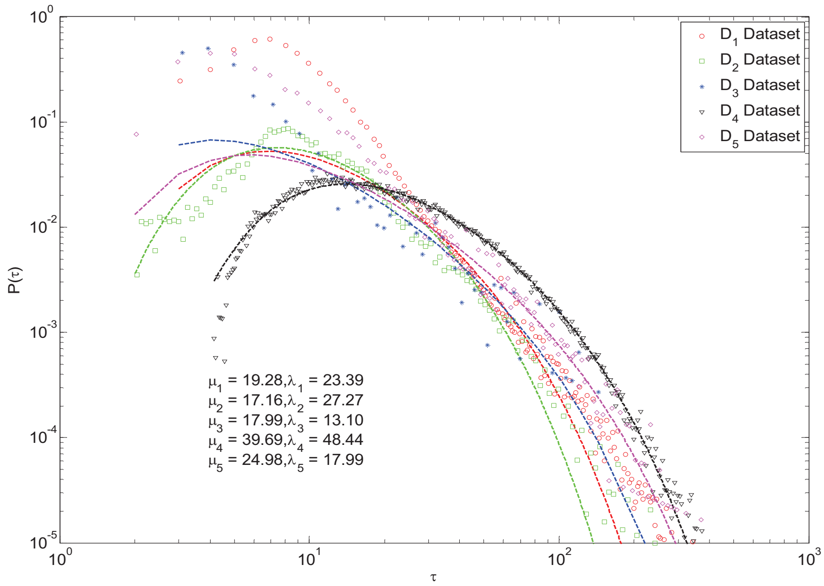


Figure 0- 5 La distribution de densité de probabilité d'inter-communication des contrôleurs

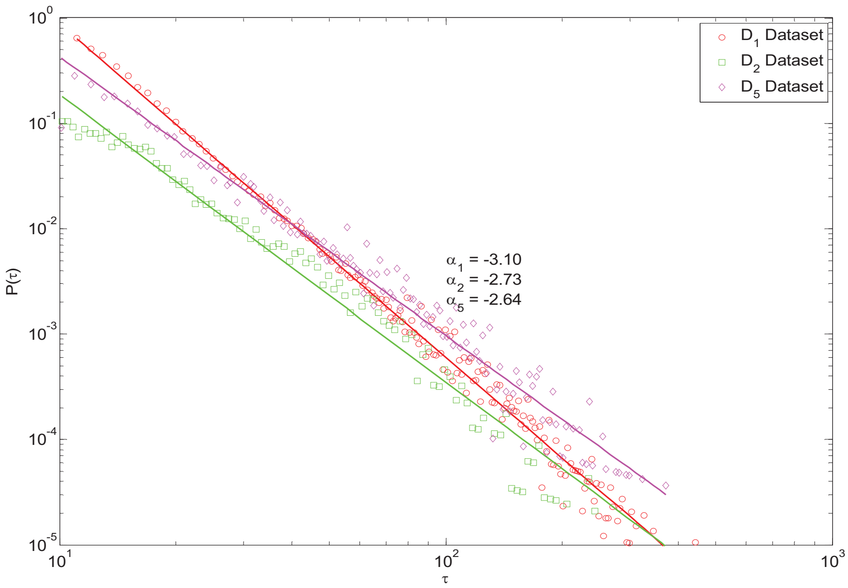


Figure 0- 6 Répartition des écarts inter-communication supérieurs à 11 secondes

0.3.4.2 Longueurs des écarts inter-communication

Les longueurs des écart inter-communication des ensembles de données D_1 et D_5 ont été obtenus en utilisant le schéma proposé. Pour estimer les exposants pour la distribution en loi de puissance, nous adoptons l'algorithme donné dans (Clauset, Shalizi et al).

Dans l'ensemble de données D_1 , il est très intéressant d'observer que les comportements dynamiques des interactivités de la plupart des contrôleurs individuels, représentés par un secteur d'un exercice, peut être décrit par une loi de puissance bien que les exposants varient entre 2.0 ~ 3.8. Nous constatons également que les exposants pour les secteurs du ACC sont normalement entre 2.0 et 3.0. En revanche, les exposants pour les secteurs d'approche sont généralement plus grands que 3.0. Cependant, les distributions de longueurs des écarts inter-communication dans les ensembles de données sont plus hétérogènes. Bien que les intervalles montrent de longues queues, la plupart des données ne peuvent pas être décrites par une loi de puissance.

0.4 Les caractéristiques spatiales des activités de communication des contrôleurs

En fait, le processus de gestion du trafic est un processus de diffusion d'informations par le contrôleur. Afin de gérer le trafic, le contrôleur doit recueillir et diffuser les informations relatives afin d'éviter les conflits de trafic et d'assurer que les avions peuvent atteindre leurs destinations avec succès. Les types d'informations et les sources pour accumuler les informations sont généralement bien connus. Cependant, on sait peu de choses sur la façon dont les contrôleurs diffusent les informations. Comme les avions se déplacent à grande vitesse dans le secteur, les relations physiques entre les aéronefs changent rapidement. Bon nombre des mesures de complexité sont basées sur les mesures de ces relations de nature physique. Au contraire, nous pensons que la distribution spatiale réelle des avions dans le secteur n'est pas exactement la même que celle présente dans les esprits des contrôleurs. Bien que certaines mesures de complexité influent les activités cognitives des contrôleurs, ces mesures ne peuvent pas prédire correctement la complexité. Ceci est en grande partie attribuable à des changements dynamiques dans les processus cognitifs des contrôleurs.

Le comportement spatial que nous avons défini capture deux aspects des activités cognitives des contrôleurs:

(1) La représentation du trafic dans l'esprit des contrôleurs, c'est à dire les relations entre les vols reconnus par le contrôleur après le traitement de la situation actuelle du trafic.

(2) Le processus dynamique se produisant sur la forme de la propagation de l'information.

0.4.1 Transformer les séries temporelles en réseau

Nous proposons une nouvelle méthode pour la transformation des données des activités temporelles en un réseau non orienté pondéré. L'hypothèse est que la communication de chaque contrôleur est liée à un vol, sans tenir compte des événements qui ne sont pas liés à des vols (par exemple la communication avec le contrôleur en second).

0.4.1.1 Définition des nœuds

Les nœuds du réseau sont les vols qui traversent le secteur. Chaque nœud aura une période de temps de validité correspondant à son temps de vol dans le secteur, de sorte que le contrôleur ne peut pas traiter le vol avant que le vol entre ou après qu'il sorte de ce secteur. Dans l'étude actuelle, les communications avec les autres contrôleurs ne sont pas encore considérées.

0.4.1.2 Détermination des arêtes

Pour déterminer si deux nœuds sont reliés ou déconnectés, nous devons d'abord calculer les distances temporelles $\delta(i,j,t)=t_j-t_i-l_i$ entre vol i et j vol au temps (t_i) où le vol i a été appelé, t_j le temps lorsque le vol j a été appelé et l_i est la durée de communication de l'événement i. Comme il n'y aura pas de relations entre l'équipage i et les vols entrants après que i a été transférée au secteur aval, nous définissons le temps de service s_i, comme la fenêtre de temps où le vol i reste au sein du secteur. Ci-dessous, nous décrivons les méthodes pour construire un réseau agrégé et un réseau temporel.

0.4.1.3 Réseau temporel agrégé

Une fenêtre de temps prédéfinie $\tau_{\min}$ est utilisée pour déterminer la connectivité entre les nœuds. Si $\delta(i,j,t)$ est plus petit que $\tau_{\min}$, alors nous disons que ces deux vols sont liés et un lien sera ajouté entre les nœuds correspondants, faute de quoi les nœuds ne sont pas connectés directement. La matrice d'adjacence A du réseau G peut être obtenue que

$$A(i,j)=\begin{cases}1, & \text{If } \delta t(i,j,t)<\tau_{\min}, \text{ and } s_i\cap s_j\neq\varnothing \\ 0, & \text{otherwise.}\end{cases}.$$

Surtout, nous définissons $A(i,i)=0$. Notez qu'il peut y avoir plus qu'un seul lien entre un vol i et vol j, nous définissons deux autres matrices N et W en plus de la matrice d'adjacence A. Alors que $N(i,j)$ est le nombre de $A(i,j)$ ayant eu lieu durant toute la période de temps considérée, $W(i,j)$ indique la force de la relation entre les deux vols. Il y a certaines circonstances où le contrôleur doit relire les pilotes ou envoyer des accusés de réception. Pour filtrer ce type de bruit, nous utilisons $N_{\min}$ le seuil pour la détermination de la stabilité. Basé sur $\delta(i,j,t)$ et $N(i,j)$, la distance relationnelle, $W(i,j)$, est calculé comme

$$W(i,j)=\left(\frac{1}{N(i,j)}\sum_{\substack{\delta t(i,j,t)<\tau_{\min}\\ N(i,j)>N_{\min}}}\frac{1}{f(\delta t(i,j,t))}\right)\exp^{N(i,j)}$$

où $f(x)$ est la fonction qui calcule le poids donné au paramètre x. Dans cette thèse, nous utilisons simplement $f(x)=x$.

A des fins d'illustration, dans la figure 0-7 et la figure 0-8, nous présentons un schéma des séries temporelles de communication et son réseau associé.

0.4.1.4 Réseaux temporels

Le réseau G construit plus haut contient beaucoup d'informations sur les activités de communication du contrôleur. Il est prévu que les propriétés du réseau peuvent décrire la dynamique du comportement du contrôleur. Le comportement en fonction du temps, c'est à dire la séquence des communications, est toutefois exclue. Afin de capturer cela, nous nous référons à (Pan et Saramäki 2011) et nous définissons le réseau temporel $G(t)$ par un ensemble de quadruplets $e=(i,j,t,\delta t)$ indiquant les vols i et j en correspondance au temps t avec une fonction de coût δt. De même, il y aura pas de relation entre les vols i et j si les temps de service s_i et s_j ne se recoupent pas. Ainsi, nous avons :

$$e(i,j,t,\delta t)=\begin{cases}1, & \text{If } \delta t(i,j,t)<\tau_{\min}, \text{ and } s_i\cap s_j\neq\varnothing \\ 0, & \text{otherwise.}\end{cases}.$$

Pour analyser les dynamiques temporelles locales, nous introduisons la fenêtre de temps d'observation τ_{tw}.

Le réseau temporel sera ensuite divisé en $n=(T_{\max}-T_{\min})/\tau_{tw}$ réseaux instantanés.

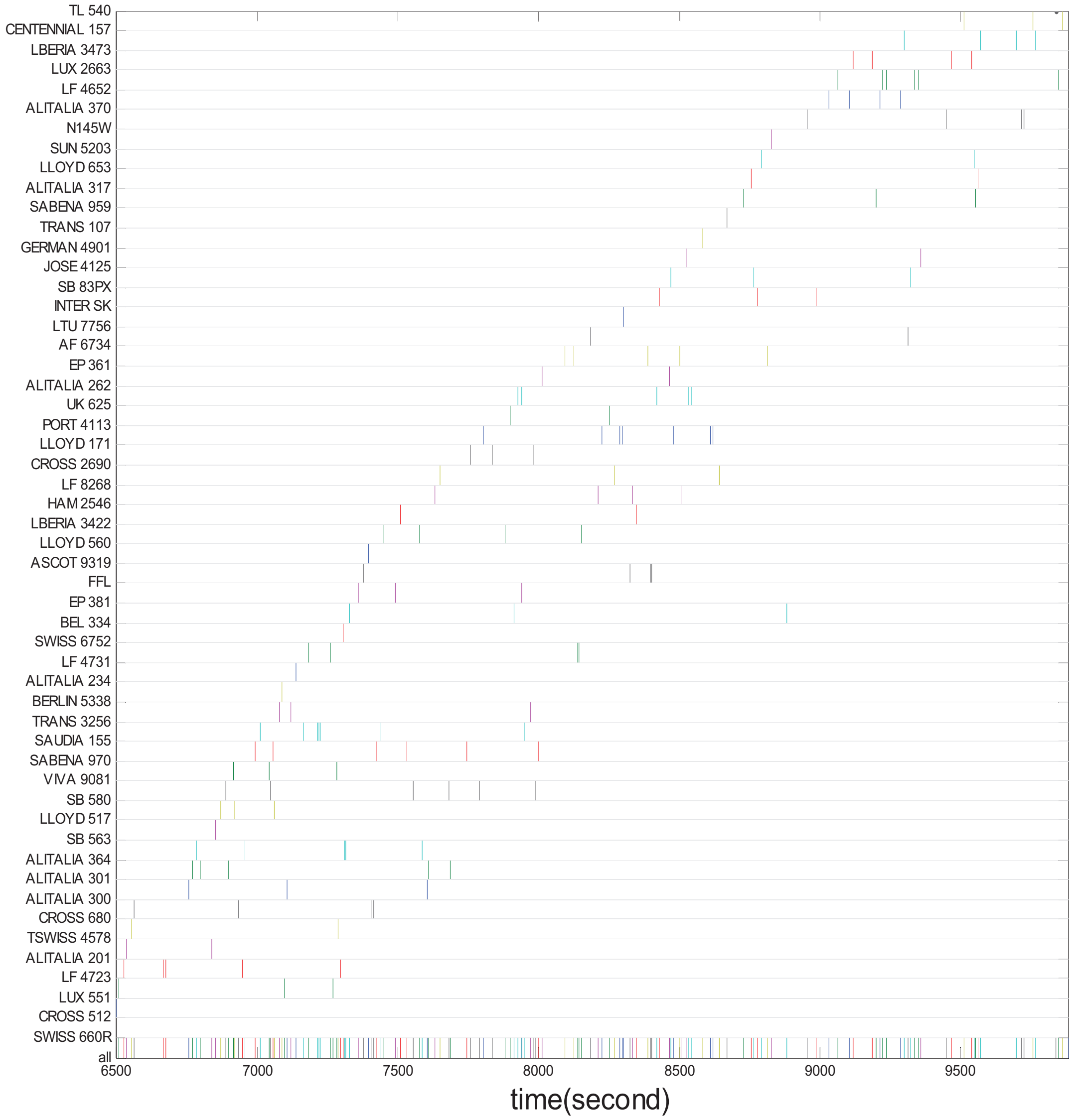


Figure 0- 7 Exemple d'une série de données de communication. Historique des activités de communication construit à partir des messages du contrôleur. La partie supérieure affiche les événements de communication de l'avion. Chaque ligne horizontale grise représente un autre avion, chaque ligne verticale correspondant à un événement de communication. Le côté bas donne la succession d'actions de communication du contrôleur, chaque ligne verticale représente un événement de communication au cours du temps.

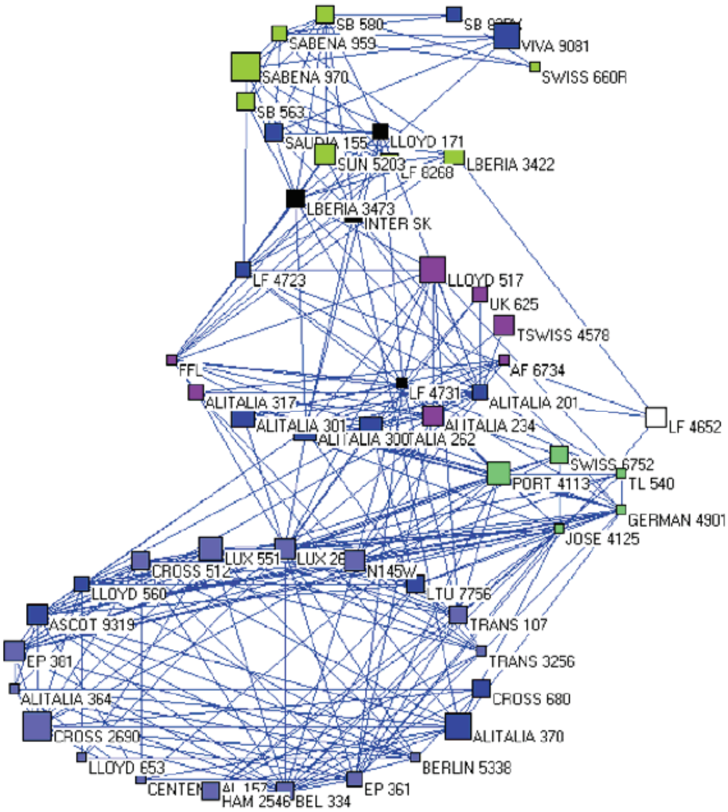


Figure 0- 8 Le réseau temporel associé aux événements de communication de la figure 0-7. Chaque nœud correspond à un vol, et la taille des nœuds correspond à la fréquence des communications avec le contrôleur. Les couleurs représentent les différentes communautés qui ont été identifiés à l'aide de l'algorithme de (Lancichinetti, Radicchi et al. 2011).

0.4.2 Résultats

0.4.2.1 Distribution des degrés (Degree Distribution)

Nous nous concentrons d'abord sur l'analyse du réseau agrégé à différentes échelles temporelles. Les changements de la topologie du réseau ont été mesurés avec des caractéristiques qui mettent l'accent sur la distribution des degrés qui ont été utilisés dans des recherches antérieures sur la dynamique du réseau. Le degré k_i du vol i est le nombre de ses voisins dans le réseau, ce qui indique combien de vols en relation avec le vol i. Par conséquent, nous avons

$$k_i = \sum_{j, n(i,j) > N_{\min}} a(i, j).$$

La distribution des degrés d'un graphe est définie comme une distribution de probabilité discrète qui exprime que la probabilité de trouver un nœud avec un degré k. Par construction, on peut dire qu'il y a une forte probabilité pour un vol i avec un grand degré s'il y a plus de vols dans le secteur quand le vol i le traverse. Pour donner une description générale, nous introduisons le degré normalisé, qui est défini comme

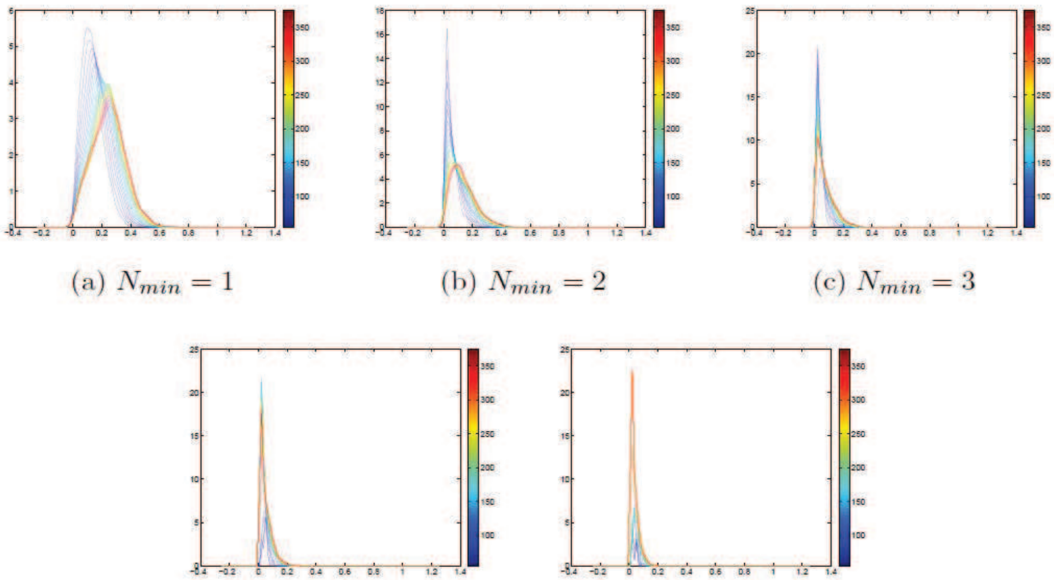
$$\hat{k}_i = \frac{k_i}{N^i_{traffic}}$$

où $N^i_{traffic}$ est le nombre de vols dans le secteur quand le vol i le traverse.

La Figure 0 - 9 montre la distribution des degrés normalisée pour le jeu de données D_1. A notre grande surprise, les distributions ont des formes assez degré similaires dans tous les secteurs. Avec $\tau_{\min}$ fixe et $N_{\min} \leq 3$, au lieu de répartitions aléatoires, la plupart des données peuvent être décrites par une distribution de Poisson ou une distribution normale. Ces tendances apparaissent fréquemment dans le réseau aléatoire étudiée par (Erdös et Rényi 1959) où chaque arc est présent ou absent, avec une probabilité égale. Ceci suggère que les paires de vols sont uniformément sélectionnées. Avec l'augmentation de $N_{\min}$, la distribution se déplace vers la gauche ce qui signifie qu'il y a moins de vols avec des degrés élevés tandis que la plupart des vols ont peu de vols voisins, et la moyenne de degré pour tous les vols diminue. Un autre type de distribution se dégage peut-être lorsque $N_{\min}$ dépasse 3. La plupart des vols ont un faible degré, tandis que très peu de vols ont encore des voisins.

Pour examiner les effets de la distance temporelle minimum $\tau_{\min}$ sur la structure du réseau, nous avons regroupé les degrés dans chaque ensemble de données. Dans la Figure 0-10, nous pouvons voir qu'il y a une tendance claire qu'à la fois le degré et le degré normalisé augmentent lorsque $\tau_{\min}$ s'accroit. Ceci n'est pas étonnant car la probabilité de lier plus de vols sera plus élevée quand $\tau_{\min}$ augmente. Il convient de noter que l'écart entre les degrés avec la même distance temporelle, mais avec des valeurs minimums de poids $N_{\min} = 1$ et $N_{\min} = 2$ sont beaucoup plus grande que d'autres différences. Nous voyons que la plupart des vols vont probablement voler sans intervention supplémentaire du contrôleur, c'est-à-dire qu'ils ne sont pas impliqués dans un conflit. Par exemple, la plupart des vols dans le secteur en route reçoivent seulement un message d'arrivée et un message de sortie si le vol n'a pas besoin de changer de vitesse ou d'altitude. Quand on augmente le seuil du nombre minimal de liens, ce bruit est éliminé par filtrage.

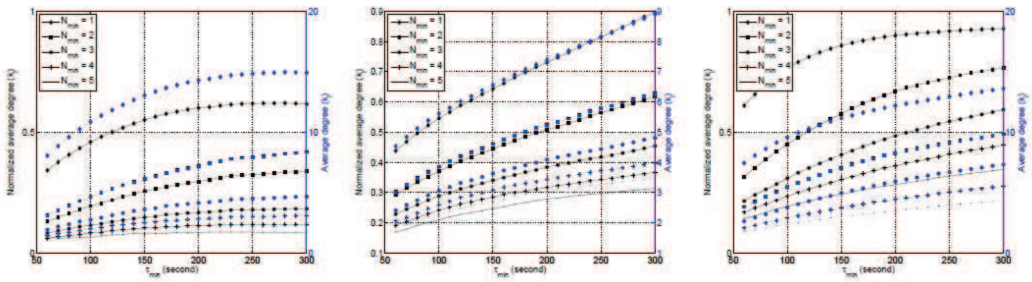
Bien que l'analyse des réseaux de temps agrégé montre une image générale de la façon dont se déroulent les communications du contrôleur avec les vols, les schémas dynamiques, tels que la manière dont l'attention du contrôleur est attirée, ne peuvent pas être identifiés. Par conséquent, nous aurons besoin des réseaux de temps ordonnés pour étudier l’évolution du comportement dans le temps.



(a) $N_{min} = 1$ (b) $N_{min} = 2$ (c) $N_{min} = 3$

(d) $N_{min} = 4$ (e) $N_{min} = 5$

Figure 0- 9 Distribution des degrés normalisé en données. L'axe x désigne le degré normalisé d'un vol, et l'axe y est la densité de probabilité. Les couleurs des lignes représentent la distance minimale $\tau_{\min}$ indiquée par la barre de couleurs



(a) D_1 (b) D_2 (c) D_3

Figure 0- 10 Effets de la distance temporelle minimum $\tau_{\min}$ sur la distribution des degrés d'agrégation. Les marqueurs bleus sont les degrés moyens k_i des nœuds, tandis que les marqueurs noirs sont le degré normalisé $\hat{k}_i$

0.4.2.2 Les corrélations entre les réseaux communautaires et le trafic aérien

Récupérer l'image détaillée du trafic à partir des communications du contrôleur est d'un grand intérêt et d’une difficulté certaine. Les relations physiques réelles entre les appareils dans le secteur ne sont pas exactement la même que celle dans l'esprit du contrôleur. Pouvoir découvrir l'anormal dans les communications du contrôleur qui correspondent à une situation de circulation dangereuse et conflictuelle aidera à prévenir que de tels événements se produisent. Voici notre offre première tentative de lier les activités de communication du contrôleur avec les activités de trafic. Une façon de se reproduire le trafic du réseau qui a généré les communications du contrôleur est l'utilisation de la technique de détection de communauté. Nous avons choisi l'algorithme qui a été développé dans (Lancichinetti, Radicchi et al. 2011) pour la détection de communauté. Les analyses ont été effectuées sur la matrice W.

Nous avons trouvé que les corrélations entre la taille de la collectivité en moyenne et la valeur du trafic dans le secteur dépend du type de secteur (voir le tableau 0-5). La plupart des secteurs en route se trouvent être mieux corrélées que les secteurs d'approche. Les p-valeurs des secteurs d'approche, par exemple ITBPG, ITMPO ITNPG, sont proches de zéro. Il se peut que les communications dans ces secteurs sont différentes des autres et que le réseau des temps agrégés est incapable de démasquer le comportement.

Table 0- 5 Les coefficients de corrélation de la taille moyenne de la collectivité et du nombre de vols dans le secteur

Sectors	Corr. Coef.	P	Sectors	Corr. Coef.	P
AOUS	0.1063	0.7175	ITMPO	0.9451	0
AP	0.9653	0	ITNPG	0.9924	0
AR	0.4314	0.1235	ITSPG	0.9871	0
CREIL	0.9272	0	OGRT	0.5729	0.0323
DENPG	0.7971	0.0006	OYOT	0.5769	0.0308
DEPPO	0.7443	0.0023	TE	0.4568	0.1006
DESPG	0.424	0.1308	THLN	0.7919	0.0007
INIPO	0.667	0.0092	TML	0.8194	0.0003
INNPG	0.5954	0.0247	TP	0.6681	0.009
INSPG	0.4672	0.0921	UJ	0.8643	0.0001
ITBPG	0.9811	0	VILLA	0.7268	0.0032

0.4.3 Réseaux temporels

0.4.3.1 Distribution des degrés dépendant du temps

Nous pensions que la structure l'espace aérien peut avoir un effet sur la dynamique des communications qui n'a pas été découvert par le réseau des temps agrégés. Les études sur les activités cognitives du contrôleur ont constaté que la structure de l'espace aérien joue un rôle important lorsque le contrôleur gère le trafic (Histon et Hansman Jr, 2008). Pour tester cette hypothèse, nous calculons la distribution empirique du degré en fonction du temps de chaque secteur dans chaque ensemble de données. A notre grande surprise, les distributions de probabilité du degré ont des formes assez similaires, ce qui suggère que la structure l'espace aérien a peu d'effet sur la communication. Pendant ce temps, nous n'avons pas vu beaucoup de différence dans les distributions par rapport à la fenêtre de temps τ_{tw}. La Figure 0 – 11 montre la répartition empirique du degré sur les données de D_2 avec τ_{tw} variant de 60 secondes à 110 secondes. Fait intéressant, les résultats statistiques révèlent que la plupart des vols ont deux voisins. La raison pourrait en être le bon ordonnancement des communications avec les vols. Pour vérifier cette hypothèse, dans ce qui suit, nous étudions les motifs du réseau.

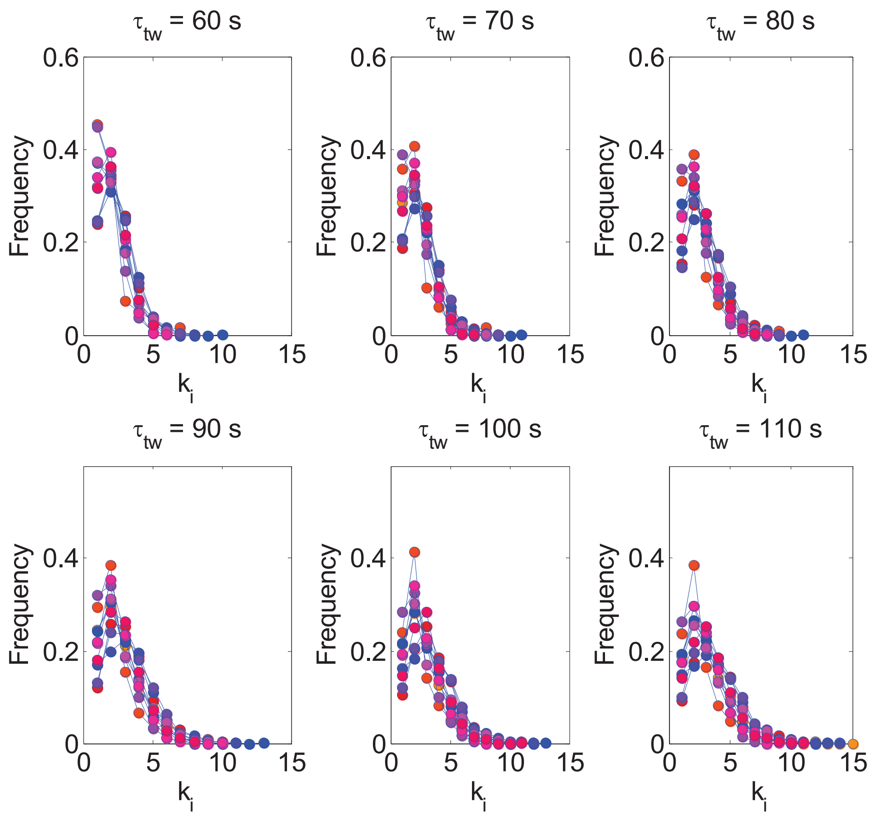


Figure 0- 11 Fréquence du degré dans chaque secteur de D_2 Dataset.

0.4.3.2 Motifs du réseau

Contrairement à la détection de motifs de réseau couramment utilisée, ce que nous essayons d'analyser sont les modèles les plus souvent apparus dans les communications des contrôleurs. Nous allons calculer les motifs du réseau temporel avec une fenêtre d'observation τ_{tw}.

La Figure 0-12 montre la fréquence des trois types de motifs en fonction de la fenêtre de temps τ_{tw}. Clairement, les topologies en chaînes sont les modèles les plus produits. Avec l'augmentation de τ_{tw}, à la fois les motifs boucles et étoiles se développent rapidement. Nous savons que si nous augmentons la durée de τ_{tw} la probabilité d'accroissement du nombre de vols augmente. Par conséquent, il pourrait y avoir une forte probabilité pour que les boucles et les étoiles se produisent. Nous pouvons voir qu'il y a un point de changement à $\tau_{tw} \approx 150$ secondes dans les trois ensembles de données, là où la possibilité d'avoir des chaînes et des boucles sont presque les mêmes. Par rapport aux motifs en boucle, les motifs étoilés croissent beaucoup plus lentement. Même quand la fenêtre de temps d'observation atteint cinq minutes, le pourcentage de motifs étoilés est inférieur à 20%. Pendant ce temps, nous notons que le pourcentage de motifs en boucle semble atteindre son point culminant à 60%.

On s'attendrait à ce que le contrôleur retourne vers un vol avec lequel il a déjà communiqué. Cependant, les résultats obtenus ici suggèrent qu'il n'est pas le cas. Les chaînes et les boucles sont les motifs apparaissant le plus souvent dans les communications du contrôleur, ces caractéristiques topologiques ont été signalées dans la propagation de l'information dans d'autres types de communication sociales humaines (Zhao, Tian et al.2010).

Dans l'analyse du réseau en temps cumulé, nous avons présenté notre hypothèse que la probabilité de choisir un avion pour communiquer est uniformément répartie dans le temps. Le réseau temporel révèle plutôt que la chaîne et les modèles de boucles sont les modèles les plus courants pour les dynamiques temporelles locales.

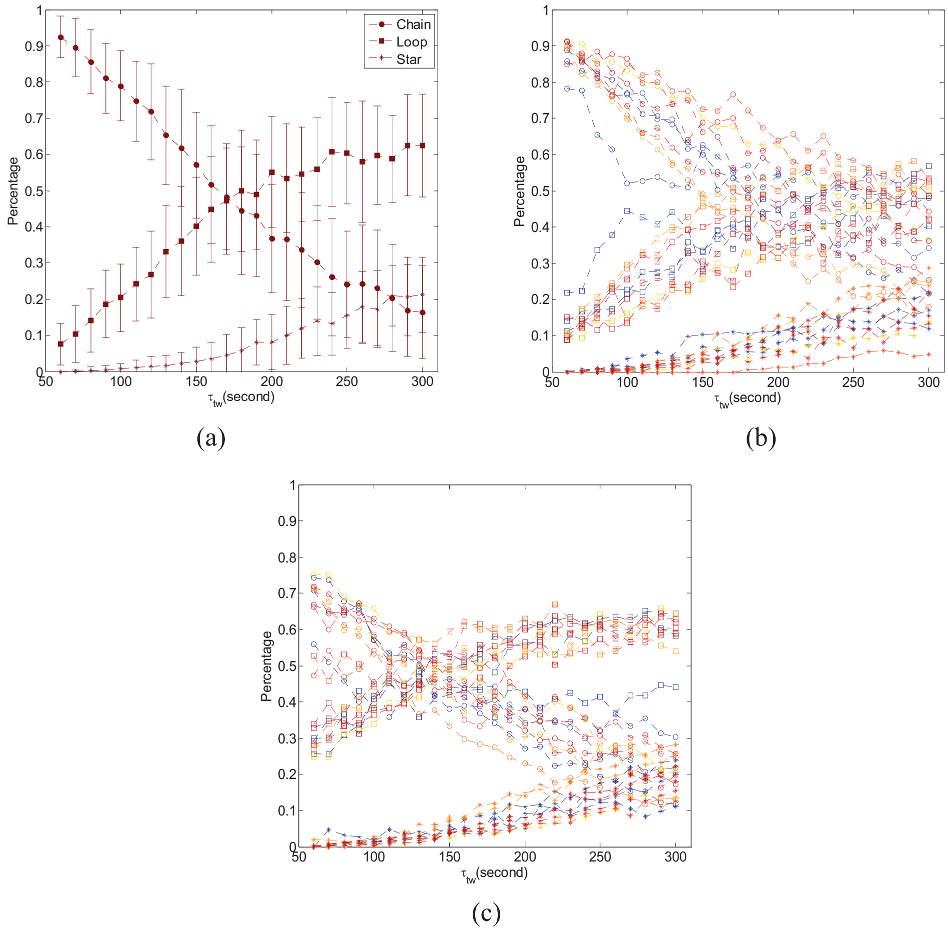


Figure 0- 12 Pourcentage de trois types de motifs détectés dans les trois ensembles de données. Les cercles indiquent le pourcentage de chaînes; les carrés représentent les boucles et les étoiles représentent les motifs étoilés. Les secteurs ont été tracées avec des couleurs différentes dans (b) et (c).

0.5 Fluctuation d'échelle des activités de communication des contrôleurs

Pour caractériser la relation entre la fluctuation de l'activité d'un élément et l'activité moyenne dans un système complexe, la loi de puissance de Taylor à été largement utilisée dans de nombreuses disciplines, par exemple l'écologie (Taylor, 1961 ; Taylor et Taylor, 1977 ; Taylor, Taylor et al, 1983 ; Grenfell, Wilson et al 1998 ; Sæther, Tufto et al 2000 ; Bjørnstad et Grenfell 2001), le débit des rivières (Sadegh Movahed et Hermanis 2008), les comportements humains (Hausdorff, Purdon et al 1996 ; Cai, Zhou et al 2007), les marchés financiers (Gopikrishnan, Plerou et al 2000 ; Sato, Nishimura et al, 2010 ; Bolgorian et Raei, 2011), et les activités sociales (Onnela et Reed-Tsochas 2010). La loi de puissance de Taylor, qui a été nommé d'après L.R. Taylor, en reconnaissance de son article (Taylor, 1961), est généralement sous la forme suivante:

$$fluctuation \approx const. \times average^{\alpha}, \text{ where } \alpha \in [1/2, 1].$$

Notre intérêt est de capter les phénomènes d'adaptation des activités de contrôleur de la circulation aérienne en utilisant les activités de communication vocale du contrôleur comme un proxy.

0.5.1 Résultats empiriques

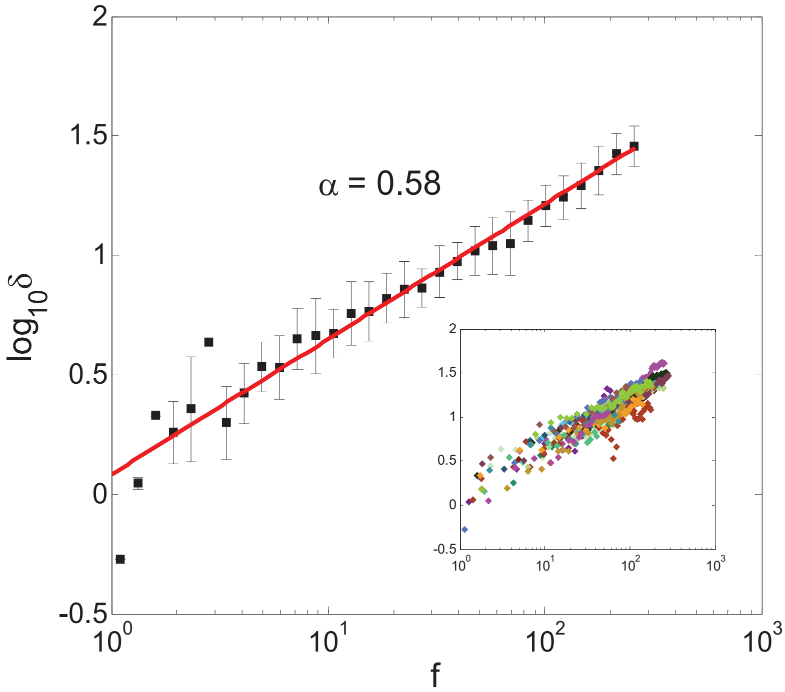
Pour minimiser les effets des facteurs énoncés ci-dessus sur les activités de communication du contrôleur, nous effectuons l'analyse des fluctuations d'ensemble. De même que pour les travaux de Taylor, nous calculons la moyenne des activités de communication du contrôleur $\overline{f_i}$ et l'écart-type $\overline{\sigma}$ en fonction des différents volumes des vols entrant dans le secteur. Quand un vol est dans le secteur, le contrôleur donne des instructions de contrôle et des autorisations pour éviter les conflits et amener le vol dans le prochain secteur. Ainsi, les activités de communication peuvent être obtenue par

$$f_i = \sum_{n=1}^{N_i} V_{i,n},$$

où N_i est le nombre de vols entrés dans le secteur i, et $V_{i,n}$ est le nombre d'activités de communication avec le vol n. Le calcul peut être fait à travers tous les secteurs avec des quantités différentes de vols entrants.

Il a été constaté que la moyenne et l'écart-type des activités de communication se développent rapidement avec l'augmentation du nombre de vols. Puis nous avons tracé l'écart-type en fonction de la moyenne des activités de communication dans la Figure 0-13. En dépit de l'hétérogénéité des modèles de trafic et des configurations de l'espace aérien, nous pouvons clairement observer un ajustement linéaire des données empiriques dans le tracé log-log (ligne rouge), ce qui indique que l'écart type des activités et les activités moyennes présentent clairement une loi de puissance de Taylor avec $\alpha \approx 0.58$. En raison de l'initialisation du trafic pour les premiers vols, il y a de fortes fluctuations au début de points de données. Lorsque nous ajoutons un autre ensemble de données, les données ATCOSIM, dans la figure, la pente de la ligne est légèrement modifiée. L'ensemble des données peut encore être décrite par des $\sigma = \langle f \rangle^{\alpha}$ avec $\alpha \approx 0.60$. Nous soulignons que l'ensemble de données ATCOSIM et les données TAM Paris ont été enregistrées en 1997 et 2010 respectivement. Au total, les données de communication de cinquante-cinq contrôleurs ont été incluses. Ici, nous avons montré que leurs comportements peuvent être caractérisés par des tendances similaires de fluctuations d'échelle.

Il est possible que la structure des routes aériennes et les types de secteurs (en-route, approche, tour et sol) puissent avoir une influence particulière sur les communications du contrôleur. Pour examiner cette question, nous répétons le traçage d'échelle pour tous les secteurs (voir **Figure 0- 14**). Nous pouvons voir que α diffère d'un secteur à l'autre, et la plupart varient entre 0.50 et 0.64. Quelques secteurs, AP, CREIL, INSPG, et VILLA présentent des anomalies, ce qui pourrait être les résultats de faibles volumes de trafic et de temps de service de courte durée. Interpréter ces derniers α est difficile en raison du fait qu'il n'y a que quatorze ensemble de données des exercices de communication pour un secteur (quelques rares secteurs ayant moins).



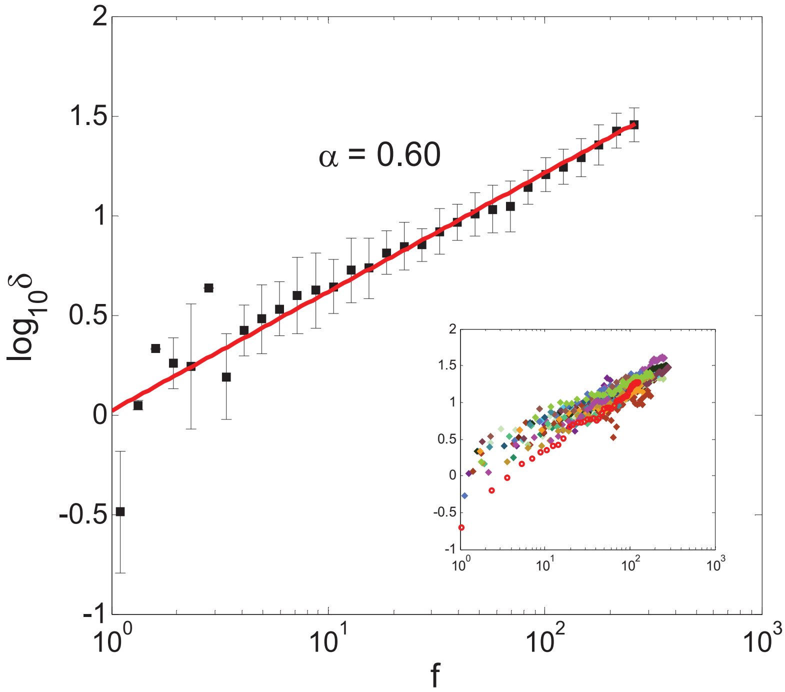


Figure 0- 13 Fluctuation d'échelle pour les activités de communication. (a) les résultats à partir de données TMA Paris, et en (b) on ajoute les données ATCOSIM (les points rouges dans la figure en médaillon). Les exposants sont montrés avec l'erreur ± 0.04 en raison de données logarithmiques classées. Des points ont été classés logarithmiquement et les log sigma ont été moyennés pour une meilleure visibilité, les barres d'erreur représentent les écarts-types à l'intérieur des bacs. L'encart montre la même chose, mais sans classement.

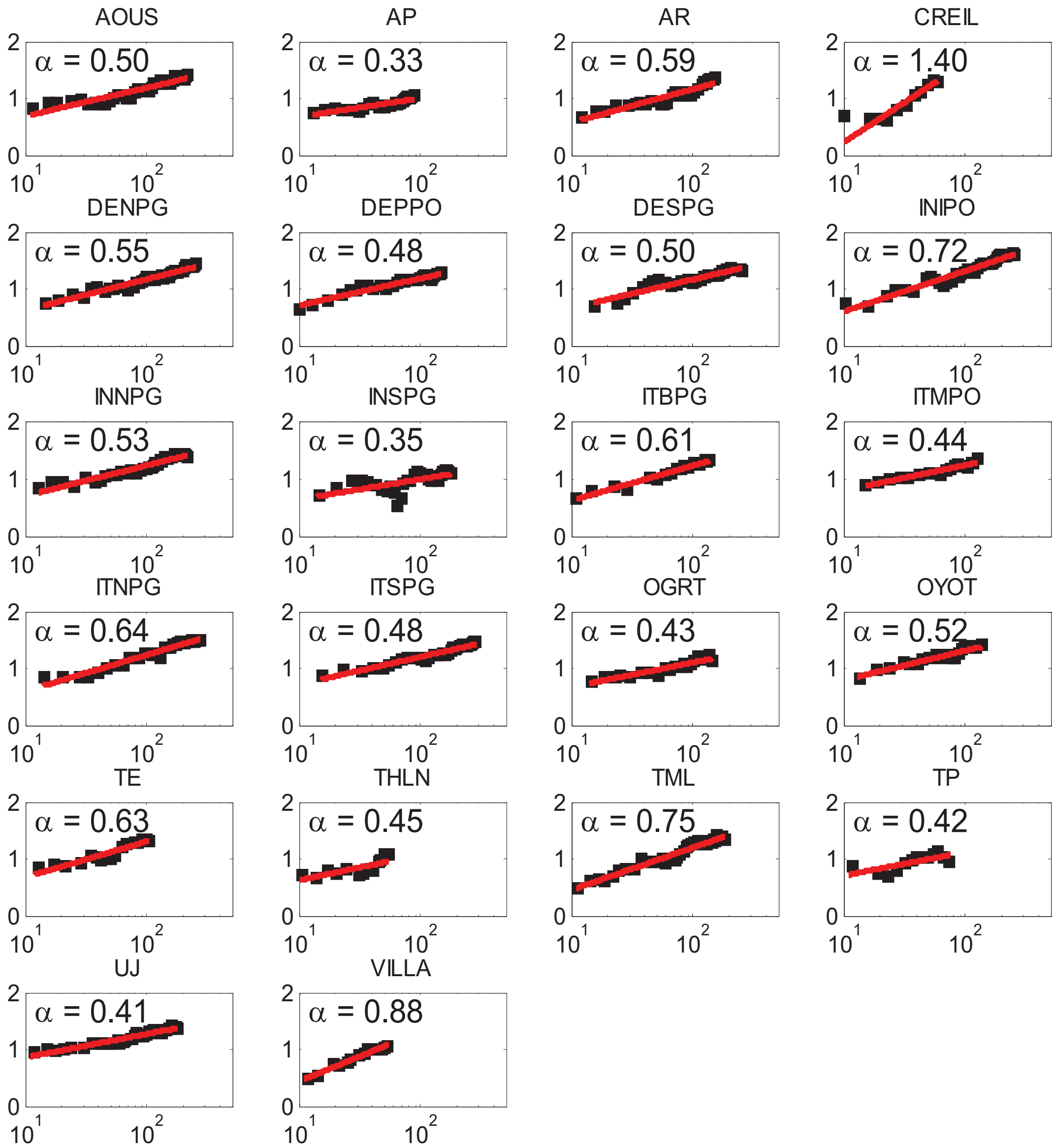


Figure 0- 14 Mise à l'échelle de fluctuation dans tous les secteurs. L'axe x est la moyenne des activités de communication, tandis que l'axe y est les écarts logarithmiques normalisés.

0.5.2 Modèle

Pour expliquer le comportement observé, on pourrait suggérer l'hypothèse du processus de jet de pièces de monnaie (Eisler, Bartos et al. 2008 ; Onnela et Reed-Tsochas, 2010). Considérons les deux systèmes suivants S_1 et S_2 les deux avec n éléments. Le i-ième élément de S_1 en i pièces de monnaie. Un côté de la pièce de monnaie est marqué zéro, tandis que l'autre côté est marqué un. L'activité du i-ième élément f_i est définie comme la somme de la valeur des pièces des lorsqu'on les jette de façon indépendante. De toute évidence, $\langle f_i \rangle \propto i$ et la variance $\sigma_i \propto \sqrt{i}$, cela donne $\alpha = 1/2$. Pour S_2, le i-ième élément es une seule pièce de monnaie qui d'un côté est égal à zéro tandis que l'autre est i. Cela équivaut à jeter les i pièces entièrement couplées. Ensuite, nous avons $\langle f_i \rangle \propto i$ et $\sigma_i \propto i$, par conséquent $\alpha = 1$. Un exemple d'utilisation de ce procédé est de modéliser le comportement de décision des utilisateurs de Facebook sur l'adoption d'application, dans lequel les pièces sont biaisées et les lancers sont couplés via des signaux locaux et mondiaux (Onnela et Reed-Tsochas, 2010).

Du point de vue contrôle du trafic aérien, nous allons prendre les deux facteurs suivants en compte.

(i) **La capacité du secteur** (C_a). La capacité du secteur est le nombre maximum nominal de vols qui peuvent être dans le secteur. Le contrôleur de la circulation aérienne n'acceptera pas de vol en entrée en son secteur lorsque la capacité du secteur est atteinte.

(ii) **Le regroupement** (G_m). (Histon et Hansman Jr, 2008) ont identifié quatre types de stratégies que le contrôleur utilise pour atténuer la complexité cognitive, parmi lesquels le regroupement est la plus commune. Selon les caractéristiques des vols, le contrôleur de la circulation aérienne considère plusieurs vols (G_m) comme un groupe à contrôler. Dans un tel cas, les communications avec ces m vols sont couplées. Par exemple, si il y a m vols ($m \geq 2$) qui sont prévus pour être impliqués dans un conflit, le contrôleur va communiquer avec ces m vols en alternance pour résoudre le conflit potentiel.

Tout en prenant la capacité du secteur et le comportement de regroupement en compte, nous développons le modèle ci-dessous pour reproduire le phénomène observé. Premièrement, nous définissons un facteur de regroupement g_f par $g_f = G_m / C_a$, qui décrit le pourcentage de vols qui seront regroupés. Puis nous changeons les règles de lancer dans le « système de pièces de monnaie » décrit plus haut : il y aura $g_f \times s$ pièces entièrement couplées lorsque la taille du système est s. Nous effectuons 1000 simulations Monte Carlo avec g_f variant de 0.01 à 1.0. Les résultats des tests sont présentés dans la **Figure 0- 15**. On peut voir sur la figure que l'exposant se situe entre 0.58 et 0.65 quand $g_f \in [0.08, 0.15]$. α atteint près de 1 lorsque le facteur de regroupement est supérieur à 0,8. En raison de la non linéarité, il y a quelques points avec α un peu fluctuant autour de 1. Par conséquent, une conclusion peut être tirée qu'il y a environ 10% des vols regroupés lorsque le contrôleur du trafic aérien gère le trafic. Notre modèle permet de capturer le comportement global du regroupement par le contrôleur de la circulation aérienne.

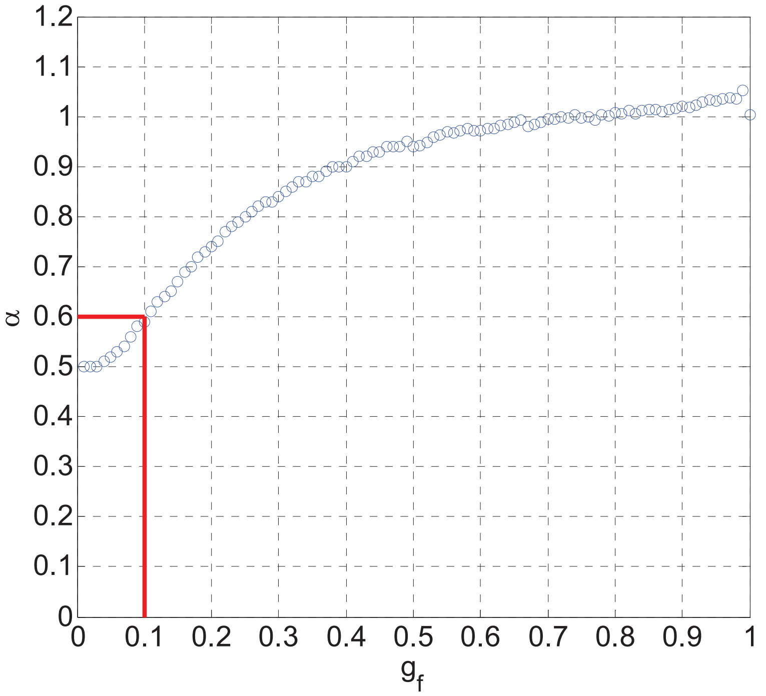


Figure 0- 15 Des résultats de simulation de α en fonction de g_f

0.6 Conclusions

Dans cette thèse, nous avons présenté les études sur les comportements des communications des contrôleurs du point de vue système complexe et dynamique des activités humaines. Plus précisément, nous avons vu le contrôleur de la circulation aérienne comme un système complexe, et avons examiné ses comportements temporels et spatiaux, et leurs fluctuations.

Cette thèse est une contribution à la fois dans le domaine de la gestion du trafic aérien et celui de la dynamique des activités humaines. Nos travaux ont été présentés lors de conférences internationales dans les domaines de la gestion du trafic aérien et dans des publications dans les revues.

Articles publiés:

- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Vu Duong, "Empirical Analysis of Air Traffic Controller Dynamics", *Journal of Transportation Research Part C*, accepted April 2012;

- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Patrick Bellot, and Vu Duong, "Spatial, Temporal, and Grouping Behaviors in Controller Communication Activities", *Ninth USA/Europe ATM R&D Seminar*, Berlin, Germany, June 14 - 17, 2011;
- **WANG Yanjun**, Minghua Hu, Vu Duong, "Fluctuation Scaling in the Air Traffic Controller Communication Activities", *2nd ENRI International Workshop in ATM/CNS*, Tokyo, Japan, Nov 10-12, 2010;
- **WANG Yanjun**, Hu Minghua, "Analysis of Air Traffic Controller Dynamics based on Data Driven Approach (in Chinese)", *First National Conference in CNS/ATM*, 2010;
- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Vu Duong, "Empirical Analysis of Air Traffic Controller Dynamics", *4th International Conference on Research in Air Transportation*, Budapest, Hungary, June 1-4, 2010;

Paper being prepared or submitted:

- **WANG Yanjun**, Vlad Popsecu, Chenping Zhu, Minghua Hu, Patrick Bellot, Vu Duong, "Fluctuation Scaling in the Air Traffic Controller Communication Activities", will be submitted to the *Proceedings of the National Academy of Sciences* (PNAS), 2012;
- **WANG Yanjun**, Minghua Hu, Patrick, Bellot, and Vu Duong, "A Temporal Network Approach for the Study of Air Traffic Controller's Activities", prepared for *PLoS ONE*;
- **WANG Yanjun**, Minghua Hu, Patrick Bellot,Vu Duong, "Rapid Decay in the Heavy Tailed Human Dynamics", will be submitted to *Physica A: Statistical Mechanics and its Applications*;

CHAPTER 1 INTRODUCTION

Air transport industry offers transport service to the general public for the purpose of enabling commence and leisure travel. To provide a safe and accurate air transport, Air Traffic Management (ATM) aims at *dynamically and integrated managing air traffic and airspace safely, economically and efficiently through the provision of facilities and seamless services in collaboration with all parties* (ICAO 2005). As the core part of ATM system, air traffic controller is closely related to the system's safety and efficiency. Ever since 1960s(Davis, Danaher et al. 1963), there have been ongoing efforts to study human factors in the ATM system, contributing to our understanding of air traffic controllers' activities. This thesis will focus on the empirical analysis of air traffic controllers' dynamics from a complex system perspective, exploring the temporal, spatial, and fluctuation characteristics of their communication activities.

1.1 Background

Air traffic controllers (ATCO), or controllers, are the people who are responsible for expediting and maintenance a safe and orderly flow of air traffic. Being supported with Communication, Navigation, and Surveillance (CNS) systems, controllers direct aircraft moving on the ground and in the air. Voice communication was the primary means used by controllers to control air traffic before the emerging of digital data communication between controller and aircraft. However, it is still the only channel for information flow between pilots and controllers in the most Air Traffic Control (ATC) centers. By delivering the instructions and clearances to the pilots through communication systems, controllers direct air traffic with several goals. The primary goal is to ensure each aircraft reach its destination without collision with other aircraft, severe weather, and dangerous area/obstacle. In other words, all the aircraft under jurisdiction must adhere to separation standards issued by the International Civil Aviation Organization (ICAO) or local authority. Other goals such as organizing an orderly and efficiency traffic flow will then be achieved.

There are typically three types of ATC centers where air traffic controllers work. These centers provide service to aircraft that are in different flights phases. The Tower Control, or aerodrome control, is responsible for the aircraft moving on airport ground, taking off, and landing. The Approach and Terminal Control, handles departures, arrivals, and over-flights. The En Route Control, or Area Control, provides air traffic control service to air craft operating en route between approach/tower control.

In order to keep the traffic manageable, the controlled airspace/airport will be subdivided into sectors. Each sector is typically positioned with one or two controller, with unique frequency for the communication between controller and pilots. There is an executive controller, (under radar control environments, is usually referred as a radar controller, i.e. "R-side" controller, or lead controller), who is responsible for radio communications with aircraft, monitoring the radar screen to maintain safe separation, and communicating with other controllers. A second controller, known as assistant controller or D-side controller, may be assign to the position assisting the lead controller with processing flight plan information and coordination with other units. In this thesis, we refer to air traffic controllers as executive controllers.

Air traffic controllers are required to make quick decision in response to the rapidly changed traffic. They maintain a valid mental representation of the current traffic situation, which is commonly referred to as situational awareness and is related to workload. Controller workload is a critical capacity constraint when sector is getting congested. To avoid high workload situations, controllers often enforce extra separations between consecutive aircraft entering sector from same transfer point, or deny any aircraft access into their sectors. To enhance controller's capability in handing traffic, various decision support tools have been developing and deploying. Despite the wider and wider range of automation that has been introduced into ATM systems, scenarios in both Single European Sky ATM Research (SESAR) and Next Generation Air Transportation System (NextGen) concepts still reckon that air traffic controllers continue to constitute the core function of the future system. The complexities of understanding of operator's and manager's behavior pose a challenge to the research community.

1.2 Problem Statement and Scope of Research

To fully understand air traffic controller's behaviors is of quantifiable importance to the system operating safety and efficiency. Duo to the nonlinear interactions between air traffic, airspace and air traffic controller, it is very difficult to capture the instinct nature of controller's activities. Research based on psychology and cognitive science has achieved important findings on how controller behaves when controlling traffic, such as the mental workload, cognitive complexity etc. However, how to quantitative describe controller's behaviors under different traffic distribution and airspace configuration, is still poorly understood.

This thesis examines the air traffic controller dynamics with controllers' voice communication as a proxy. The empirical data investigated in this thesis was the voice communication data between controllers and pilots. Both operational and simulation data were recorded in the radar surveillance approach or en route sectors without data communication activities, where voice communication is the only way that controllers and pilots communicate. Thus, controllers' voice communication activity encapsulates both cognitive efforts and physical efforts to accomplish the mission of ensuring traffic safety and efficiency.

Controller communication activity 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- 1 gives an example of the communication activities between controllers and pilots.

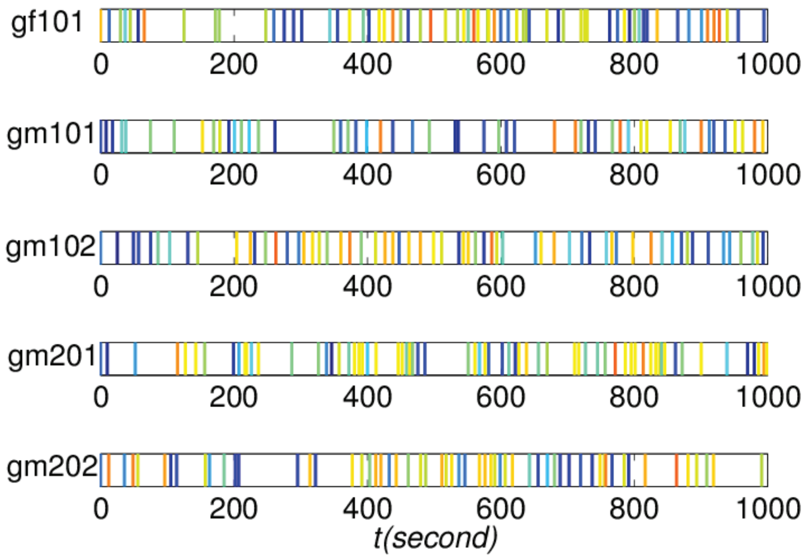


Figure 1- 1 Visualized communication trunks between controllers and pilots.

1.3 Motivation

Science and engineering have long sought the principles for understanding of complex systems(Guckenheimer and Ottino 2009). The impetus to this study is driven by the need to fundamentally model and understand the ATM system. Stronger foundations for the knowledge of human activities are needed to mitigate unsafe events of the system. In this complex system, controller as a core part has direct influence on the system evolving. Great efforts have been made into measuring and predicting of the workload and taskload of the controllers. These work are still inadequate to predict controller's behavior and performance due to the unknown dynamic property of the workload (Loft, Sanderson et al. 2007).

Since 2005, investigations on various kinds of human activities data show that there are similar activities patterns among human beings which are irrelevant to the context of activities. These activities are ranging from human correspondence(Barabasi 2005), email communication(Malmgren, Hofman et al. 2009), short message communication(Wu, Zhou et al. 2010), through printing(Harder and Paczuski 2006), on-line film rating(Zhou, Kiet et al. 2008), to human mobility(Gonzalez, Hidalgo et al. 2008). Empirical results indicate that there may be universal laws that govern human activities.

From a complex system point of view, human, evolves in response to contextual environment changing requirements through adaptation, to avoid failure and for useful and reliable performance at minimum cost. Activities which have been analyzed in human dynamics research are typically with low pressure. Up until now, there is no activity with high pressure such as air traffic control has been well investigated. A deeper understanding of human activities under high pressure will facilitate to avoid human errors that may result in system catastrophe.

1.4 Objective of Research

Given the motivation presented above, the objective of this research was to explore human dynamics in air traffic controller communication activities, to provide an initial demonstration of the physical understanding of the rules by which air traffic controller control the traffic. Specifically, the objective was to

(i) investigate temporal behaviors of controllers' communication activities;

(ii) demonstrate the use of network dynamics to study spatial behaviors;

(iii) explore the fluctuation scaling of communication activities while taking controller as a component of ATM complex system;

and (iv) model and simulate the underlying mechanisms that controllers employ which could also extend to explain and predict other similar human activities.

1.5 Contributions

The main proposal of this thesis is to provide a physical understanding of air traffic controllers' activities. Based on the analyses of the air traffic controllers' voice communication activities, we provide a systematic study of the statistical properties of their communications.

We have found that controllers' communications appear to be long-memory processes by the use of Detrended Fluctuation Analysis;

We have shown that controllers' communications exhibit heavy tailed feature. The collective behaviors of controllers are characterized by the power law form, while the individual patterns show much more heterogeneous.

A temporal network approach has been proposed to trace the controllers' activities, contributing to the quantifying of human activities.

We have captured the fluctuation scaling phenomena of controllers' communication activities. Such phenomena were well explained by the model that mimics controllers' grouping behavior. The fluctuation scaling may lead us to evaluate the capacity of the sector.

Note that although this dissertation is focusing on the air traffic controllers' activities, it rather offers the approaches and results beyond the ATM domain.

1.6 Organization of the Thesis

Following this first introductory chapter, the thesis is structured as follows:

Chapter 2 describes the background of air traffic control and air traffic controllers' activities. The air traffic control system was decomposed into three distinct parts, i.e. the physical part (static part), the dynamical part, and the human part. Related work on the study of air traffic controllers are reviewed and discussed.

Our main contributions are presented in chapters 3, 4, and 5.

Chapter 3 presents the analysis of the temporal characteristics of controllers' communication activities. The correlations between air traffic complexity and communications is fist examined. Then a Detrended Fluctuation Analysis was performed to investigate the long range correlations of controllers' communications. The inter-communication times are analyzed in the last part of this chapter.

Chapter 4 proposes a temporal network approach to study the spatial behavior of air traffic controllers' communications. A novel method is proposed to transfer controllers' communication time series into a network. By leveraging the network science, we analyze the degree distributions, the community structure, and the network motifs, to quantify controllers' communication trajectories.

Chapter 5 induces the fluctuation scaling methods to uncover the grouping behavior from the observed phenomena. Both temporal fluctuation scaling and ensemble fluctuation scaling are analyzed. Based on the empirical results, we develop a model to explain the underlying mechanism, capturing the grouping behavior of controllers' communications.

Chapter 6 discusses the implications of our study on the air traffic controllers' dynamics in the ATM field and other human-driven systems.

Finally, **Chapter 7** concludes this thesis and gives a discussion of the achieved work and highlights the future research directions.

CHAPTER 2 AIR TRAFFIC CONTROL AND AIR TRAFFIC CONTROLLERS' ACTIVITIES

As a human-driven system, Air Traffic Management (ATM) system has been progressed with the introduction of new technologies together with the enhancements from the methods employed by the operators. The system has been significantly improved its capability, safety and efficiency. But how to meet the continuous growth of traffic demand is still an urgent and practical task being faced by the researchers and the engineers of the field. The technologies and the methodologies not only improve the system capability but also increase the system complexity. Large number of parts of the system being interconnected keeps the structure of the whole system unportrayable. Prediction and control of the system is quite difficult due to the linear and non-linear interactions between the elements. For instance, although the local sectors' behavior may be clear, the global picture of the system could be still unknown.

Modeling the ATM system from a complex system approach may be an effective way to analyze the whole system and the subsystems. Although there is a rich literature in modeling and analysis of sector-based system, little has been done toward understanding of the mechanism by which ATM system evolves. The difficulty roots in the inadequate knowledge of the underlying system dynamics. In particularly, air traffic controllers' dynamics has less been quantitatively analyzed. As the decision-maker and executor of the system, the performance of the controller is closely interconnected with the system safety and efficiency. Although the automation systems have been progressively deployed in the system, scenarios in both SESAR and NextGen concepts still reckon that air traffic controllers continue to constitute the core function of the future system. The prediction of controller's performance with respect to traffic activities is therefore of quantifiable importance.

In order to investigate air traffic controllers' activities, it is very important to understand their tasks and operational context within which they operate. This chapter first presents a short overview of the air traffic control and air traffic control system based on the book by Nolan (Nolan 2010) in Section 2.1, then followed with the detail description of the role of air traffic controller in Section 2.2. Related work on air traffic controllers' activities are reviewed in Section 2.3. This chapter ends with summary in Section 2.4.

2.1 Air Traffic Control (ATC) and ATC System

Air traffic control (ATC) is the service provided by the air traffic controllers or controllers, who are responsible for expediting and maintenance a safe and orderly flow of aircraft traffic. The history of air traffic control can be traced back to 1920s shortly after Wright brother's experiment in flight. In the early period, air traffic controllers used colored flags standing in a prominent location on the airfield to communicate with pilots. There are several drawbacks of this form of air traffic control. The first one and the most important one is that the flags were difficult to be seen by the pilots, which will result in the misunderstanding between controllers and pilots. The second one is that controllers had to stand near the approach end of the runway, which is subjective to the weather conditions. Flags were soon replaced by light guns due to these limitations. Controller manipulated a light gun that can direct a narrow beam of high-intensity colored light to a specific flight. Meanings of the messages sent to pilots are indicated by the color of the light.

With the development of radio communication technologies, voice communication between air traffic controllers and pilots emerges, and it soon becomes the prevalent way for air traffic control. Apart from the advancement of the communication technology, the developments of navigation systems and surveillance systems have also improved the way of air traffic control. In the early days, pilots had to use landmarks for navigation, thus controllers had to calculate aircraft's position through the aircraft speed and the position reported by the pilot, which is known as procedure control. Currently, most of the air traffic control centers have been equipped with radar surveillance systems. Radar surveillance control is predominant in the ATC control centers around the world.

To ensure that aircraft in the airspace are manageable, the airspace is divided into different classes then into small units that are referred as sectors. Facilities that provide air traffic control service are known as control centers. There are typically three types of control centers where air traffic controllers work. These centers provide service to aircraft that are in different flights phases. The Tower Control, or Aerodrome Control, is responsible for the aircraft moving on airport ground, taking off, and landing. The Approach or Terminal Control, handles departures, arrivals, and over-flights. The En Route Control, or Area Control, provides air traffic control service to air craft operating en route between approach/tower control. The service provided by the control center may be combined or subdivided mainly according to historical traffic volume.

The organization of the current ATM system is very complicated and differs from nation to nation. However, from a system point of view and based on the characteristics of its elements, the current ATC system can be roughly divided into three parts, namely the static part, the dynamical part, and human part (see Figure 2-1).

2.1.1 The Static (Physical) Part of ATC System

The static part, or physical part, of the ATC system is the resource of the system, including airspace, airports, and other facilities such as communication, navigation, and surveillance systems. To enhance the capability of this part will always need huge financial support and long time to implement. For example, it typically takes more the one year to build another runway in an existing airport in order to meet the growing traffic demands. Compared to the CNS and decision support tools, the airspace and airports are the two major resources of the ATC system.

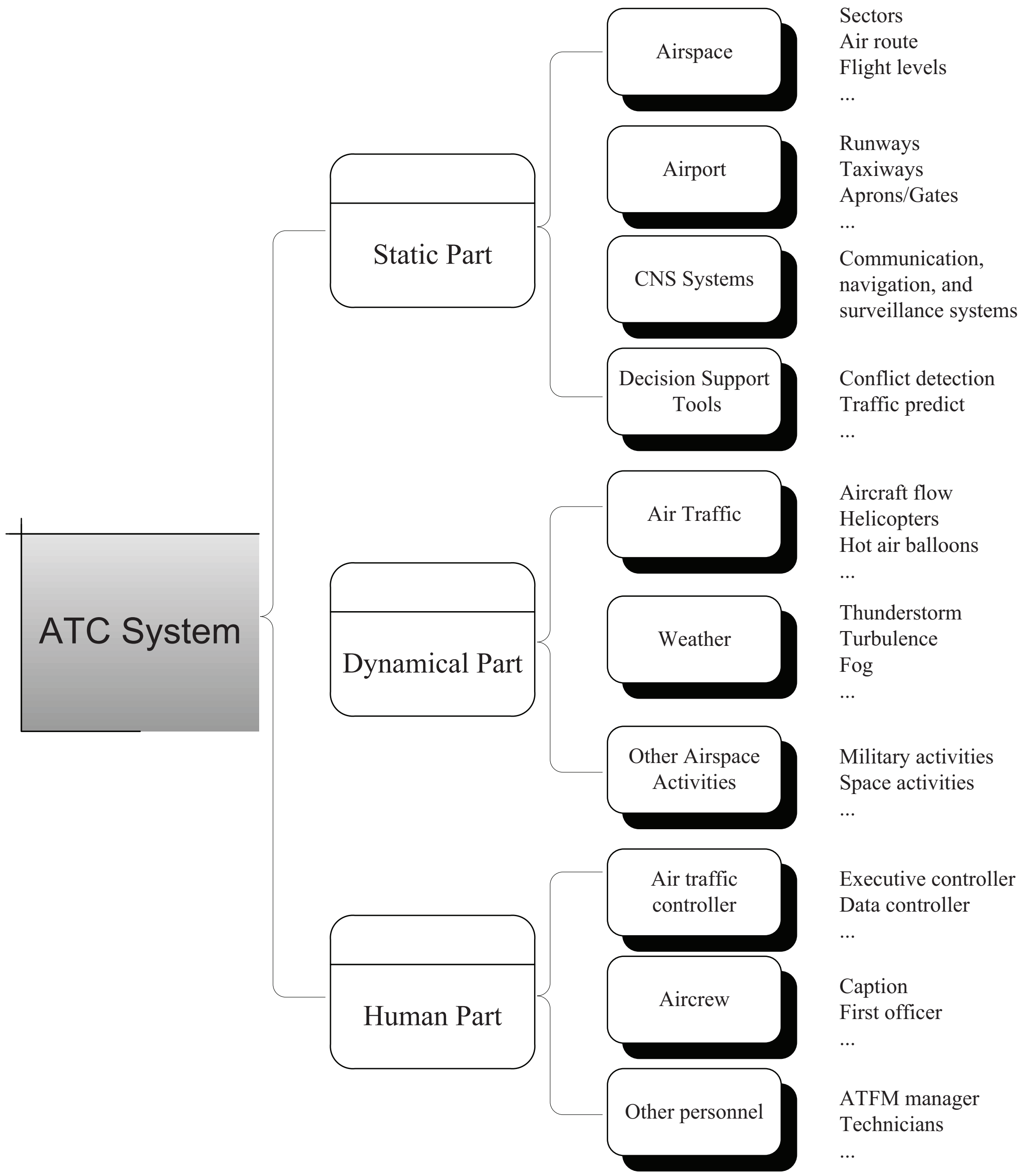


Figure 2-1 Three parts of the ATC system

2.1.1.1 Airspace

The airspace above a notion or union will be categorized by the authority with the intension of providing pilots maximum flexibility with acceptable levels of risk. It also facilitates the national agencies to provide different levels of security and control. ICAO has adopted the classification scheme based on the flight rules and interaction between aircraft and air traffic controller. The airspace are recommended to be classified into seven categories, known as Class A, B, C, D, E, F and G. Classes A to E are referred to as controlled airspace, while Classes F and G are uncontrolled airspace. The classification scheme will differ from nation to nation according to the nation's needs.

In order to keep the traffic manageable, the controlled airspace will be subdivided into sectors. The three dimensional boundaries of a sector adapt to the air route structure and other local operation needs. In general, sector boundaries are static. Sector may be combined or split depending on the traffic situation or operational constraints. Figure 2-2 shows the non-uniformed sector boundaries in the MUAC (Maastricht Upper Area Control Centre), which is operated by EUROCONTROL providing air traffic control for the upper airspace above 24,500 feet of Belgium, the Netherlands, Luxemburg and north-west Germany, covering 55% of European air traffic. The three dimensional volume, the route structure, and the availability of flight levels will determine the sector's instinct capability in serving air traffic.

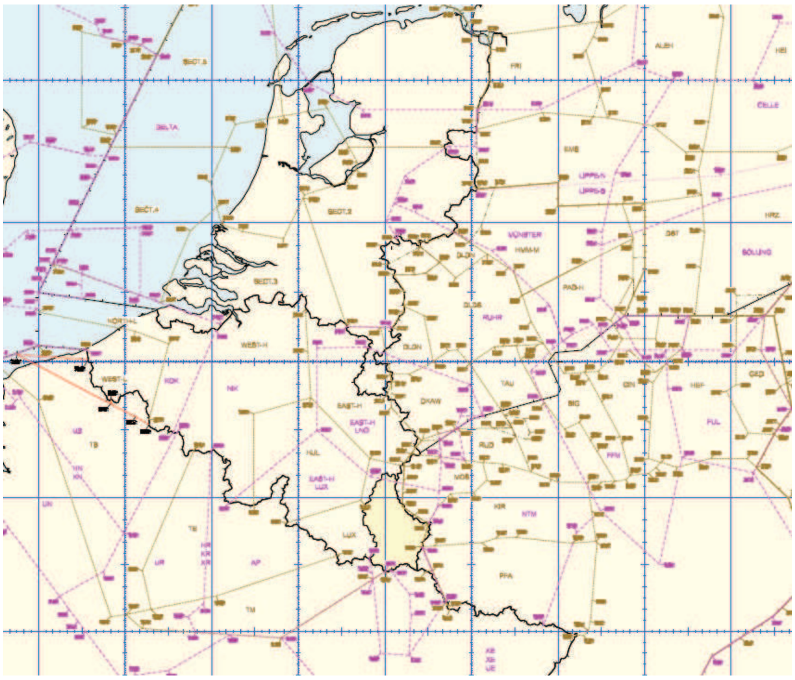


Figure 2-2 Sectors' boundaries in the MUAC. Sectors are separated by the pink dot lines.

2.1.1.2 Airport

Airport is the place where aircraft take off and land. In the civil aviation, passengers and cargo are loaded into an aircraft in an airport. Major physical resources of an airport include the runways, taxiways, and apron/gates. Usually, the runway system is the most critical resource. Most of flight delays are due to the limited capacity of the runway system. For the controllers, the operating of aircraft on the airport's ground is different from that operating in the air.

2.1.1.3 Regulations

Out of the safety, security, and efficiency concern, Separation standards, procedures, and other rules regarding on air traffic control are detailed in the regulations by the ATC authorities.

2.1.1.4 Software

There is a lot of computer-aided software being used in the ATC system, improving the performance of data-processing and providing advices for the controllers. Such tools include flight plan pre-processing tool, conflict detection tool, departure/arrival managers, etc.

2.1.2 The Dynamical Part of ATC System

Two major elements in the dynamical process in the sector are the aircraft and the weather.

2.1.2.1 Aircraft

Air traffic controller provides service to the aircraft in the sector while keeping all the aircraft operate safely. Aircraft in the sector operate under a variety of rules depending on the sector category and air traffic control requirements. These rules refer to flight rules, including:

- IFR (Instrument Flight Rules). Aircraft flying under IFR rules are obliged to fly by reference to instruments in the flight deck and electronic signals.
- VFR (Visual Flight Rules). Pilot flying under VFR rules is responsible for separation from other aircraft and dangerous obstacles. Generally, the weather condition is clear that allows pilot to see where the aircraft is going.
- SVFR: i.e. Special visual flight rules.

Aircraft flying in the sector may follow the route formed by the navigation aids or follow the instruction issued by the controller. The temporal-spatial distribution of aircraft in the sector forms air traffic situation that will impact on air traffic controllers' activities.

Aircraft moving in the sector is the process of consuming the resource of the system. Once there is not enough available capacity for the incoming air traffic flow, airspace congestion will appear. In Figure 2-3, the trajectories of flights in the Paris terminal areas show the aggregated results of the consuming process.

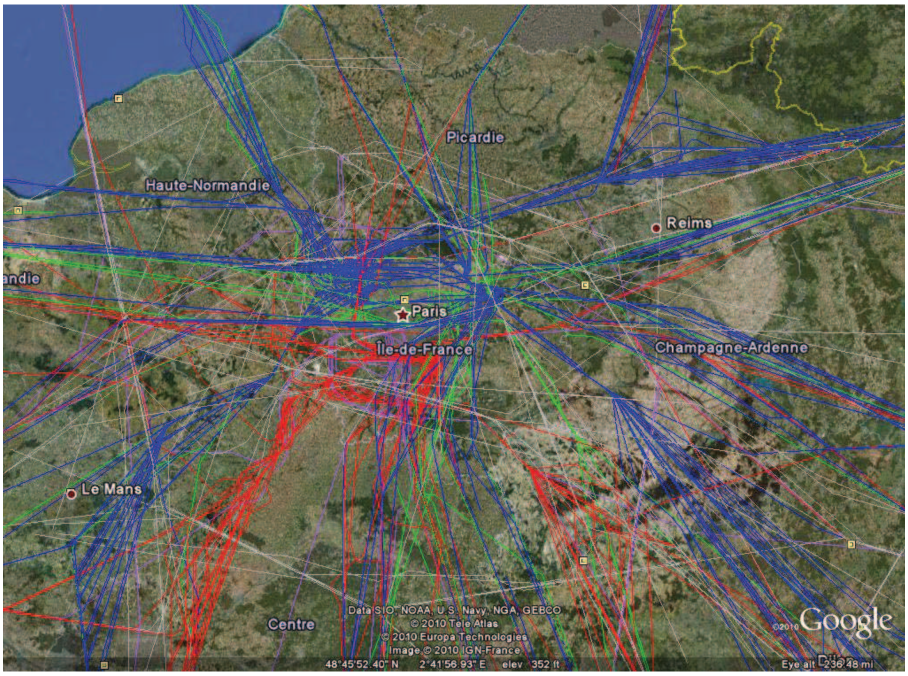


Figure 2-3 Trajectories of Aircraft Flying in the Paris TMA

2.1.2.2 Weather

Weather is the second dynamical element that consumes the resource in the airspace system. Severe weather such as thunderstorms and turbulence will result in the dramatically reduction of sector capacity. For example, airport will have to close due to the unexpected snowstorm. Weather's activities also influence the behavior of aircraft, as pilots will not fly the predefined route to avoid the weather. Unlike aircraft, the movement of weather cannot be controlled, and it is difficult to be predicted.

2.1.3 Human Part of ATC System

The staffs involved in the ATC system are two kinds, air traffic controllers and pilots. For the system point of view, pilots can be represented by the aircraft. Although pilots in certain circumstance retain the responsibility for the separation, e.g. under VFR rules or in the free flight context, the only manager in the system is the controller.

Each sector is typically positioned with one or two controller, with unique frequency for the communication between controller and pilots. There is an executive controller, (under radar control environments, is usually referred as a radar controller, or "R-side" controller), who is responsible for radio communications with aircraft, monitoring the radar screen to maintain safe separation, and communicating with other controllers. A second controller, known as assistance controller or D-side controller, may be assign to the position assisting the executive controller with processing flight plan information and coordination with other units(see (Academies 2010)[p.14 - 17]). Note that executive controller is the one who gives instructions and clearances to the pilots (Figure 2-4).

Figure 2-4 Air traffic controllers are in the continuous environment: executive controller and the assistance controller. Picture was exactly copy from (Academies 2010)

2.1.4 Characteristics of ATC System

In the above described the air traffic control system is mainly from a sector's perspective. The air traffic control system is a typical complex system. It exhibits all the characteristics that a complex system has (Duong 2009):

1. Structural Complexity (Combinatorial or detail complexity). The whole ATC system is composed of a large number of interconnected parts. The interactions among the elements are non-linear, and cannot be described.

2. Behavioral Complexity (Dynamic complexity). When a small part of the system changes its behavior, the impacts of the change are not predictable.

3. Nested Complexity (Multi-levels organizational complexity). The complex physical/technical systems are embedded in a larger system. The two-way interactions between adjacent levels create nested complexity.

4. Evaluative Complexity. In the system, it is difficult to evaluate the stakeholders' performance, because the good performance to one may not be good to anther. That will result in the difficulty in decision making.

2.2 The Role of Air Traffic Controller

Being supported with communication, navigation, and surveillance systems and other automation systems, controllers direct aircraft moving on the ground and in the air through delivering the instructions and clearances to the pilots (see

Figure **2-5**). Air traffic controllers are required to make quick decision in response to the rapidly changed traffic. Under high pressure, controllers have to achieve several goals. The primary goal is to ensure each aircraft under jurisdiction must adhere to separation standards issued by the ICAO or local authority. Other goals such as organizing an orderly and efficiency traffic flow will then be achieved.

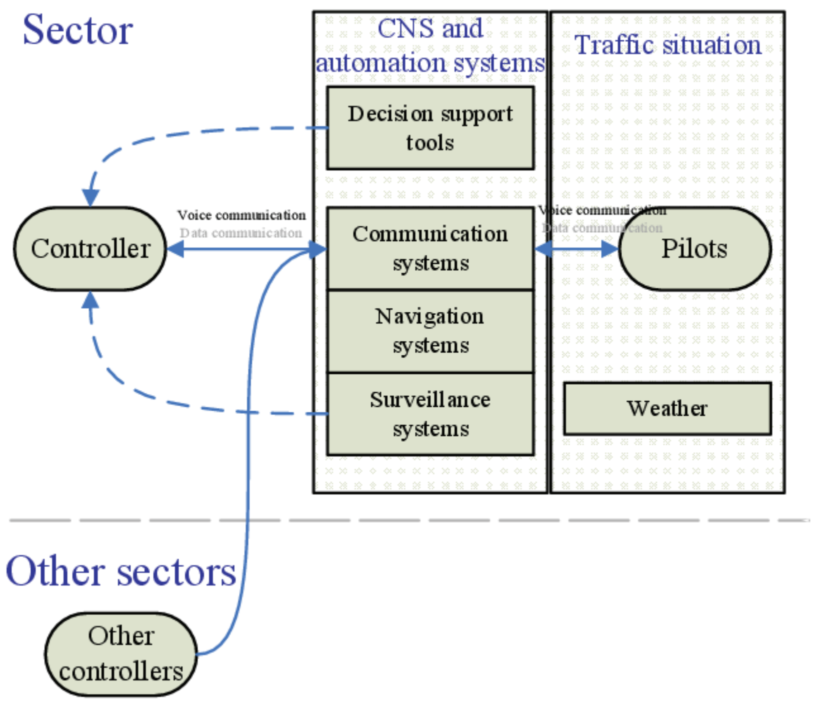


Figure 2-5 The role of air traffic controller.

2.2.1 ATC Tasks

The tasks performed by the air traffic controller are interdependent. Rodgers et. al. have extensively studied the tasks and goals of controllers (Rodgers and Drechsler 1993; Endsley and Rodgers 1994). Based on these research, Histon and Hansman summarized seven categories of tasks:

- Separation tasks

- Monitoring tasks
- Constraint tasks
- Request tasks
- Coordination tasks
- Information tasks
- Other tasks.

Many of controllers' tasks are time-shared, and they may be implemented simultaneous. For example, when controller accepts a constraint tasks, he/she has to keep the aircraft with accepted separation and monitoring the conformance of the aircraft to the ATC clearance. The deploying of automation systems has been alleviating some of controllers' taskload; however controllers still have to perform most of the tasks. In the following, we briefly summarize the descriptions of each task based on (Endsley and Rodgers 1994; Histon 2002).

2.2.1.1 Separation tasks

The primary objective of air traffic control is to ensure the safety of aircraft. Separation rules are made according to the performance of aircraft, airspace structure, terrain, and weather condition etc. Aircraft in flight are defined as a moving cube with three dimensions in order to calculate the probability risk of collision. Both lateral and vertical distances should be met for the separation with other aircraft, obstacles, weather, and other hazardous areas such as the military airspace.

Under radar surveillance, the separations are normally defined in physical distance. For instance, the separation standards for en route flights are 5 nautical miles in lateral and 1000 feet in vertical in the United States. In the airspace where there is no radar surveillance or satellite surveillance, aircraft will have to maintain the separation standard in minute. In the airport, the required time separation for two consecutive aircraft taking off will be determined by the wake types of two aircraft and the standard Instrument Departure (SID) routes which they are using. Standard for aircraft taxing is also depending on the types of aircraft.

2.2.1.2 Monitoring tasks

Pilots are obliged to implement the clearance issued by the air traffic controllers. However, controllers have the responsibility to monitor the conformance of the aircraft to prevent the deviation from the intentions of controllers. Besides, by monitoring the air traffic situation and airspace, controllers can prepare the necessary traffic control strategies for both expected and unexpected situations.

2.2.1.3 Constraint tasks

Histon and Hansman have defined constraint tasks based on the sources of constraints.

This kind of tasks is imposed to the aircraft when crossing sector boundary. The main reason for such constraints is the limited capacity in the downstream sectors or airports. One common constraint occurs when implements the traffic management initiatives. Aircraft being handed into the same downstream sector has to meet the flow restrictions that are either in the form of minutes-in-tail or miles-in-tail. Performing constraint tasks will cost aircraft delay and the constraints may propagate in the whole air transport network.

Letter of Agreement (LOA) is signed by the adjacent agencies if the constraints occur regularly. For instance, the LOA regarding flow restriction when there is thunderstorm in the terminal area will be used by all the parties who involved in the LOA.

2.2.1.4 Coordinate tasks

When there is no need for the officially implement a traffic management initiatives and the problem can be solved locally, controller has to communicate with other controllers, and pilots for the coordination. In the sector with high traffic volume, there may be a controller who is in charging coordination. The coordination is commonly happened between the sectors that are in the same ATC control center.

2.2.1.5 Information tasks

The automation systems and decision support tools provide the important information for the controllers, whereas the value of the information provided by the systems depends on the accuracy of the input. Once controller modifies the flying route of an aircraft, he/she has to update the information that will be used by such tools. Another source of the tasks is to disseminate information to pilots regarding on the altimeter settings, weather conditions, and other operational information. It is the responsible of controller to distribute flight data in cases of automation links failure.

2.2.1.6 Request tasks

Pilots would request to controller to fly the preference route if airspace environment allows. In the airspace where the presence of weather is different from forecasted, pilots usually request to deviation from the predefined trajectory. In the abnormal situation, for instance the fuel of the aircraft reaches emergency, pilot will ask for the priority of landing or a shortcut flying.

2.2.1.7 Other tasks

There are tasks that depend on the airspace. In detail, these tasks include:

- providing advisory services to the flights;
- providing full route clearances to departure from non-towered aircraft;
- dealing with "pop-up" aircraft;
- responsible for ensuring the other controllers are not overwhelmed;

- Others.

2.2.2 Controller as a Black Box

From a system perspective, air traffic controller is the control part of the ATC system. The operation process is outlined in Figure 2-6. The inputs of the controllers are the air traffic situation information and advices information given by the decision support tools. The outputs are the commands that modify aircrafts' motions after evaluating the current traffic, which will have further impact on the air traffic situation.

2.2.2.1 Inputs of the controller

The information flows into air traffic controller are from three sources: the pilots, surveillance systems, and decision support systems.

In the radar surveillance control center, there is a radar screen at controllers' workstation, which displays the information about the flights' positions and speeds depending on the types of the radar. Primary radar can detect the distance and azimuth of aircraft from radar site through the delay between the transmission and reception the pulse reflected by the aircraft. The secondary radar can compute both lateral position and altitude of the aircraft if aircraft equipped with an operating transponder. There are four types of radar systems that are used in air traffic control in the United States: precision approach radar, airport surveillance radar, air route surveillance radar, and airport surface detection equipment(see (Nolan 2010) on pp. 342-343). Aside from the main radar screen, there might be a small screen displays weather information in the sector obtained from primary radar or weather surveillance radar.

Pilots are the most important source of information in the area where there is no radar coverage. Controller has to calculate the positions of aircraft from the reports of pilots. Even under radar surveillance control, control will have to confirm certain information through the communication with pilots. Such information as pilots' intension will help controller to predict traffic situation.

In the current system, most ATC centers are equipped with decision support tools that can alleviate the workload and taskload of air traffic controller. For example, the trajectory predicted by the automation system can detect potential conflicts between aircraft; the departure manager and arrival manager provide the optimized departure and arrival sequences of flights respectively. The information from decision support tools is necessary in some busy control centers.

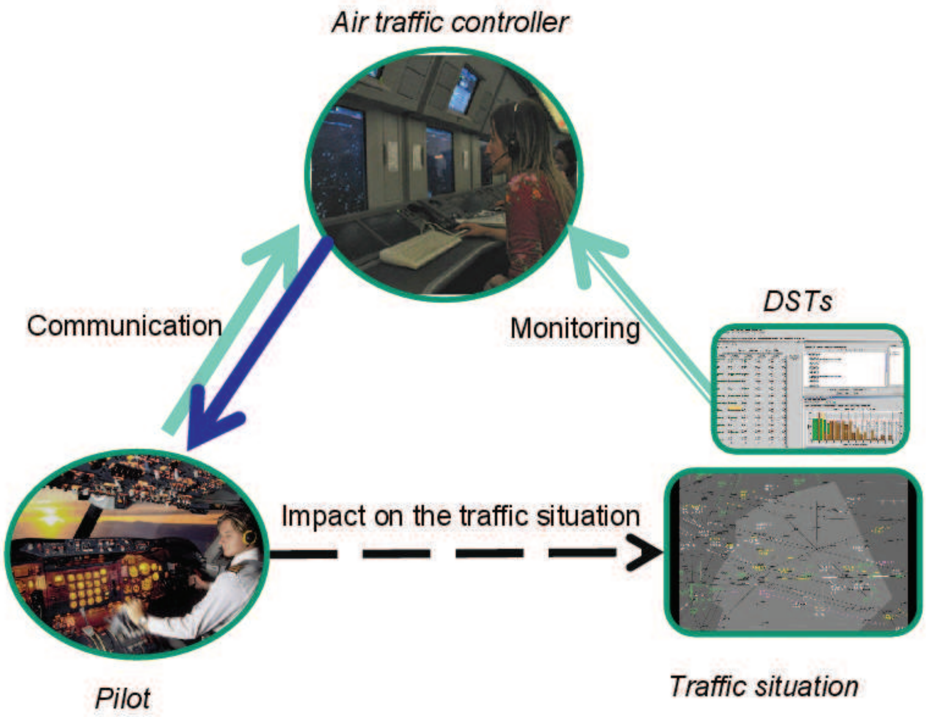


Figure 2-6 Systematic perspective of air traffic controller in the ATC system.

In summary, the information from all the sources that may be processed by the controller is categorized into the following groups:

I. Airspace information. It is used to estimate the availability of controlled airspace, including air route, flight levels, navigation aids, and special used airspace.

II. Aircraft positions and aircraft performance data. It's about aircraft type, position, speed, destination, pilot's intentions. From these data, controller can project aircraft positions so that can form a picture of future traffic situation.

III. Weather information. Present weather and forecasted weather are being used by controller to determine the implementation of related control strategies such as flight rerouting.

IV. Advised information. Given by the decision support tools, the advised information shows the overview of current and future air traffic situation. However, controllers do not need to accept the recommended control initiatives.

V. Regulations and other constraints. Separation standards and additional constraints must be complied by the aircraft by means of implementation of ATC clearances issued by the controllers.

Information I, III, and V can be further grouped as the contextual information. In practice, air traffic controllers establish the "knowledge library" about the contextual information and the traffic control strategies regarding on different traffic situations.

2.2.2.2 Outputs of the controller

Having processed the information described above, the main out comings of the controller are a series of clearances and instructions that change aircraft states. Such clearances can either directly modify aircraft's motion in heading, altitude, speed, and rate or climb/descend, e.g. "Air France 605, heading 160", or place requirements on the flights that indirectly changes aircraft dynamics (e.g. "Air France 605, reach FL 270 in five minutes). Pilot's requests on the change of trajectories should be approved by the controller. Other outputs are to perform the information tasks or to communicate with other controllers.

2.2.3 Voice communication

ATC clearances and instructions are sent to pilots through communication systems. Therefore, the safe operation of air traffic control system ultimately depends on the reliable and accurate communication between controllers and pilots. Any miscommunication between them might contribute to an aircraft accident. Ever since radio communication being used in air traffic control in the early 1930s, verbal communication has being a primary way for information flow between air traffic controllers and pilots. Although there have been significant improvement in the ATC communications system, such as the data communication, human communication between air and ground is still the most reliable way in the air traffic control.

In the current system, each controller is assigned one or more radio frequencies for communication with pilots, while the communication with other controllers in the same facility or in adjacent facilities may use telephone equipment. In order to ensure the safe and efficient of air traffic, communication between pilots and controllers must be in a clear and unambiguous way.

2.2.3.1 Standard Phraseology

To maximum utilize the capacity of communication channel while reducing the risk of misunderstanding, controllers and pilots use standardized phraseology during air-ground communication based on ((ICAO) 2007). The content of a transmission made by controller should always use the following message format:

1. Identification of the aircraft, which will alert the intended receiver of the coming transmission.
2. Identification of calling controller. It is to identify who is initiating the communication. This will not always appear when the communication between controller and pilot has been established.
3. The contents of the message. Both ICAO and local authority can defined the format of the message.
4. Termination. It happens in the communication with other ATC facility.

Table 2- 1 shows the items in communication that air traffic controllers should use standardized phraseology.

Table 2- 1 List of items pronounced with standardized phraseology

• Numbers and letters	• Minimum descent or decision height altitudes
• Time	• Radio frequencies
• Altimeter settings	• Runway numbers
• Altitudes	• Microwave landing system or TACAN channels (in the United States)
• Flights Levels	• Route and navigation aid descriptions
• Headings	• Air traffic control facilities
• Speeds	• Wind direction and velocity

2.2.3.2 Contents of the ATC communications

Manning et. al. have classified ATC communications into seven groups based on the contents of the communication events, namely *address, courtesy, advisory, request, readback, instructional clearances, and frequency changes* (Manning, Mills et al. 2002). In the book by Nolan (Nolan 2010), most common phrases used by controllers are described in detailed. The following up summarizes the standard communication phrases that can change traffic dynamics.

- Clearance

Pilot's request on the perform a specific maneuver has to be agreed by the controller. Then a clearance is issued by the controller authorizing pilot to proceed the request. A clearance is general began with aircraft identification followed with "clear for doing something". For example, "Air France 654 cleared for take off" authorizes AF 654 to take off.

- Departure instructions

When aircraft is taking off from an airport, a departure instruction will be issued by controller either use Standard Instrument Departure routes or a heading.

- Altitude assignment

There are several ways on the change of aircraft's altitude. Air traffic controller has to clearly direct pilot to reach the desired flight levels.

Maintain: Controller will assign an altitude or flight level at which aircraft has to fly further on after it reaches the altitude. The communication phases are "climb and maintain" or "descend and maintain".

Cruise: It is used by controllers to authorize an aircraft to operate an any altitude between the assigned altitude and the minimum IFR altitude. It can also be used to authorize pilot to conduct any instrument approach procedure published for the destination airport.

Cross at: By using this clearance, air traffic controller requires an aircraft to cross a particular navigational fix at a predefined altitude.

- Required Reports

Controllers may request pilot to report the state of the flight, such as altitude, speed, rate of climb/descend. Sometimes, they will ask pilots to report when aircraft crossing a particular fix or intersection, reaching an altitude, or leaving an altitude.

- Holding Instructions

Due to the traffic in downstream sectors or airports reaching saturation, air traffic controller may issue handing instructions to the aircraft. A holding pattern requires pilot flying a modified racetrack patterns in reference to a fix or a navigational aid.

2.2.4 Information Diffusion via Voice Communication

Many of the tasks presented in Section 2.2.1 are done through communicating with an aircraft or after communicating with an aircraft. In performance these tasks, a controller accepts inputs, process information, prioritizes, and acts(Rodgers and Drechsler 1993). Controllers' response to these tasks, are all communication-related which are reflected in the controllers' workload (Stein 1985). Before the slowly emerged data link communication, verbal communication was the only way for controller and pilot to exchange information. Recent work have demonstrate that controllers have clear preference for the data communication while pilots are reluctant to use data communication (Lacher, Battise et al. 2011). Therefore, verbal communication is likely to remain the prime means for controller-pilot communication for many years. Although there are many factors affecting controllers' activities and consequently influence the system, from a system perspective, it is the controller's voice communications that influence the system operation. By definition, the *activity is a coherent system of internal processes and external behavior and motivation that are combined directed to achieve conscious goals* (Bedny and Meister 1997). Thus we assume controller’s voice communication activity encapsulates both cognitive efforts and physical efforts to accomplish the mission of ensuring traffic safety and efficiency.

Controller’s communication activity is referred as the event that controller press the push-to-talk button and hold in order to send the transmissions to aircraft. Normally the contents of the transmission should contain the information that to which aircraft the communication is addressed. It is very rare that one transmission includes more than two flight call-signs separated by ”break”. Hence, air traffic controllers' communication activity with pilots can be seen as the information diffusion process.

2.2.5 Summary

Air traffic controllers are inter-linked with the other parts of the ATC system, and play a vital role to keep the system operate safely and efficiently. In the en route or approach sector, air traffic controller has to deal with a large number of aircraft that come from variety of directions with diverse speeds and altitude, heading to different destinations. There are two important issues regarding on the controller element in the ATC system. The first one is safety concerned. To prevent aircraft accident or incident occurs, air traffic controllers have to work avoiding high workload and fatigue. The second is the capacity constraints. When controllers cannot maintain a safe traffic flow in the sector, then the sector resource cannot meet traffic needs. Constraints will be issued to limit incoming traffic.

Researchers and engineers have long sought to analyze the air traffic controllers' activities. In the Section 2.3, a brief literature review on the studies of air traffic controllers shall be presented.

2.3 The State-of-the-Art on the Research of Air Traffic Controllers' Activities

In this dissertation, air traffic controller is regarded as an adaptive element of ATC system. The dynamics of controllers' behaviors is of particular interest to us. To have a systematic view of air traffic controllers' activities, we organize the related research work into three parts according to the structure illustrated in Figure 2-7, the tasks demands, internal activities, and the output strategies. It should be mentioned that the research work in each part are not independent, with many of which are related to the mental workload.

2.3.1 Tasks Demands: Air Traffic Complexity

Investigation on the tasks demands as the factors that drive controllers' activities has a very long history (Arad 1964; Couluris and Schmidt 1973; Hurst and Rose 1978). Examinations on the relationships between workload and task demands are extensively conducted. Existing work on the analysis of tasks demands that affect controllers' workload are mainly focusing on three aspects, air traffic factors, airspace factors, and operational constraints(Loft, Sanderson et al. 2007). In fact, distinguish either one of the three to analyze will lead to inappropriate. In this part, our focus is given into the work on air traffic complexity.

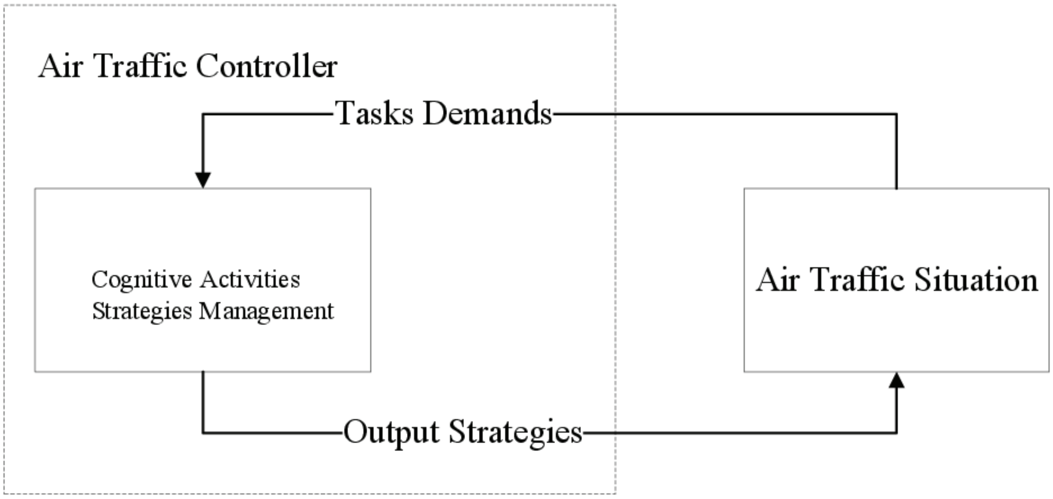


Figure 2-7 Three aspects of the study on air traffic controllers' activities: tasks demands, internal activities, and output strategies.

2.3.1.1 Dynamics Density

In earliest work, factors that have been examined to relate to workload were the observable variables. These traffic factors include: air traffic density, the distribution of arrival/departure/overflying flows(Rodgers and Drechsler 1993), the number of airports(Davis, Danaher et al. 1963), number of aircraft under control, peak value of the traffic, time spent on communication(Hurst and Rose), changes of flights routes, number of aircraft handle in/off (Stein ; Mogford, Guttman et al.).

With the dramatic growth in traffic demands, solely depending on the observable traffic factors is incapable to capture the characteristics of workload. There were consensuses among research and operational communities that the understanding of the inter-correlations between traffic factors is essential to measure and to predict workload. Many researchers have tried to demonstrate the complexity factors that reduce sector capacity by increasing controller workload. Metrics derived from traffic data, such as dynamic density to indicate traffic complexity, were proposed as an important input for workload models.

The dynamic density concept attempts to measure control-related workload as a function of both the traffic volume and traffic complexity (Mogford, Guttman et al. 1995; Laudeman, Shelden et al. 1998; Sridhar, Sheth et al. 1998). Mogford and Guttman et al. summarized more than 40 types of complexity factors based on observation and interview. They found that air traffic complexity is closely related to the number of aircraft, airspace structure, separation standard, aircraft performances, traffic flow, and weather. A specific research about airport tower ATC complexity was conducted by Koros et al.(2003). Heavy traffic, congestion of communication channel, and runway/ taxiway configuration are the major complexity factors affecting controller workload.

Especially when heavy traffic interacts with other complexity factors, it will have a great impact on ATC complexity.

The first mathematical model to quantify dynamic density was developed by Laudeman et al (1998). They defined dynamic density as the method to estimate workload as a function of aircraft density and control complexity. Dynamics characteristics, aircraft density, and conflicts are three kinds of complexity factors. In detail, there are nine factors f in total: (1) Number of aircraft with heading change; (2) Number of aircraft with speed change; (3) Number of aircraft with altitude change; (4) Number of aircraft with 3-D Euclidean distance between 0-5 NM excluding violations; (5) Number of aircraft with 3-D Euclidean distance between 5-10 NM excluding violations; (6-8) Number of aircraft with 3-D Euclidean distance between 0-25NM, 25-40NM, 40-70NM and vertical separation less than 2000/1000 feet above/below 290,00 feet; and (9) Number of aircraft in the sector. The equation to calculate dynamic density is

$$DD = \sum_{i=1}^{9} w_i \times f_i \,,$$

where w_i is the associated weight. The weights are obtained and validated through the regression tests on the observations data from Oakland control center.

There are main drawbacks of the approach for dynamic density, which include overly relying on linear technology, ignoring the self-adjustment of controller workload, and the predefined problem solving method violating with the real source of workload (Averty, Athenes et al.). In fact, most of traffic factors are non-linearly interacted (Chatterji and Sridhar 2001; Kopardekar and Magyarits 2002; Kopardekar and Magyarits 2003). Chatterji et al.(2001) pointed out the limitations of existing approach to calculate the dynamics density. One reason is that the non-linear relationship existing between different complexity factors. Another aspect is that the cognitive factor should be considered when analyzing the impact of traffic geometry on ATC control progress. Simply depending on controller's observable behavior to reflect controller workload has huge limitation.

The performance of dynamic density predictability depends on time window (Baart 2001). Masalonis et al.(2003) investigated the validity of the dynamic density when used in tactical traffic flow management. They integrated four types of dynamic density factors and obtained 41 types of complexity factors. After refinement of these complexity factors, a dynamic density adaptive model including twelve complexity factors was developed.

To anticipate and quantify workload ahead of time, some researchers proposed using dynamic density as an estimator of workload, which can be obtained through the linear combination of the predicted dynamic density factors(Kopardekar and Magyarits 2002; Klein, Rogers et al. 2008; Bloem, Brinton et al. 2009).

Although the study of dynamic density has been extensive, there are still essential questions that cannot be answered. A key hurdle is the nonlinear inter-correlations among the complexity factors. A contradiction exists between this methodology and its objective. The basis of derivation of dynamic density is the correlations between dynamic density and workload, whereas the workload cannot be estimated correctly.

2.3.1.2 Other Complexity Metrics

Beside dynamic density, there are other approaches being proposed to measure sector complexity (Chatterji and Sridhar 2001; 2002; Masalonis, Callaham et al. 2003; Busing and Hansman 2006; Kopardekar, Rhodes et al. 2008).

The first type is based on the dynamical system modeling approach. To avoid measuring workload, Delahaye and Puechmorel et al. attempted to define and calculate traffic complexity from flights' trajectories, which they believe it can capture the instinct characteristics of complexity(Delahaye, Paimblanc et al. 2002; Delahaye, Puechmorel et al. 2004; Delahaye and Puechmorel 2010). The brief idea is to compute the disorder of traffic geometry using the relative positions and velocities of the aircraft. Noted that the overall evolution of traffic situation was not involved, Delahaye et al. proposed a non-linear dynamical modeling approach. The trajectories of aircraft are represented as a vector field. Complexity maps are measured as the Lyapunov exponents of the associated dynamical system.

Another approach to define and compute traffic complexity is based on the analysis of the disturbance of the traffic, i.e. the Input-Output approach (Lee, Feron et al. 2007; Lee, Feron et al. 2009). Control activity was illustrated in detail in respond to operation environment change. They introduced a “complexity map” that provides complexity for a given traffic situation. Then a scalar measure of air traffic complexity can be extracted from the complexity map.

A third trend in the study of complexity is the use of probabilistic measure accounting for the uncertainty in the future aircraft positions (Prandini, Putta et al. 2010; Prandini, Piroddi et al. 2011). Aircraft trajectory is predicted by the nominal trajectory based on current state and intent, together with the prediction error modeled by Brownian motion. Manipulating on the proximities in time and space of the aircraft will obtain the complexity maps for different consecutive time intervals.

With the deployment of new automation system, the determination of complexity factors has to change accordingly. For example, to evaluate the relationships between air traffic complexity and controllers' workload in the data communication environment, a link between complexity and controllers' subjective workload has to be reestablished by relating new complexity factors to workload indicators (Djokic, Lorenz et al. 2010).

Air traffic complexity should account for the traffic dynamics to measure the difficulty and effort to safely managing the traffic within a sector, aiming at evaluating controllers' mental workload. In the future air traffic control system with separation responsibility delegated to air crew, air traffic complexity could be useful for predicting conflicts and trajectory management. Traffic factors that may drive controllers' activities have been commonly identified. How these factors interact with each other is poorly understood. Description of the inter-relationships of the complexity factors based on the observation or enumerating cannot measure and predict complexity correctly, because that there are too many traffic situations which could not be anticipated. Thus, a great deal of work remains. How to account for controller active behavior is very critical. In the following, cognitive analyses on controllers' activities will address this important issue.

2.3.2 Internal Activities: Cognitive Activities and Workload

It is thought that workload, at a microscopic level, is one of the main factors affecting controllers' performance. Great efforts have been focusing on measuring and predicting controllers' 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 (Schmidt 1976; Schmidt 1978; Robertson, Grossberg et al. 1979). Gawron (Gawron, Ball et al. 1989) 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 (Manning, Mills et al. 2002). 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.

While tasks demands factors derived from traffic and airspace configuration provide us a general picture of the origin of workload, investigation on how controller mitigates the impact of these factors by making and selecting strategies is the core to model and predict workload. As stated in (Kopardekar and Magyarits 2003; Masalonis, Callaham et al. 2003; Loft, Sanderson et al.), the dynamics properties of workload incorporated with controller strategies management should be investigated in order to measure workload correctly. Cognitive task analyses have demonstrated that air traffic controllers have to achieve many tasks. Three higher level control tasks are (1) the control task of maintaining situation awareness; (2 the control subtasks of detection conflicts and (3) resolving conflicts(Kallus, Van Damme et al. 1997; Neal, Griffin et al. 1998; Hilburn 2004; Loft, Sanderson et al. 2007). Such cognitive tasks management is directly related to the controllers' workload. When managing the traffic, controllers maintain a valid mental representation of the current traffic situation, which is referred to as situation awareness. Conflict detection is connected to the workload in that the difficulty to detect conflicts imposes additional constraints on the controllers, because it will decrease the time available to resolve the conflict. Most of the ATC control systems have the function to detect the conflicts in user defined time horizon. Literatures on the conflict resolution report various algorithms for conflict resolution. Interviews with controllers explicated that controllers have a "conflict resolution library" for the sectors they are working in(Neal, Griffin et al. 1998; Kallus, Van Damme et al. 1999). Such knowledge is accumulated during their daily operations. When to resolve the conflict is depending on the traffic and varies from controller to controller.

The sources that attribute to cognitive complexity are proposed and classified into three distinctly different classes, environmental, operational, and display(Cummings and Tsonis 2006). Environmental sources include the number of aircraft in the sector, weather, and congestions etc. When the airspace reaches saturation, the requirement to maintain traffic operated under operational constraints will increase controllers' workload, which is the operational source of cognitive complexity. By transferring the high level cognitive tasks that needs for mental computation to low level cognitive tasks and visualizing that in the display, will alleviate controllers' workload. Environmental sources are found to be the predominant among the three during two experimental tests.

A brief summary of some relevant work on cognitive complexity is presented by Hilburn (2004). Decomposing cognitive tasks reveals what controllers have to do in an abstract level. The understanding of the shift of strategies between the cognitive tasks is far behind. That is about the strategies created by controllers about how to use the available resources to achieve these tasks. Notably, few work have significantly contributed to our understanding of the mechanisms that radar controllers use to mediate cognitive complexity so that simplifying mental workload(Kirwan, Scaife et al. 2001; Schaefer, Meckiff et al. 2001; Histon 2002; Histon, Hansman et al. 2002; Histon and Hansman Jr 2008; Histon and Hansman 2011). For instance, Busing et al.(2005) analyzed the traffic characteristics both in the structure route environment and in the free flight environment. They believed that the operate mode used by controller can be reflected through his external behavior. By changing the system performance (e.g. efficiency), controller internal cognitive method could be obtained. In the work done by Histon et al, it 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 types of structure-based abstractions. The most effective way to mitigate cognitive complexity is to reduce the “order”. To test the hypothesis, transitions between operation modes of controllers were observed during human-in-the-loop experiments that were set with different traffic levels. The results suggest that controllers modify their structure-based strategies in response to the change of traffic situation (Histon and Hansman 2011).

The last groups of studies on workload are based on controllers' physiological indicators that are recorded when they are controlling air traffic (Collet, Averty et al. 2009; Dasari, Crowe et al. 2010). For instance, research on eye movement parameters has found that eye activities are correlated with cognitive demands. In (Ahlstrom and Friedman-Berg 2005; Martin, Cegarra et al. 2011), Ahlstorm and Friedman-Berg measured controllers' eye movement activities during real-time simulation, including blink durations, mean pupil diameter etc. They concluded that eye movement activities measures can provide a measure of controller workload. The statistical analyses of these measures can indeed capture the fluctuations in workload levels. However, both the difficulty of recording physiological parameters and the highly dependent factors such as airspace configuration, air traffic distribution, and controller's experience etc., make it unsuitable for predicting workload or available resource of controller (Di Stasi, Marchitto et al. 2010).

In a paper that deserves to be better known, Loft et. al. present an exhaustive review on the modeling and predicting workload in en route air traffic control(Loft, Sanderson et al.). They argue that the link between task demands and workload is largely connected to the manner in which controllers manage their resources. Building on the previous research, a model that integrate the tasks demand and controllers' capability has been proposed (Figure 2-8). A recent report found that spatial context can help air traffic controller to reduce prospective memory error and the response costs to ongoing tasks, providing evidences the effective use of appropriate decision support tools in the air traffic control(Loft, Finnerty et al. 2011).

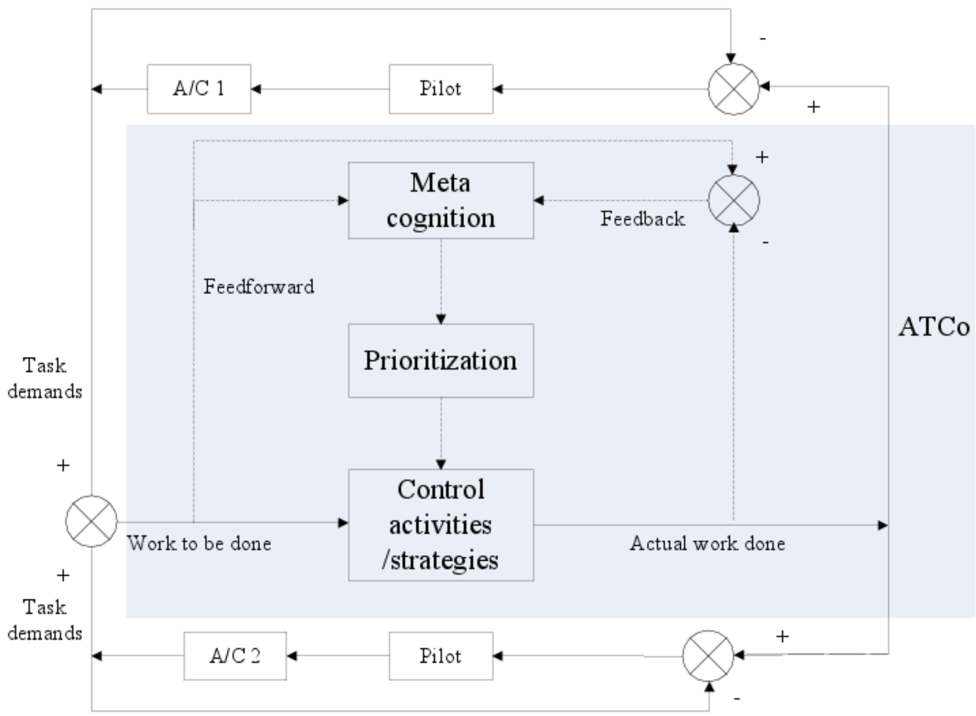


Figure 2-8 Model air traffic controller's mental workload. Picture was exactly copied from (Loft, Sanderson et al.)

2.3.3 External Activities: Voice Communication Activities and Performance

Before the slowly emerged data link communication, for instance the Controller Pilot Data Link Communication (CPDLC), voice communication was the only way for controller and pilot to exchange information. It is still the primary controller-pilot communication way in most of air traffic control centers.

Analysis of air traffic controller voice communication data has a long history. In the past, communication events were extensively used to measure workload (Cardosi 1993; Manning, Mills et al. 2002; Manning, Fox et al. 2003; Coffey, Harrison et al. 2011; Lamb, Bartlett et al. 2011). Communication times (Corker, Gore et al. 2000), Communication durations are all found to be good measures of workload (Porterfield). The number of communications between controller and pilots were found significant related to both traffic volume and traffic complexity (Bruce, Freeberg et al.). Porterfield investigated the correlations between the controller's communication duration of the 4 minutes prior to a rating and the controller's subjective workload ratings. It was found that the correlation coefficient was 0.88 with $p < 0.01$(Porterfield). Rantanen et. al. investigated the impact of audio delay and pilot delay in air traffic controllers' communication on controllers' performance and workload(Rantanen, McCarley et al. 2004). 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 indicates that voice communication metric does not make a unique contribution to the workload evaluation (Manning, Mills et al. 2002; Manning and Pfleiderer 2006).

There are researchers investigating controllers' communication from other perspectives. A series of reports on the statistical analyses of voice communications between pilots and controllers' can be found in (Hunter, Blumenfeld et al. 1974; Hunter and Hsu 1977; Hunter, Blumenfeld et al. 1998). Based on a two-hours voice communication during peak traffic period in the New York area on April 30, 1969, Hunter et al. analyzed the controllers' communications, then developed a simulation model that is able to characterize "general" sector functions (as contrasted with individual sectors). Recent work on the study of radio channel utilization can also be found in (Popescu, Augris et al. 2010).

Time required for an air traffic controller to successfully transmit a message containing a maneuver required for traffic avoidance to a pilot was analyzed in (Cardosi 1993). According to the procedure and practices in air-ground communication, the required time can be broken down into three components:

(i) the duration of controller's message;

(ii) time between the end of the controller's message and the beginning of the pilot's message;

(iii) the duration of the pilot's acknowledge.

Analysis on forty-six hours voice communication data that was recorded from Air Route Control Centers show that it takes **ELEVEN seconds** in average for a successful message transmission. These findings are very important for our analysis of temporal behavior of controllers' activities.

A model of air ground communications in air traffic control has been develop in MITRE with the aim to add communication process in a fast time simulation models of Center for Advanced Aviation System Development (CAASD) of the MITRE Corporation (Monticone, Snow et al. 2006; Monticone, Snow et al. 2006). In **Table 2- 2** a comprehensive list of communications messages is presented. In the model, triggers that cause a communication event are based on aircraft proximities (aircraft to airspace proximity and aircraft to aircraft proximity), voice tape transcription data, or obtained from host amendments.

Table 2- 2 Communication Messages Categories

Message Category	Data	Voice
Logon (data communication only)	DLIC	N/A
Handoff: Transfer of communications (pilot must change frequencies) and Initial Contact (an initial contact with the controller using next frequency)	TRACON-to-Center	Boundary Crossing
	Sector-to-sector within Center	
	Center-to-Center	
	Center-to-TRACON	
	N/A	ATCT-to-TRACON
	N/A	TRACON-to-ATCT
Controller Initiated Status/Advisory	Altimeter setting Instruction	Altimeter setting Instruction
	Beacon code setting instruction	Beacon code setting instruction
	Weather advisory	Weather advisory
	Traffic advisory	Traffic advisory
Controller Initiated Clearance	Heading Change	Heading Change
	Altitude Change	Altitude Change
	Route Change	Route Change
	Speed Change	Speed Change
	Crossing Constraint	Crossing Constraint
Pilot Initiated Clearance Request	Altitude Change	Altitude Change
	Route Change	Route Change

2.3.4 Discussion

To summary, there are three major problems in the study of air traffic complexity. The first one is the deadlock in the calculation of complexity by correlating to workload, i.e. the contradiction between its approach and its objective. The objective is to obtain the metrics that is able to reflect the role of traffic in controllers' mental workload, whereas controllers' workload cannot be measured and predicted correctly so we have to look at the traffic. Second, the analysis of traffic complexity through the aircraft trajectories has difficulty to capture controllers' and pilots' intentions. Although one may argue that some complexity metrics reflect the intrinsic characteristics of the traffic, it is human at the end that are responsible for ensuring aircraft safely, either by manually management or by the design of automation system to manage it. Finally, identifying the complexity at the microscopic level focusing on the local dynamics fails to explain the emerged macroscopic characteristics of system behavior observed in a larger scope. It roots back in the inadequate knowledge about how air traffic controllers carry out control tasks.

Although the studies on workload and other human factors related topics have been impressive, up until now, quantifying and predicting the controllers' activities remains an open problem. One might think that a key hurdle that prevents us from an in-depth investigation of the air traffic controllers' activities is the limit knowledge about the correlations between air traffic dynamics and air traffic controller's dynamics. Classical methods usually focus on the specific problems, e.g. analysis of controller's workload in a certain sector. With a few exception (Histon and Hansman Jr 2008; Clarke, Durand et al. 2011), much less has been done toward the understanding of the dynamics process of air traffic controllers' activities.

Deviated from our ever believed hypothesis that human activities are randomly occurred and are difficult to describe, the patterns of human activities do exhibit similarity among human beings, suggesting that there exist universal mechanisms govern human activities (Barabasi 2005; Malmgren, Stouffer et al. 2009). Research on human dynamics sheds light on the study of controllers' activities. A straightforward question is that whether there are the same types of activities patterns among the controllers. We would argue that the data-driven approach can be adapted to the analysis of controllers' activities with the knowledge of controllers' internal activities. This thesis will study the temporal, spatial, and fluctuation scaling behaviors of air traffic controllers' activities with controllers' voice communication as a proxy. We believe that such approach can be easily extended into the future operation environments.

2.4 Chapter Summary

Air traffic controllers are in a continuous environment, and they are inextricable linked with the system. Their behaviors might depend 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 adaptive property of the controllers' activities.

CHAPTER 3 THE TEMPORAL CHARACTERISTICS OF CONTROLLERS' COMMUNICATION ACTIVITIES

Previous investigations on controllers' communication are focusing on the relationships between communication events and controllers' mental workload rather than the dynamical property of the communication. So far, there is a lack of quantitative understanding of the mechanisms that govern controllers' activity.

As a matter of fact, it has been long assumed that most of human activities are randomly occurred which are described by the Poisson process. Because of the electronic devices being widely used in human daily life, the historical data of human activities can then be recorded forming large empirical datasets. Analyses on various ranges of human activities' datasets have shown that, different from common belief respecting random-based Poisson distributions, patterns of human activities are fitting into power law distribution with heavy-tail patterns. Burgeoning empirical evidences from human dynamics recently founded the similar patterns among human being, suggesting that there exist universal mechanisms governs human activities. One would argue that there are significant differences between air traffic controllers' activities and other human daily activities. Nevertheless, the emerged human dynamics research provides the methodological aspects of the understanding of air traffic controllers' activities, which we shall discuss in this chapter.

The organization of this chapter is as follows. Section 3.1 presents the brief literature review on human dynamics, as well as the comparisons between examined human activities and air traffic controllers' communication activities. In Section 3.2, we show the five different datasets that have been analyzed, which includes two real-time simulation datasets and three operational datasets. Then the correlations between air traffic and controllers' communication are given in Section 3.3. Two widely studied complexity metrics, the Dynamic Density (DD) and the Complexity based on Dynamical System Modeling (C-DSM) approach, have been constructed from the aircraft trajectory data to examine the interaction between traffic activities and controller’s communication activities. The investigation on the temporal characteristics of controller activities is presented in Section 3.4. Psychological interpretation of the temporal characteristics of controllers' activities is discussed in Section 3.5. This chapter ends with conclusions and discussions in Section 3.6.

3.1 Introduction

3.1.1 Human Dynamics: Empirical Evidences

We used to assume that most of human actions occur randomly. The basic assumption of human dynamics models, which are used from communications to risk assessment, had been that the temporal characteristics of human activities could be approximated by Poisson processes. The difficulty of collecting experimental and real data had limited the quantitative investigation of human activity, which resulted in that the hypotheses and conclusions were given in qualitative. Thanks to the rapid development in electronic information technology, human activities data can be easily record which provides a perfect platform for studying human behavior. 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. Heavy-tailed distributions of inter-event times have been widely reporting from various kind of human activities, ranging from correspondence (Oliveira and Barabasi 2005), email communication (Malmgren, Stouffer et al. 2008; Malmgren, Hofman et al. 2009), through printing behavior (Harder and Paczuski 2006), online films rating (Zhou, Kiet et al. 2008), short message texting(Wu, Zhou et al. 2010), to human mobility (Gonzalez, Hidalgo et al. 2008). 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. The similarities of the distribution of inter-activities times among human beings indicate that the way human do things is irrelevant to the contextual conditions. For example, Figure 3- 1 plots the distributions of response times for the letters replied by three famous scientists. In can be seen from the figure, all the inter-events times are well described by the Power Law form with exponent $\alpha = 1.5$. In Appendix I give the summary of different human activities that have been analyzed.

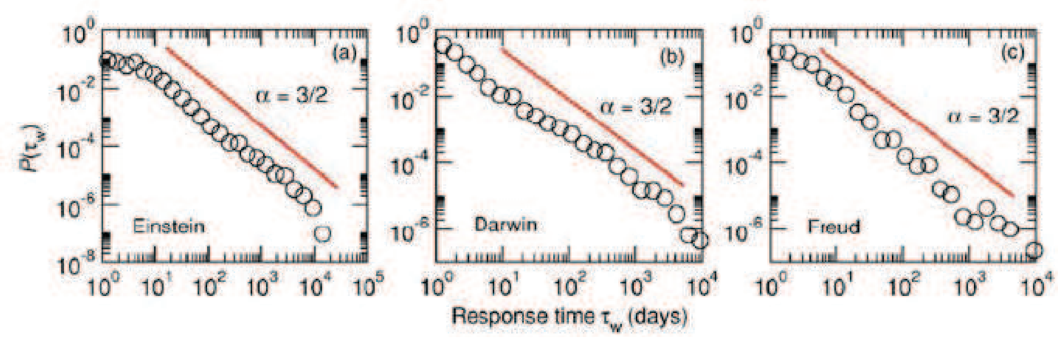


Figure 3- 1 The distributions of response times for the letters replied by Einstein, Darwin and Freud respectively. It is an exact copy from(Vaquez, Oliveira et al. 2006).

The statistical characteristics of the inter-activities indicate there may exist universal mechanism underlying that govern human activities. Based on the observed phenomena, relative models have been proposed to mimic how human behave when execute tasks.

3.1.2 Human Dynamics: Models

3.1.2.1 B-A Model

For the first time, a priority queuing model was developed by Barabási to show the bursty nature of human activity rooted from the decision-based queuing process when human execute tasks (Barabasi 2005). Heavy-tailed distributions can be explained by a simple hypothesis, i.e. humans execute their tasks based on some perceived priority, setting up queues that generate very uneven waiting time distribution for different task. In detail, when human has a list of tasks with different priorities to do, the rule by which he selects a task to execute was given as:

- with a probability of p choosing the highest priority one; or
- with a probability $1-p$ randomly selecting a task.

After the execution, the task will be removed from the task list, and a new task assigned with a different priority will be added in the task list. Such simply rule can reoccur the bursty phenomena of activities' pattern.

3.1.2.2 Cascade Poisson Model

Malmgren et al argued that the correspondence patterns are better described by a lognormal distribution rather than a power-law distribution (Malmgren, Stouffer et al.). They 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 (Malmgren, Hofman et al. 2009; Madl, Baars et al. 2011; Shafiq and Liu 2011).

Poisson process has been long used to simulate the arrival rate of events. A homogeneous Poisson process has a constant rate ρ, whereas a non-homogeneous Poisson process has a rate $\rho(t)$ that depends on time. To account for the circadian cycle, the rate of the non-homogeneous Poisson process is related to the daily and weekly distributions of active interval initiation, p_d and p_w:

$$\rho(t) = N_w p_d(t) p_w(t),$$

where N_w is the average number of active intervals per week. Then from this process, a secondary process is initiated which can be modeled by a homogeneous Poisson process with rate ρ_a, during which N_a additional events occur. N_a is drawn from some distribution $p(N_a)$.

3.1.2.3 Interaction Model

To examine the interaction among individuals, Wu et al. found a bimodal distribution, the combination of Poisson and Power-law, of inter-events times of human short message correspondence activities(Wu, Zhou et al.). To mimic this phenomenon, they developed a model which contains three important ingredients: (i) independent random Poisson processes that initiate tasks; (ii) decision making based on a priority-queuing mechanism for task execution in individual; and (iii) the interaction among individuals.

Based on observation, two types of tasks of an individual were identified, namely the interacting task (I-task) and non-interacting task (O-task). To account for the interaction, the model consisted of two main parts: Priority-queue of tasks of individuals and the interaction between individuals. The idea of Priority-queue tasks of individuals is the same as B-A model, except that a processing time t_p is introduced. The probability of adding an I-task is $\lambda_p = \lambda t_p$, where λ is the rate of initiating an I-task with $t_p = 1$ s. Denote P_A and P_B as the probability of A and B to respond to the received I-task respectively. If A decides to reply the I-task, then the task will be added into A's task list with random probability. When the I-task has been executed, it is B's turn to decide whether or nor to reply with probability P_B. Consequently, there will be a number of mutual interactions until someone decide not to reply.

3.1.3 Comparison with Air Traffic Controller's Activities

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. 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 controllers' activities, for example, the dependence on environmental conditions, and urgency or time pressure. In summary, there are three major characteristics of air traffic controllers' activities that are different from the above listed activities.

a) ***Dependence on environmental conditions***. The main goal of air traffic controller is to ensure the aircraft under jurisdiction reach their destinations respectively while adhere to the separation standards and operation regulations. The characteristics of sector configuration, operational procedures, and air traffic are the main objective factors that may determine controllers' behavior. Hence, the activities dynamics should be sector-specific and thus depending on the sector configuration, procedures, and traffic.

b) ***Urgency or time pressure.*** The air traffic controller has to complete many tasks to meet the rapidly changed situation. Compared with daily activities, such as email communication, many of controllers' tasks are more time-pressuring. The competent controller has the ability to appropriately utilize the resources in the finite time. It is the strategies which the controller uses to maintain acceptable workload and performance level that determine his/her activities.

c) ***Frequently interacting with pilots.*** Previous studies on ATC communications classify controllers' communication activities into several types based on the contents of transmissions (Manning, Fox et al. 2003). Most of controller communications are the interacting with pilots. Normally, controller should give a prompt response to the pilot when a pilot talks to controller.

To make a further comparison between air traffic controllers' activities and examined human activities, Figure 3- 2 reports the benchmarking of human activities. **Table 3- 1** shows the comparisons in the main characteristics, common methodologies used to study, and the disadvantages of the methodologies.

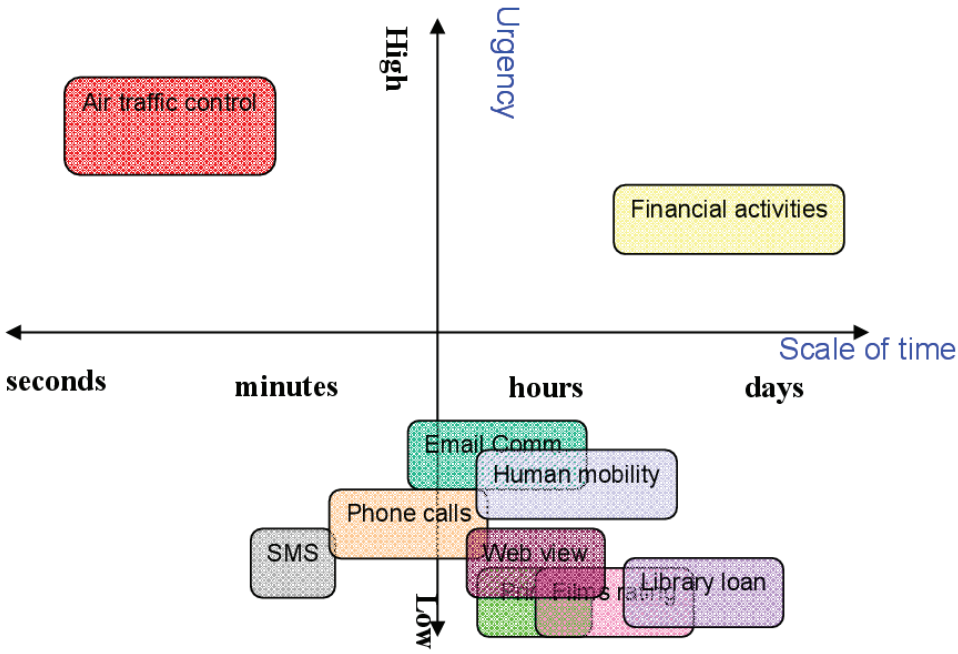


Figure 3- 2 Benchmarking of human activities in terms of task urgency and timescale of responding to a task.

In spite of the above listed issues in air traffic control, controllers still have the flexibility to manage the resources, including airspace/airport resources and their own resources. For example, Histon and Hansman (Histon and Hansman Jr 2008) 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. However, the quantified description of the mechanisms by which controller uses to manage the air traffic are still unknown.

Table 3- 1 Comparison between air traffic control and other human activities

	Air traffic controller's activities	Human daily activities
Characteristics	High pressure Typically 2 hours work	Low pressure Very long range of activities
Methodologies to investigate	Psychological and Cognitive science	Data mining Statistical mechanics
Results	Descriptive results of human behavior Explained from internal activities	Quantitatively capture activities measures Unmask the universal patterns
Disadvantages	Most of results cannot be predicted Results depend on traffic and airspace, and other factors. Too microscopic to be adopted to the whole system	There is few investigation on a specific task-driven activities Cannot be applied into air traffic control directly
The common point between controllers' activities and other activities is: **ADAPTATION**.		

3.1.4 Objective

The understanding of mechanisms that underlie air traffic controllers' activities is fundamental to predict and control their activities, which in turn to manage the ATM system. Inspired by the human dynamics research, our purpose here is to investigate the tasks execute mechanisms of the controllers. More precisely, the similar data-driven approach has been employed to analyze the temporal behavior of controllers' communication. Our hypothesis lies upon the question whether or not controllers' dynamics obeys the same power law patterns. In spite of the variety of tasks, the underlying cognitive process might be universal.

3.1.5 Definitions

As described in the previous chapter, there is unique frequency in a sector for as the communication channel between air traffic controller and each aircraft pilot with that sector's jurisdiction. Air traffic controller and pilots have to use this channel to exchange information alternately. To examine air traffic controllers' activities, we shall give the following definitions that will be used in this chapter and hereafter.

(1) **Communication event.** It is defined as that controller press the push-to-talk button and hold in order to send the message to aircraft, which is also termed as "**Transmission**" (TR). Particularly, empty transmission is also seen as a complete communication event.

(2) **Communication Transaction**. A complete conversation between aircraft and controller is composed of separate TRs, which are alternatively made by controller and pilot. This is defined as "Communication transaction" or "CT"(Hunter and Hsu 1977). For example, the first two blue communication events in Figure 3- 3 could be a CT if the first four strips are about the conversation between PL1 and the controller.

The timing measurements that will be used include:

(1) L_i : the length of communication event i ;

(2) τ_i : the inter-arrival time, i.e. the time difference between two consecutive communication events;

(3) τ_w : the inter-communication gap Length. It is defined as the time length between two consecutive CTs'.

Figure 3- 3 also illustrates the example of the timing measurements.

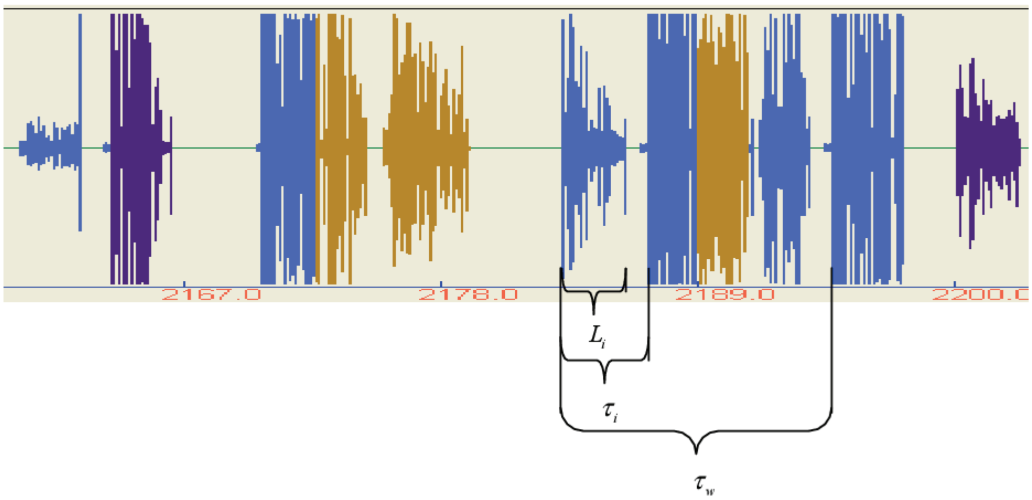


Figure 3- 3 Definitions of communication activities of a controller. Blue trunks are the communications made by controller, while yellow and dark pink trunks are made by pilots. Data was recorded in ATC Chicago Center.

3.2 Data

Both operational data and real-time simulation data were collected to study the controllers' communication behaviors. Two real-time simulation datasets, namely Paris TMA simulation data and ATCOSIM corpus data, are from EUROCONTROL Experimental Center, while two real datasets were recorded in the different ATC centers in the United States of America and one is from Chinese ATC center.

3.2.1 D_1 Dataset

The first dataset is Paris TMA simulation data, which was recorded during a two weeks real-time simulation at EUROCONTROL Experimental Center 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 one hundred participants over two weeks: forty-five controller positions and thirty-five pilot positions. Thirty sectors were simulated, which includes eleven sectors of the Athis-Mons Control Center, thirteen approach positions, two military positions and four feeds. 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.

There are twenty exercises, with an average of two hours long for each exercise. Among them, fourteen exercises are identified as good exercises that can be analyzed. Apart from traffic initialization and the end of simulation, each exercise has about one hour and thirty minutes long. There are 79,847 controllers' communication activities in total (4,885 were with length of one seconds, and 12 were more than 30 seconds). Form the recorded data we pick up three data sets that are necessary for our investigation. For each exercise, the data include:

a) ***Radio communication data.*** This one contains the start times and end times of the communication made by the controller and pilots. The content of communication is unavailable. An average of 300 communication events made by the controller were identified in each sector of each exercise.

b) ***Pilots manipulating data.*** Pilots' data was retrieved from the flight simulator. The simulator recorded every manipulation related to changes of flight motion. Hence, we could find in this data set 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.

c) ***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 during the measured period.

d) ***Trajectory***. Similar as radar surveillance environments during ATC operation, the simulation system has recorded the position of every aircraft in terms of longitude and latitude, every five seconds. Each piece of record consists of simulation time, sector on the frequency, position (longitude, latitude, altitude), and velocity (TAS/CAS, turning rate, climb/descend rate) etc.

3.2.2 D_2 Dataset

The second dataset has been analyzed is the ATCOSIM Air Traffic Control Simulation Speech corpus of EUROCONTROL Experimental Center. 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 (Hering 2001). 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 any information on traffic or airspace corresponding to the communication data.

The general information of the whole fifty exercises is shown in Table 3- 2, while detailed information on each exercise is not given here.

Table 3- 2 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 (has only one transfer)	3121 (1966)	62.42 (4)
Number of the communication events that identified with flight call-signs (unidentified)	10078 (1276)	201.56 (26)

3.2.3 D_3 Dataset

To investigate the other factors' effects on the controller's communication, such as culture, we obtained the operational data from several air traffic control centers in the United States of America. D_3 Dataset 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 (Manning, Mills et al. 2002) 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. It could be used to test the collective phenomena from human dynamics point of view. Therefore, we complement the temporal part with this dataset.

3.2.4 D_4 Dataset

D_4 dataset was collected from around 840 hours controllers/pilots voice communication data that have been recorded in Chicago (ZAU) Air Route Traffic Control Center during daily operation. Speech analysis was firstly conducted in order to retrieve the temporal information of communication from the voice data. By the use of speech segmentation toolkit, such as Spkdiarization toolkits (Meignier and Merlin 2010), silence/audio activity were identified under a 2 seconds threshold. Then the start time and end time of each communication event can be obtained. In total, there are 59,589 controller/pilot communication events in this dataset. Speech diarization to calculate accurate data on 'who spoke when' is under investigation.

3.2.5 D_5 Dataset

D_5 dataset was collected from Shanghai Air Traffic Control Center in the early of 2012. Controllers' communication activities were recorded manually on site during the traffic busy hours. There are more than twenty pieces of records, including in total 6,025 controllers' communication activities.

Table 3- 3 shows the general information about this dataset.

3.3 Correlations between Airspace Activities and Controllers' Communication Activities

In this section, we show the results on the correlations between controllers' communication activities and airspace activities. The airspace activity is the activity associated with the aircraft and weather moving through the sector. The measurement of airspace activity can be the counted number of aircraft under control of the sector during a traffic sample (T_t^N), or be other air traffic complexity measures. Here we use traffic count and another two air traffic complexity metrics, namely the dynamic density (DD) and the air traffic complexity based on dynamical system modeling approach (C-DSM). Because the computation of air traffic complexity and traffic count will need detailed air traffic information, therefore the analysis in this section is based on the D_1 Dataset.

3.3.1 Communication Measurements

Research on the air traffic controllers' communication have defined several measurements of communications to identify the relationships between communication and controllers' taskload or workload, many of which are related to a time window t_w (Bruce, Freeberg et al. 1993; Cardosi 1993; Porterfield 1997; Morrow and Rodvold ; Corker, Gore et al. 2000). Following the work in (Manning, Mills et al. 2002), we list two measurements in the study:

- C_t^N : the number of communication events occurring in t_w ;
- C_t^D : the communication density, which defined as $C_t^D = L_t (C_t^N)^\beta$, and β is the parameter to balance the frequency of communication.

Table 3- 3 General information on the D_5 Dataset

Sector type	Sector name	Record date	Time period	Num. of flights	Num. of comm	Duration
APP	1	N/A	1300	74	287	1h49m
APP	1	N/A	1500	81	367	1h49m
APP	2	N/A	0900	34	191	0h53m
APP	2	N/A	1300	57	310	1h25m
APP	2	N/A	1400	46	237	1h03m
APP	2	N/A	1500	58	326	1h26m
APP	3	N/A	0900	44	247	1h31m
APP	3	N/A	1300	48	264	1h40m
APP	3	N/A	1500	43	194	1h34m
APP	4	N/A	0900	20	230	1h11m
APP	4	N/A	1500	25	247	2h07m
ACC	9	0320	1000	39	190	1h26m
ACC	9	0320	1200	37	156	1h42m
ACC	9	0320	1400	68	253	2h16m
ACC	9	0321	1000	31	108	1h21m
ACC	10	0300	1000	31	138	1h37m
ACC	10	0300	1300	53	220	2h03m
ACC	10	0300	1400	35	125	1h22m
ACC	14	0319	1300	62	235	1h47m
ACC	14	0319	1500	79	277	2h08m
ACC	14	0321	1300	72	329	1h57m
ACC	14	0321	1500	52	259	1h31m
ACC	91	0321	1000	49	237	1h43m
ACC	91	0322	0900	38	178	1h54m
ACC	91	0322	1300	49	222	1h58m
ACC	91	0322	1500	43	200	1h38m

3.3.2 Dynamic density (DD)

The first complexity metric that was selected here to correlate controller's communication dynamics is the dynamic density (DD) (Laudeman, Shelden et al. 1998; Sridhar, Sheth et al. 1998). Nine traffic factors considered to contribute to the air traffic complexity can be obtained from the trajectory data. Then DD is calculated as

$$DD = \sum_{i=1}^{9} w_i \times f_i \, ,$$

where

- f_1 : Number of aircraft in the sector;
- f_2 : Number of aircraft with heading change greater than 15°;
- f_3 : Number of aircraft with speed change greater than 10 knots or 0.02M;
- f_4 : Number of aircraft with altitude change greater than 750 feet;
- f_5 : Number of aircraft with 3-D Euclidean distance between 0-5 NM excluding violations;
- f_6 : Number of aircraft with 3-D Euclidean distance between 5-10 NM excluding violations;
- f_7 : Number of aircraft with 3-D Euclidean distance between 0-25 NM and vertical separation less than 2000/1000 feet above/below 290,00 feet;
- f_8 : Number of aircraft with 3-D Euclidean distance between 25-40 NM and vertical separation less than 2000/1000 feet above/below 290,00 feet;
- f_9 : Number of aircraft with 3-D Euclidean distance between 40-70 NM and vertical separation less than 2000/1000 feet above/below 290,00 feet;
- w_i : the associated weight.

3.3.3 Complexity based on dynamical system modeling (C-DSM)}

The second complexity metric being constructed is from dynamical system modeling approach (Delahaye, Puechmorel et al. 2004; Delahaye and Puechmorel 2010). The objective of dynamical system modeling is to uncover the inherent complexity of the air traffic by the means of measuring the disorder of the traffic pattern, to capture all the feature of complexity. Given a set of N observations of aircraft with each observation containing time-related position and velocity, it is first to find a vector field $\aleph : \mathbb{R} \times \mathbb{R}^3 \to \mathbb{R}^3$ which meet certain criteria. Based on this vector field, the Lyapunov exponents are then computed indicating the sensitivity to the initial conditions of the underlying dynamical system.

As the complexity map built from Lyapunov exponents presents the aggregate metric of the complexity, our purpose is however to investigate the characteristics of the dynamic process of controller. Therefore, we employ the linear dynamical system modeling from (Delahaye and Puechmorel 2010) to calculate the traffic complexity. From the aircraft position $\overrightarrow{X} = [x_i, y_i, z_i]^T$ and the speed $\overrightarrow{V} = [v_x^i, v_y^i, v_z^i]^T$, the dynamical system is given as:

$$\dot{\overrightarrow{X}} = A\overrightarrow{X} + \overrightarrow{B}.$$

By minimizing the error

$$E(X) = \sum_{i=1}^{N} \left\| \overrightarrow{V_i} - (A\overrightarrow{X} + \overrightarrow{B}) \right\|^2,$$

the coefficient matrix A can be obtained. Consequently, we compute the Eigen values of the matrix A that control the evolution of the system, with the real part of the values relating to the convergence or the divergence property of the system.

3.3.4 Results

For each sector in the exercise, we calculate the number of aircraft in the sector during the t_w, the DD, and the real-part of the Eigen values of matrix A obtained from the C-DSM approach.

The calculation of DD needs the predetermined weighting factors, and these factors differ from sector to sector. Past work on the DD is aiming at predicting workload. Thus, the determination of weighting factors are based on either the regression tests on the relations between workload and DD elements or on controllers' subjective rating. Here our purpose was to find the relationships between controllers' communication activities and traffic factors. Considering the diversity of traffic patterns, we calculate the nine traffic factors f_i in the same sector of all the simulation exercises, as well as the numbers of communication events occurred in the same widow. Then a multiple regression test on the communications and nine factors is conducted, and the results of the weights are presented in Table 3- 4. The last two rows of the table are the regression results and controllers' subjective rating in (Sridhar, Sheth et al.). Not surprisingly, it is found that the average values of fitting coefficients of our dataset are different from that was used by Sridhar et. al. It is mainly because of the responses variables we used are the number of communication events, whereas Sridhar et. at used workload. Traffic factor f_1, i.e. the number of aircraft in the sector, is significantly contributed to the communication, whereas it does partly contribute to the workload. Both the regression tests with workload or with communication are failed to capture impact of the traffic factors f_7 on controllers' workload, the number of aircraft with 3-D Euclidean distance between 0-25 NM and vertical separation less than 2000/1000 feet above/below 290,00 feet, which controllers think is important to their workload but the regression tests show no impact. Nevertheless, we use both the coefficients obtained from regressions and those from Sridhar et al. to calculate DD then compare DD with controllers' communication activities.

Table 3- 4 Regression results of the values of weight w_i. Values in the parentheses are negative.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9
AOUS	0.64	0.41	0.37	0.59	0.08	(0.02)	0.08	(0.11)	0.06
AR	0.59	0.04	0.51	0.24	(0.49)	0.02	0.11	(0.01)	0.17
AP	0.56	(0.03)	(0.39)	0.21	(0.35)	0.23	0.01	0.22	(0.24)
OYOT	0.57	0.16	0.56	0.50	0.29	(0.22)	0.05	0.09	(0.06)
OGRT	0.57	(0.09)	0.41	0.38	(0.31)	0.22	(0.10)	(0.37)	0.67
TE	0.84	0.05	0.22	0.44	(0.02)	(0.14)	0.29	(0.07)	(0.10)
THLN	0.69	0.47	0.02	0.42	(0.17)	(0.19)	0.13	(0.09)	(0.03)
TML	0.77	0.12	0.33	0.25	(0.10)	0.12	(0.24)	(0.05)	(0.18)
TP	0.53	(0.05)	0.77	0.35	(0.06)	0.23	0.09	0.00	(0.06)
UJ	0.64	0.21	0.42	0.16	(0.29)	(0.08)	0.25	(0.09)	0.01
DENPG	0.91	0.15	0.43	0.16	(0.10)	(0.07)	0.18	(0.15)	(0.59)
DEPPO	1.24	0.01	(0.03)	0.49	0.00	(0.00)	(0.11)	(0.16)	(0.19)
DESPG	1.03	0.16	0.19	0.27	(0.23)	0.16	(0.24)	(0.44)	(0.55)
INIPO	0.99	0.25	0.39	0.23	0.28	(0.02)	(0.38)	(0.13)	(0.07)
INNPG	0.72	0.19	0.13	0.50	(0.39)	0.18	0.02	0.02	0.04
INSPG	0.57	0.30	0.05	0.28	0.71	(0.37)	(0.00)	(0.17)	0.11
ITBPG	0.90	(0.03)	(0.06)	(0.26)	0.31	0.15	(0.11)	(0.21)	(1.35)
ITMPO	0.35	0.48	(0.45)	0.07	0.04	0.25	(0.24)	(0.64)	(0.31)
ITNPG	1.32	(0.25)	(0.17)	0.00	0.10	0.04	0.12	(0.64)	(0.55)
ITSPG	1.58	(0.52)	0.15	0.14	0.07	(0.11)	0.00	(0.38)	0.03
VILLA	0.26	0.55	(0.05)	0.16	0.43	0.07	(0.19)	(0.16)	(0.94)
CREIL	0.43	(0.08)	0.31	(0.04)	(0.05)	(0.14)	0.08	(0.47)	(0.39)
Mean	**0.76**	**0.11**	**0.19**	**0.25**	**(0.01)**	**0.01**	**(0.01)**	**(0.18)**	**(0.21)**
Regression Results in [26]	**0.79**	**2.17**	**0**	**0.88**	**1.02**	**1.18**	**0**	**1.85**	**1.85**
Subjective Ratings	**1**	**2.4**	**2.45**	**2.94**	**2.45**	**1.83**	**4**	**3**	**2.11**

3.3.4.1 Correlations between C_t^N and T_t^N

Given the transfer in/out times of each aircraft, the number of aircraft under control within predefined duration is obtained by iteration. The dynamics on traffic volume and communication events in ACC sectors of Exercise 100607B are illustrated in Fig. 3- 1.

It can be seen in Figure 3- 4 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 can have the correlations between them. To examine the effect of traffic flow patterns on the correlation results, we calculate the correlations between C_t^N and T_t^N in each sector with time steps vary from 10 seconds to 300 seconds. It was observed that the relationships between two quantities fluctuate with time steps (see Figure 3- 5). Although the total number of aircraft under control is highly correlated with the number of communication events, which is in agreement with previous study (Manning, Fox et al. 2003), the strength of the relationships change with the time step. Meanwhile, it suggests that traffic diversity does influence the correlations results. Communication in the en route sectors, such as AOUS, TE, are much more likely to link with traffic volume than that in the Approach sectors, e.g. ITMPO, ITNPG. Possible reason could be that, traffic in the approach sectors are smoother and order than the traffic in the en route sectors. Controllers in charge of en route sectors have more flexibility to control the traffic.

3.3.4.2 Correlations between communication, DD, and C-DSM

In the Table 3- 5, we present the correlation coefficients which show the relationships between controller's communication activities and different air traffic factors of each sector. Both the time window t_w and the sampling time in DD are set to 2 minutes, while the exponent β is 2. The weighted parameters for computation DD are obtained by the regression tests.

It can be seen from the table that DD has quite correlated with both communication events and communication density. Whereas the C-DSP shows very weak relationship with communication, the C-DSM in most of the sectors are negative correlated with the DD. The last two columns present the average correlation coefficients and the associated standard deviation. Again, the DD and C-DSM seem to be independent from each other.

From the results obtained so far, we draw the conclusion that air traffic complexity has little impact on the controller's communication dynamics.

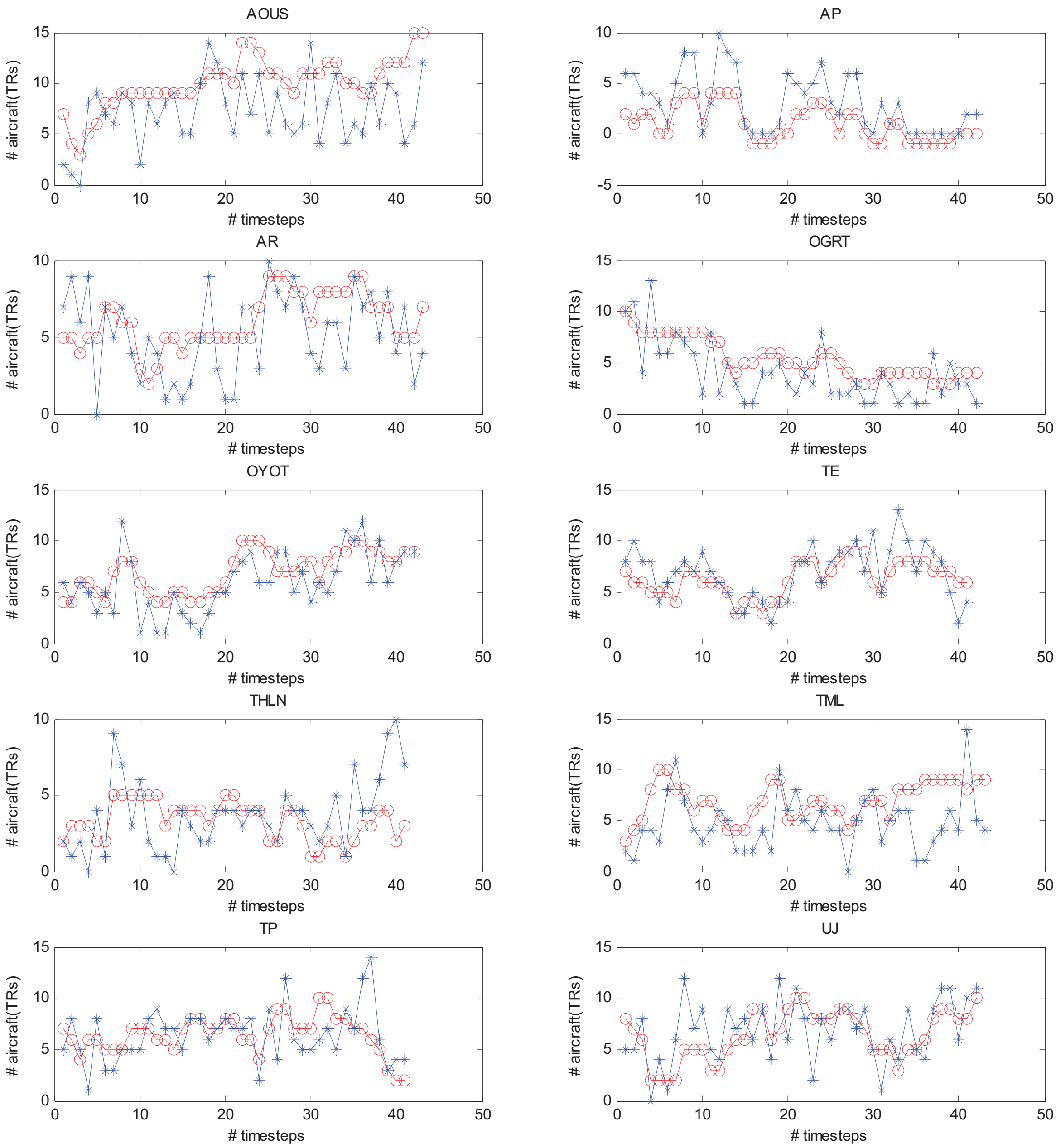


Figure 3- 4 Statistical results on traffic volume and communication activities (time step: 2 minutes). The red ○ markers stand for the number of aircraft in the sector, while the blue * denote the number of communication events in each time step.

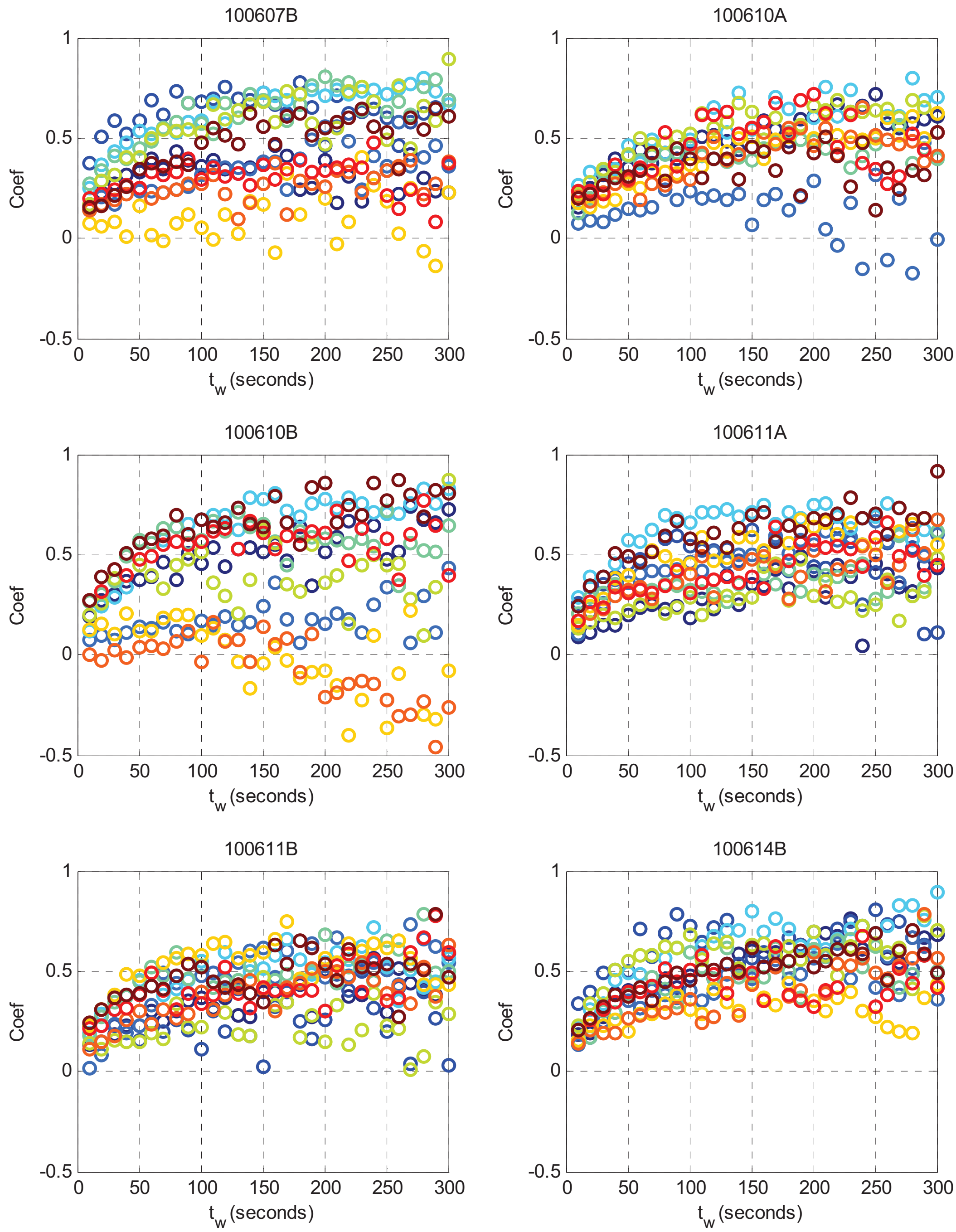


Figure 3- 5 Correlation coefficients as a function of observation time window t_w in ACC sectors of six exercises. Colors of markers are represented different sectors.

Table 3- 5 Correlation coefficients between communication and traffic factors. Values in the parentheses are negative.

	Number of communication events				Communication density				DD VS C-DSM	
	COMM VS DD		COMM VS C-DSM		COMM VS DD		COMM VS C-DSM			
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
AOUS	0.74	0.06	(0.10)	0.08	0.67	0.13	(0.08)	0.03	(0.26)	0.10
AP	0.36	0.19	(0.01)	0.03	0.31	0.19	(0.00)	0.03	0.17	0.20
AR	0.54	0.12	(0.06)	0.10	0.55	0.15	(0.03)	0.03	(0.13)	0.09
CREIL	0.26	0.18	0.00	0.02	0.22	0.21	(0.00)	0.02	0.21	0.16
DENPG	0.57	0.09	(0.01)	0.03	0.53	0.07	(0.02)	0.02	(0.12)	0.08
DEPPO	0.71	0.09	(0.02)	0.04	0.59	0.13	(0.02)	0.03	(0.12)	0.08
DESPG	0.55	0.14	(0.01)	0.03	0.50	0.09	(0.02)	0.02	(0.15)	0.05
INIPO	0.55	0.16	(0.01)	0.05	0.49	0.15	(0.01)	0.03	(0.09)	0.15
INNPG	0.68	0.09	(0.02)	0.02	0.65	0.05	(0.03)	0.02	(0.21)	0.06
INSPG	0.42	0.23	(0.01)	0.03	0.45	0.24	(0.02)	0.03	(0.15)	0.13
ITBPG	0.50	0.14	0.02	0.03	0.33	0.16	0.01	0.03	0.12	0.11
ITMPO	0.26	0.30	(0.04)	0.04	0.20	0.27	(0.03)	0.05	(0.02)	0.17
ITNPG	0.68	0.11	(0.04)	0.04	0.49	0.09	(0.05)	0.03	(0.07)	0.10
ITSPG	0.64	0.13	(0.04)	0.05	0.46	0.13	(0.03)	0.03	(0.09)	0.21
OGRT	0.62	0.07	(0.02)	0.05	0.64	0.04	(0.03)	0.04	(0.11)	0.12
OYOT	0.67	0.21	(0.00)	0.03	0.65	0.14	(0.01)	0.04	(0.10)	0.09
TE	0.65	0.16	(0.01)	0.04	0.64	0.14	(0.02)	0.03	(0.04)	0.20
THLN	0.70	0.20	0.03	0.06	0.57	0.16	0.03	0.07	0.06	0.18
TML	0.62	0.26	(0.01)	0.05	0.50	0.25	(0.01)	0.02	(0.16)	0.07
TP	0.65	0.13	(0.02)	0.09	0.60	0.12	(0.01)	0.05	(0.05)	0.16
UJ	0.62	0.15	(0.05)	0.05	0.56	0.17	(0.02)	0.04	(0.06)	0.14
VILLA	0.26	0.27	0.02	0.05	0.20	0.22	0.04	0.07	(0.04)	0.12

3.4 Temporal Characteristics of Controller's Communication

To explore the statistical properties of air traffic controllers' communication, we measured the length of communication L_i, the inter-communication times τ_i, and the inter-communication gap length τ_w, capturing necessary temporal information for all the first three datasets. Regarding on the D_4 dataset, speech recognition is being performed to distinguish the controllers' communication and pilots, and we have succeed in detecting silence and speech. At the moment, segments clustering are being tested to group the communication events. Here, we add the inter-events times of radio communication (including both controllers' and pilots') of D_4 Dataset, under the assumption that controller's communication is closer to the pilots' communication.

3.4.1 Periodic Patterns of Controllers' Communication

We acknowledge that controller's communication is highly depending on the air traffic flow input and output. Apart from D_1 Dataset, traffic information on the flights in the sector can be derived from the content of communication in D_2 Dataset and D_3 Dataset. We cannot, however, get the detail traffic data from D_4 Dataset, because it is impracticable to decode flights' information manually.

For the purpose of simulation, the D_1 and D_2 Datasets were based on the normal traffic samples, i.e. the busy hours' traffic, whereas the D_4 Dataset were basically recorded during 24-hours daily operation. Thus, traffic flow characteristics are more heterogeneous in the D_4 Dataset. Consequently, traffic heterogeneity will influence communication activities. For instance, there would be more traffic in the sector between 10:00AM to 11:00AM, than that between 01:00AM to 02:00AM. We plot the distribution of the numbers of communication events every hour in Figure 3- 6. It can be seen from the figure, that there is a clear trend that communication is distributed according to the time of the day. Nevertheless, the traffic flow characteristics have not been considered in this work.

The empirical distribution of the length of communication in all four datasets that made by both controllers and pilots are plotted in Figure 3- 7. While the communications with the length less than 1 second were disregarded, the ones that are longer than 60 seconds were considered to be the combination of several consecutive events which are within one minute. In total, 188,499 communication events were identified. It can be seen from Figure 3- 7 that over 63% events last 3~5 seconds, with few events (less than 13% of the total) lasting over 10 seconds.

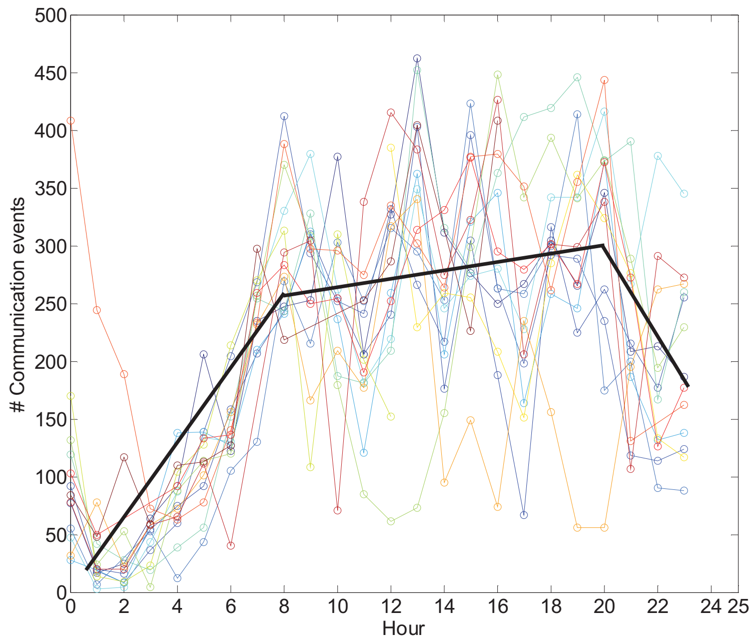


Figure 3- 6 Number of communication events per hour of US datasets. Colors of markers represent different days. From the picture, it can be seen that the overall communication activities of controllers' are heterogeneous in a working day, mainly being divided into three parts, from 00:00 to 08:00, from 08:00 to 20:00, and from 20:00-24:00

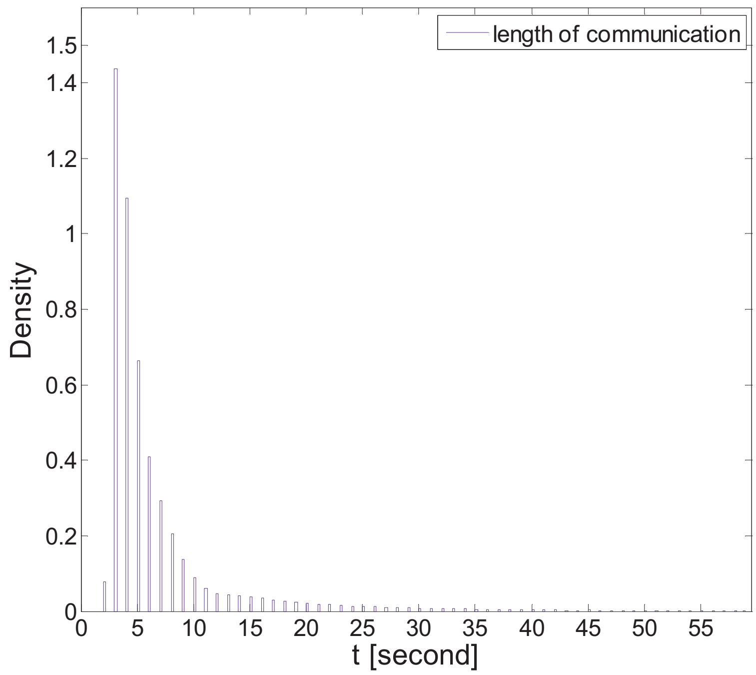


Figure 3- 7 Distribution of the length of communication of controllers and pilots

3.4.2 Detrended Fluctuation Analysis (DFA)

To examine the statistical self-affinity of the inter-communication events of each dataset, a 2nd-order Detrended Fluctuation Analysis (DFA) was performed. DFA has been widely used to analyze the statistical characteristics of various stochastic processes (Peng, Buldyrev et al. 1994; Kantelhardt, Zschiegner et al. 2002). In brief, the time series $x_t, t \in N$, is first converted into an unbounded process Y_t by cumulative summation. Then the converted time series is divided into $N_s = N / s$ observations with the length of window s. Local trend can be found by the linear or polynomial fitting of the data Y_t in the window, and the fluctuation $F(s)$ is computed by the root-mean-square deviation from the trend. Typically, $F(s)$ will increase with the window length s. A log-log plot of $F(s)$ against s is constructed, with a linear relationship indicates that $F(s) \propto s^{\alpha}$ which can tell the time series whether appear to be long-memory processes or $1/f$ noise. Typically, the statistical property of the time series will be revealed by the exponent α as

- $\alpha < 0.5$: anti-correlated;
- $\alpha \approx 0.5$: uncorrelated, white noise;
- $\alpha > 0.5$:correlated;
- $\alpha \approx 1$: $1/f$ noise, pink noise;
- $\alpha > 1$: non-stationary, random walk like, unbounded;
- $\alpha \approx 1.5$: Brownian noise.

Below we report the results using the region of $5 \le s \le 100$ for estimating α.

As shown in the Figure 3- 8, four exponents of the five are around 0.65, indicating the datasets are long-range correlated. Note that D_3 Dataset was constructed from eight 15-minutes long samples, and there are in total less than 470 controllers' communications. Few data points in D_3 Dataset could be the main reason that controllers' communications are uncorrelated. In contrast, the other four datasets exhibit a power-like form which is slower than exponential decay. It suggests that controllers' communication behaviors are long-range dependent. The exponents of each sector of each exercise of D_1 is given in the Table 3- 6.

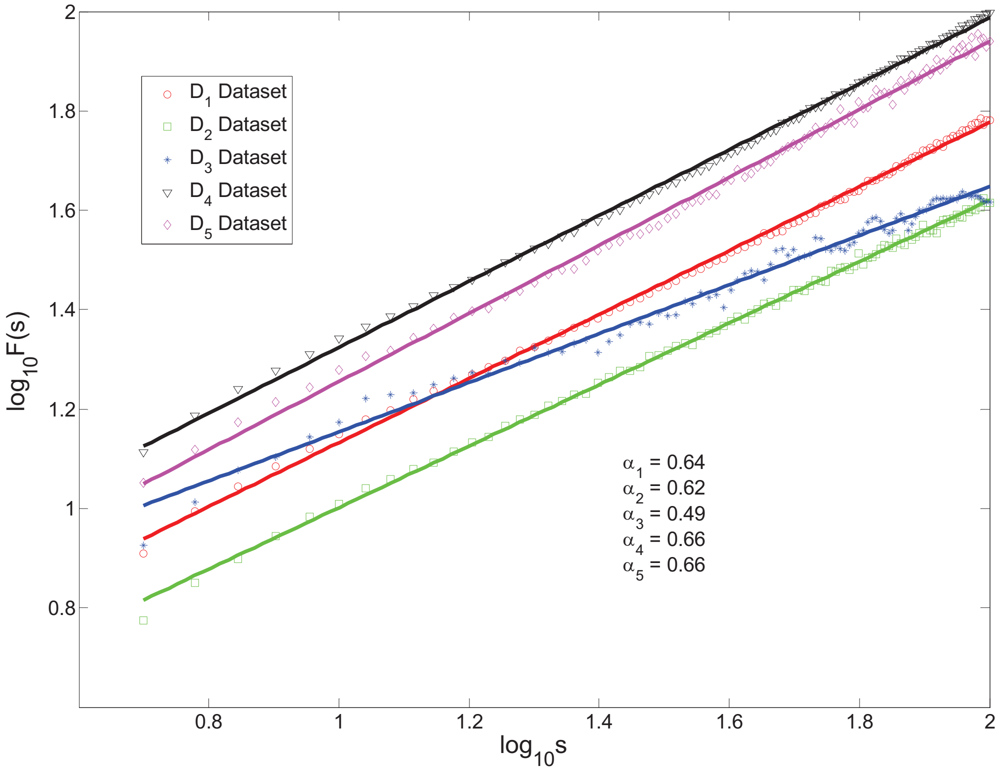


Figure 3- 8 DFA 2 function $\log_{10} F(s)$ versus timescale $\log_{10} s$

Table 3- 6 DFA scaling exponents of each sector of each exercise

	100607B	100610A	100610B	100611A	100611B	100614B	100615A	100615B	100616A	100616B	100617A	100617B	100618A	100618B	Mean	Std
AOUS	0.47	0.50	0.49	0.44	0.54	0.49	0.73	0.50	0.57	0.51	0.54	0.47	0.57	0.51	0.52	0.07
AP	0.45	–	–	0.56	0.61	0.61	0.56	0.41	0.62	0.59	0.84	0.69	0.62	0.58	0.60	0.11
AR	0.62	0.51	0.46	0.61	0.44	0.64	0.60	0.61	0.44	0.63	0.57	0.46	0.70	0.37	0.55	0.10
CREIL	0.75	0.56	0.97	0.42	0.37	0.54	0.78	0.45	0.60	0.62	0.60	0.59	0.76	0.75	0.62	0.16
DENPG	0.69	0.50	0.57	0.68	0.49	0.61	0.59	0.55	0.72	0.43	0.62	0.64	0.66	0.61	0.60	0.08
DEPPO	0.67	0.54	0.60	0.47	0.62	0.75	0.71	0.66	0.56	0.47	0.65	0.64	0.48	0.54	0.60	0.09
DESPG	0.53	0.56	0.65	0.53	0.56	0.49	0.65	0.62	0.62	0.45	0.66	0.53	0.59	0.53	0.57	0.07
INIPO	0.61	0.53	0.47	0.53	0.65	0.54	0.67	0.74	0.54	0.68	0.68	0.50	0.60	0.46	0.59	0.09
INNPG	0.67	0.63	0.66	0.61	0.79	0.63	0.55	0.57	0.59	0.72	0.48	0.53	0.62	0.67	0.62	0.08
INSPG	0.53	0.47	0.60	0.56	0.54	0.61	0.65	0.61	0.55	0.49	0.52	0.59	0.59	0.42	0.55	0.06
ITBPG	0.60	0.58	0.49	0.78	0.74	0.76	0.77	0.71	0.90	0.55	0.71	0.59	0.65	0.54	0.67	0.12
ITMPO	0.61	0.61	0.58	0.61	0.46	0.62	0.73	0.57	0.68	0.65	0.62	0.57	0.70	0.54	0.61	0.07
ITNPG	0.56	0.57	0.55	0.62	0.57	0.53	0.54	0.63	0.61	0.71	0.49	0.61	0.63	0.68	0.59	0.06
ITSPG	0.53	0.64	0.48	0.56	0.56	0.49	0.61	0.59	0.55	0.51	0.56	0.56	0.58	0.49	0.55	0.05
OGRT	0.58	0.60	0.49	0.74	0.93	0.46	0.70	0.52	0.59	0.46	0.58	0.56	0.68	0.43	0.60	0.14
OYOT	0.73	0.63	0.71	0.72	0.43	0.54	0.52	0.53	0.63	0.60	0.58	0.64	0.59	0.64	0.61	0.09
TE	0.74	0.73	0.49	0.50	0.42	0.69	0.70	0.54	0.67	0.61	0.82	0.57	0.64	0.58	0.62	0.11
THLN	0.61	0.71	0.82	0.48	0.73	0.69	0.55	0.53	0.74	0.58	0.49	0.66	0.58	0.57	0.62	0.10
TML	0.74	0.66	0.61	0.45	0.43	0.48	0.70	0.65	0.46	0.26	0.69	0.59	0.63	0.35	0.55	0.15
TP	0.61	0.51	0.56	0.56	0.61	0.69	0.36	0.62	0.56	0.56	0.53	0.38	0.76	0.43	0.55	0.11
UJ	0.57	0.64	0.63	0.58	0.49	0.53	0.61	0.70	0.65	0.47	0.48	0.58	0.48	0.63	0.57	0.07
VILLA	0.74	0.62	0.60	0.83	0.64	0.76	0.57	0.77	0.76	0.18	0.71	0.72	0.69	0.38	0.64	0.17
Mean	0.62	0.58	0.59	0.58	0.57	0.60	0.63	0.59	0.62	0.53	0.61	0.57	0.63	0.53		
Std	0.09	0.07	0.12	0.11	0.14	0.10	0.10	0.09	0.10	0.13	0.10	0.08	0.07	0.11		

3.4.3 Inter-communication Times Distribution

Building upon prior research on human dynamics, we investigated the distribution of inter-communication times, the inter-arrival times τ_i, and inter-communication gap lengths τ_w. The determination of the inter-arrival times is straightforward, whereas to calculate the inter-communication gap lengths we need the detailed communication contents which are unavailable. Because it is impractical to listen to the large datasets to separate the communication events. Note that Cardosi has examined the time that is required to successful transmit a message containing a maneuver to a pilot(Cardosi 1993). She found that the average total time required is 11 seconds. Based on this result and the empirical distribution of the length of controllers' communication, we propose a simple scheme to compute the inter-communication gap lengths. Consider that the most of communication (for both controllers and pilots) last 3~5 seconds and controllers has to listen to the readback of pilots to ensure pilots understand the instructions correctly, thus it is assumed that the minimum inter-communication gap lengths might be 8 seconds. Accounting for Cardosi's founding, the minimum inter-communication gap length is 11 seconds while with a vey small probability the minimum varies between 8 and 11. We then combine the inter-arrival times that less that the minimum into a communication transaction.

In the following, we examined the empirical inter-communication data using Maximum Likelihood Estimation (MLE) to estimate four types of distribution, namely Exponential distribution, Lognormal distribution, Power law distribution, and Inverse Gaussian distribution.

(1) Exponential Distribution

Poisson process has long been used to model the stochastic events from various fields, to express the probability of a given number of events occurring in a fixed interval of time, e.g. the arrival flights in an airport. An exponential distribution is used to describe the time between events in a Poisson process. The probability density function of an exponential distribution is given as

$$f(x;\lambda)=\begin{cases}\lambda e^{-\lambda x}, & x\ge 0,\\ 0, & x<0.\end{cases}$$

where λ is the arrival events rate. If λ is constant, then the process is known as homogeneous Poisson process, whereas if λ is depending on time, then the process is referred as non-homogeneous Poisson process.

(2) Lognormal Distribution

Although the Poisson process has been well applied to mimic the arrival aircraft in a sector or in an airport, Popsecu et. al. have detected a lognormal distribution of inter-arrival times of air-ground communication from operational voice data (Popescu, Augris et al. 2010). It might indicate that there should be the similar distribution for the incoming traffic. The lognormal distribution has also been reported in biology, hydrology, and finance, etc. In probability theory, the probability density distribution is

$$f(x;\mu,\sigma)=\frac{1}{x\sqrt{2\pi\sigma^2}}\exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right], x>0,$$

where μ and σ are the parameters that are related to the log-scale and shape respectively.

(3) Power law Distribution

Power law distribution has been reported in human dynamics studies to describe heavy-tailed features of human activities. It has attracted particular attention due to its mathematical properties. Furthermore, power law statistics are a hallmark of critical phenomena, which appear in a diverse range of natural and man-made systems, ranging from physics, through biology, to economics, and sociology. In practice, few empirical data obey power laws. For the most cases, it is convenient to assume a lower bound $x_{\min}$ over which the data can be described in the form of power law. The power law for a continuous variable has the form

$$f(x)=\frac{\alpha-1}{x_{\min}}\left(\frac{x}{x_{\min}}\right)^{-\alpha}.$$

A brief history of power law and the empirical evidences of power law distribution can be found in (Mitzenmacher 2004) and (Clauset, Shalizi et al. 2009).

(4) Inverse Gaussian Distribution

The last probability distribution we shall fit is the inverse Gaussian distribution, also known as Wald distribution. It describes the distribution of the time a Brownian Motion with positive drift takes to reach a fixed positive level, i.e. the first passage time of the Brownian process. The probability density function is in the form of

$$f(x;\mu,\lambda)=\left[\frac{\lambda}{2\pi x^3}\right]^{1/2}\exp\frac{-\lambda(x-\mu)^2}{2\mu^2 x},$$

where $\mu>0$ is the mean and $\lambda>0$ is the shape parameter. The distribution is bounded below by zero. To allow for a lower bound greater than zero, a shifted Wald distribution is defined as

$$f(x;\theta,a,\gamma)=\frac{a}{\sqrt{2\pi(x-\theta)^3}}\exp\left[\frac{-(a-\gamma(x-\theta))^2}{2(x-\theta)}\right],\theta>0.$$

Compared with the standard inverse Gaussian Distribution, the mean of shifted Wald distribution is $\mu=a/\gamma$, and the shape parameter $\lambda=a^2$. Interestingly, shifted Wald distribution generally produces an excellent fit to the empirical Response Times distribution in cognitive psychology. We will introduce it in more detail in the psychological interpretation part.

3.4.3.1 Inter-arrival Times

To estimate the parameters of each model, we use the method of Maximum Likelihood Estimation. Table 3- 7 gives the fitting results on every dataset. LR in the table is the log-likelihood ratio, while the $Prop$ shows the proportion of data points in the dataset that have value bigger than $x_{\min}$. The probability density functions of inter-communication events time for the datasets have been plotted on log-log scale (Figure 3-9). The data points were logarithmic binned for better visualization. Dash-lines are the inverse Gaussian fitting to the each dataset. It can be seen that communication activities do exhibit the heavy tailed patterns.

As shown in Table 3- 7, the best model to fit the data differs from dataset to dataset. the Inverse Gaussian is the best to fit the data obtained from D_3 and D_4 datasets, while it is failed to capture the inter-arrival times less than 15 seconds (see Figure 3- 9 at $\tau \approx 10^{1.2}$ seconds) of D_1 and D_2 datasets. The power-law distribution is much better to describe all the inter-arrival times in the D_1 and D_2 datasets, with a minimum thresholds at 12 seconds and 13.3 seconds respectively. The diversity of the distribution of inter-arrival times might lie in the traffic patterns that have been discussed above. Compared to operational data in D_3 and D_4 datasets, the communications made by controllers of the first two datasets are operated during busy traffic hours. The power-law fittings for the first two datasets require the minimum inter-arrival times longer than 11 seconds. It can be seen in the **Figure 3- 10**, the inter-communication intervals that are larger than 11 seconds are exhibiting the power law decay. The power-law forms with exponents 2.64 and 2.71 seem to capture the collective behaviors of the controllers, suggesting that the underlying decision processes of the controllers are the similar ones explained by the human dynamics models. Whether or not individual controller follows the same rule is unclear. To test the hypothesis, we analyze the inter-communication gap lengths of the controllers computed from D_1 datasets and D_5 datasets.

Table 3- 7 Probability fitting to the empirical data (inter-TRs)

Name	PDF	Parameters	D_1	D_2	D_3	D_4	D_5
Exponential	$\lambda e^{-\lambda x}$	λ	19.1842	17.0713	17.9953	39.6385	25.6036
		LR	-314251	-37863.6	-1657.19	-250009	-25307
		AIC	628504	75729.2	3316.38	500020	50616
Lognormal	$\frac{1}{x\sqrt{2\pi\sigma^2}}\exp\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right]$	μ	2.59313	2.56279	2.38417	3.36411	2.70115
		σ	0.756983	0.686706	0.946182	0.779025	0.977448
		LR	-296732	-35578.7	-1596.06	-242184	-24661
		AIC	593468	71161.4	3196.12	484372	49326
Power Law	$x^{-\alpha}$	α	2.42	2.7078	2.8	4.4108	3.9468
		$x_{\min}$	**12**	**13.3387**	29	133.3269	97
		LR	-155460	-15598	-332.322	-7706.4	-1039.2
		AIC	**310924**	**31200**	668.644	15416.8	2082
		$Prop$	46.62%	43.41%	**17.61**	**2.91%**	**3.49%**
Inverse Gaussian	$\left[\frac{\lambda}{2\pi x^3}\right]^{1/2}\exp\frac{-\lambda(x-\mu)^2}{2\mu^2}x$	μ	19.1842	17.0713	17.9953	39.6385	24.6435
		λ	23.5348	27.5143	13.1099	48.5121	15.9193
		LR	-223361	-26511	-1188.36	-192603	-19067.9
		AIC	446726	53026	**2380.72**	**385210**	**39219.8**

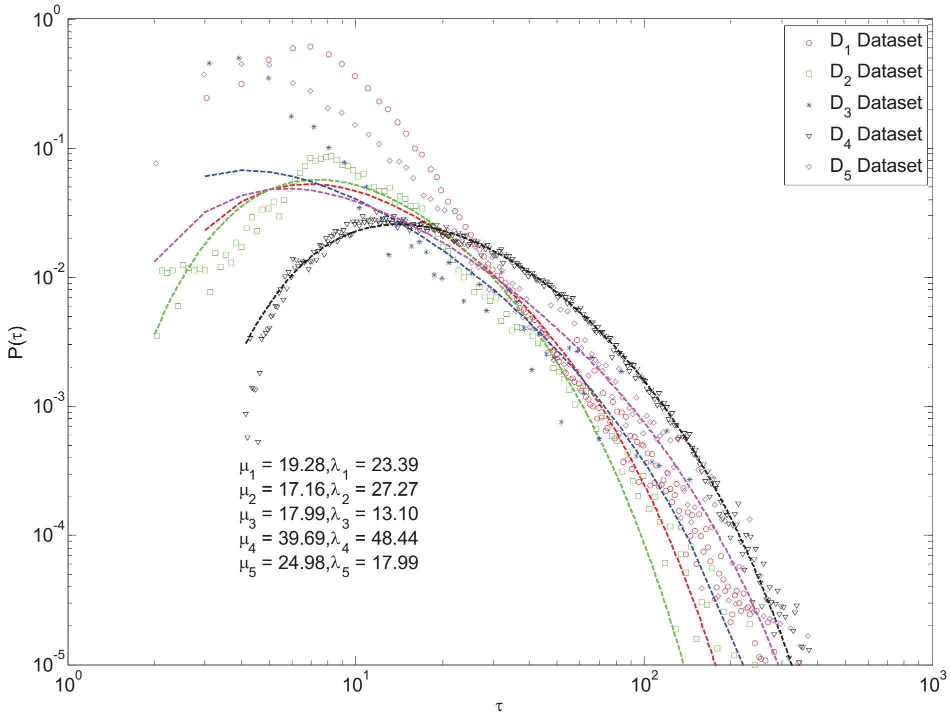


Figure 3- 9 Probability density distribution of inter-communication of controllers

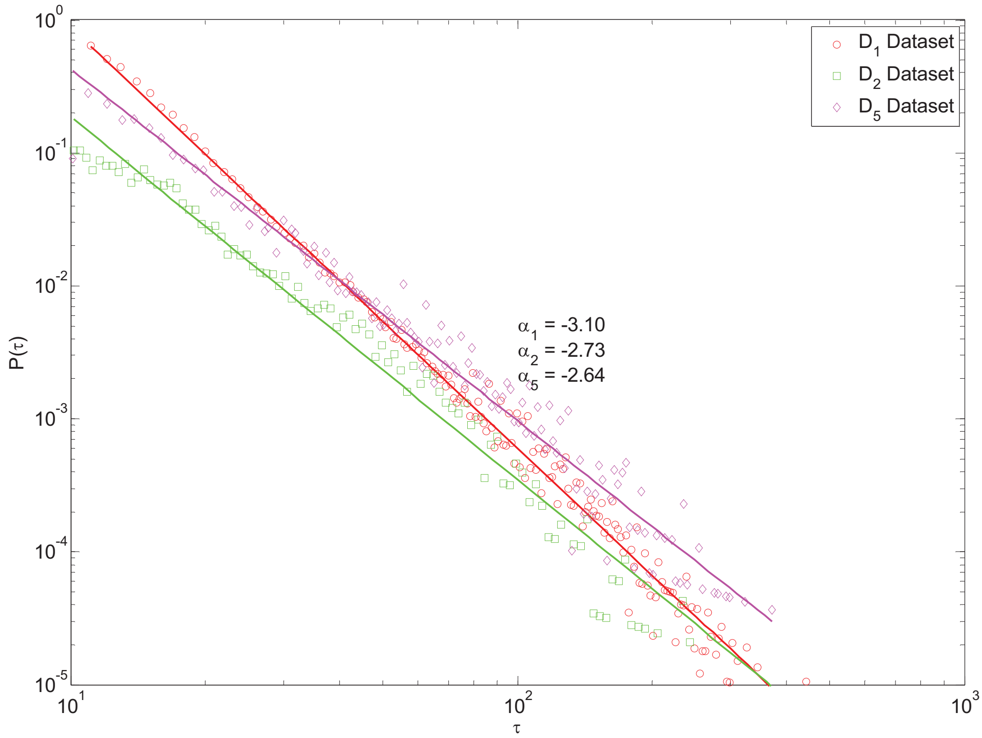


Figure 3- 10 Distribution of inter-gap lengths larger than 11 seconds

3.4.3.2 Inter-communication Gap Lengths

Inter-communication gap lengths of D_1 dataset and D_5 datasets have been obtained using the proposed scheme. To estimate the exponents for the power-law distribution, we adopt the algorithm illustrated in (Clauset, Shalizi et al.).

In the D_1 dataset, it is very interesting to observe that the behaviors of inter-activities dynamics of the most of individual controller, represented by a sector in an exercise, can be fitted with power-law form, although the exponents vary between 2.0 ~ 3.8. We also find that the exponents fitted for the ACC sectors normally are between 2.0 and 3.0. In contrast, the exponents for the approach sectors are generally bigger than 3.0. Figure 3-11 plots the distribution of inter-communication gaps of each sector in exercise 100607B (the distributions of 13 other exercises are given in the Appendix). However, the distributions of inter-communication gap lengths in datasets are more heterogamous. Although the intervals show long tails, most of data can not be fitted with power law (see Appendix).

A recent report of human dynamics (Wu, Zhou et al. 2010) 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 Barabási's model (Barabasi 2005) 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. We note that controller's communication shows a heavy tailed behavior, and it is not the bimodal distribution uncovered in short message-sending activities (Wu, Zhou et al. 2010), 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 Lévy process with positive drift that will well explain the priority of strategies management process and the adaptive behavior of the controller.

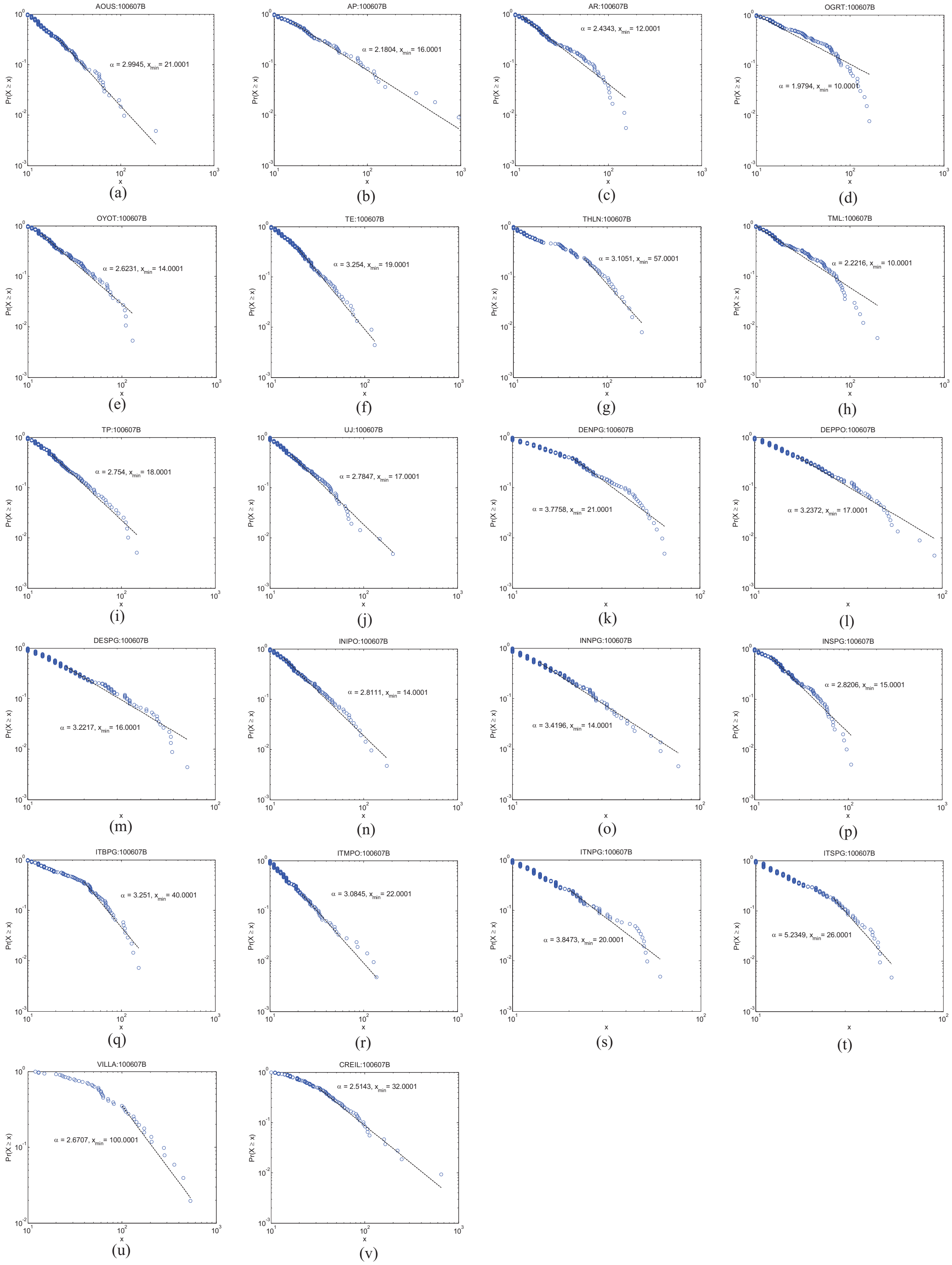


Figure 3- 11 Distribution of inter-communication gap lengths of all sectors in the exercise 100607B. ACC sectors are the figures (a)~(j), while approach sectors are the figures (h)~(t). The last two figures (u) and (v) are the military sectors.

3.5 Psychological Interpretation of the Intervals

We do observe the heavy-tailed features in the air traffic controllers' communication activities. Although human dynamics models may explain the origin of the distribution of the inter-communication gap intervals, the interpretation of controllers' communication activities should be validated through other theoretical approach.

The communication behaviors of air traffic controllers are the outcoming of their cognitive processes which have been long investigated in the previous work. To further investigate the temporal behavior of air traffic controllers' communication activities, we turn to psychological interpretation. In the psychological item, air traffic controllers' communication behavior can be represented as a one-choice decisions' activities, decisions that are based on information varying along with time. Inter-communication intervals, i.e. when to communicate with pilots, are therefore defined as the response times. The study of such response times is one of the central questions in psychology. Experimental investigations of the response times have been conducting aiming to analyze the psychological process of human being. Based on the analyses of response times, the computational models have been developed to account for the cognitive process during a decision making. Prevalent model that has been successfully applied to a wide range of paradigms is the diffusion model (Ratcliff and Murdock 1978), that provides a theoretical account for the parameters estimation that can be interpreted in terms of the cognitive components underlying the decision process. Previous research has shown that the parameters of the model correspond to the psychological processes that they are assumed to represent, such as the rate of information accumulation which is influenced by task difficulty or participant ability, response caution, a priori bias, and the time taken by processes unrelated to decision making(Ratcliff and Murdock 1976; Ratcliff and Murdock 1978; Ratcliff, Van Zandt et al. 1999; Ratcliff and Rouder 2000; Ratcliff 2001; Ratcliff and McKoon 2008; Matzke and Wagenmakers 2009; Ratcliff and Van Dongen 2011; Jepma, Wagenmakers et al. 2012).

There are four main factors of the diffusion model, the drift rate v, boundary separation a, starting point z, and non-decision time T_{er}. Drift rate v accounts for the mean rate of information accumulation. It is determined by the quality of the information extracted from the stimulus. The second parameter a is used to quantify the distance between the two response boundaries, i.e. the time for information accumulated to make a decision. While the starting point z can be represented as participants' a priori bias for one the two response alternatives. Non-decision time T_{er} measures the duration of processes that are unrelated to the decision process. Figure 3- 12 depicts the diffusion model.

The primary statistical models that have been generally employed in the cognitive psychology to analyze the reaction times are ex-Gaussian (i.e. exponentially modified Gaussian (EMG)) and shifted Wald distributions. Several studies have tried to interpret the statistical modeling with the help of diffusion model(Schwarz 2001; Heathcote 2004;

Matzke and Wagenmakers 2009; Jepma, Wagenmakers et al. 2012). For example, Schwarz used shifted Wald model to analyze the response times, and concluded that the shifted Wald model offers a broad cognitive interpretation of its parameters(Schwarz). The interpretation of the parameters can be tested using standard statistical tools, such as likelihood ratio tests.

Here we have found the inverse Gaussian distribution, i.e. the Wald distribution, for the inter-communication times of the two operational datasets, and the power-law distribution for the inter-communication gap lengths of the two real-time simulation datasets. Although the related models can well explain the underlying mechanisms, there are still on going questions about the temporal behavior of the air traffic controllers' activities.

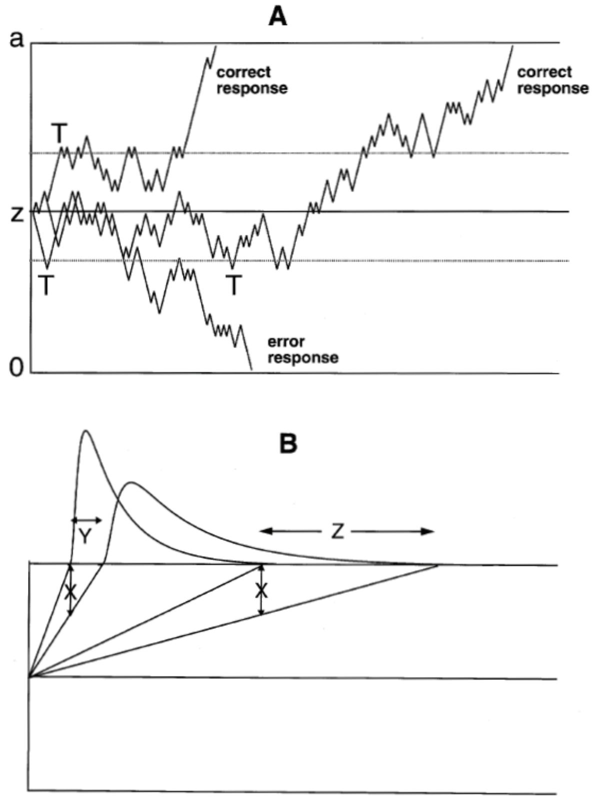


Figure 3- 12 Illustration of the diffusion model. Picture is drawn from (Ratcliff and Rouder 1998)

3.6 Chapter Summary

The use of the underlying mechanisms that govern system evolution is a basic way to model, predict and control system. 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. Air traffic complexity has been studied as one the main factors affecting air traffic controller's workload. The results clearly show that complexity cannot reflected by the communication activities, thus suggesting the adaptive nature of the human system. Then we use detrended fluctuation analysis to study the controller's inter-communication activities and found that controllers' communication activities are long-range correlated. Finally we show that controller's inter-communication does exhibit the heavy-tailed feature similar to other daily human interactive activities.

The study of temporal characteristics of the controllers' communications, unmask the underlying rules that controllers execute the tasks. The temporal behavior, defined as the selective behavior of choosing an aircraft to communicate, may be driven by other mechanisms that are still unknown. 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. We believe that human activity will be quickly adapted to the contextual environment while human brain, which drives the external activity, evolves slowly.

CHAPTER 4 THE SPATIAL BEHAVIOR OF CONTROLLERS' COMMUNICATION ACTIVITIES

Air traffic controllers are able to create control strategies according to the traffic distribution and airspace environment. The understanding of mechanisms that controllers use has the potential to both academic and engineering fields. Cognitive studies have demonstrated the role of structure-based abstraction in mitigating air traffic controllers' cognitive complexity (Histon, Hansman et al. ; Histon and Hansman Jr ; Histon and Hansman). They mainly use four types of abstractions that are standard flow, critical points, grouping, and responsibility. Such findings provide insights into our understanding of the spatial behavior of the controllers, which is likely related to the dynamics of their cognitive activities. We define spatial behavior as the way that controller select an aircraft to communicate with, which is regarding on the information gathering and diffusion processes during air traffic control. Thus, the study of spatial behavior has significant scientific and engineering potential. First, it will advance our knowledge about quantitative description of underlying mechanisms of human not only doing air traffic control task, but also to other tasks that are with high pressure. Second, the understanding of spatial behavior can be applied to the development of artificial intelligent automation systems improving the ATM system performance.

This chapter presents the methodology to investigate the spatial behavior of air traffic controllers' activities through their communication. In Section 4.1, we first define the problem, and then summarize the related work. Section 4.2 presents the temporal network approach that we propose to the analyze controllers' spatial behavior. Empirical data and network analysis are reported in Section 4.3 and Section4.4. Finally, conclusion remarks are drawn in Section 4.5.

4.1 Introduction

The last decade has witnessed the improvement of the ATM system in its safety, capacity, and efficiency. Great efforts have been done to enhance the performance of the ATM system, ranging from the introduction of new operation concepts, through the deployment of the advanced automation systems, to the long-term research activities. In spite of the ongoing deployment of the new technologies and operational concepts in both SESAR in Europe and NextGen in the US, air traffic controller is, and continues to be, in the core the ATM system. The understanding of controller’s activities is therefore critical to the system safety.

In many problems arising in a human-driven complex system, it is necessary to evaluate the operator's activities. Among various internal activities and external activities, controllers' mental workload has long been investigated in the air traffic management society (see review on controllers' activities in Section 2.3). Since the ATM system is in the way of transforming, there are also ongoing attempts to analyze the controller's activities in the future operation environment. Human-in-the-loop studies have been conducted either to develop new cognitive metrics, or to evaluate the decision support tools under the future operation concepts (Li and Hansman 2009; Kupfer, Callantine et al. 2011). Issues for the implementation of key operational change, such as trajectory-based operation and data communication, have been progressively identified (Lacher, Battise et al. 2011). Although the studies on workload and other human factors related topics have been impressive, up until now, quantifying and predicting the controllers' activities remains an open problem. Classical methods usually focus on the specific problems, e.g. analysis of controllers' workload in a certain sector. With a few exception (Histon and Hansman Jr ; Clarke, Durand et al. 2011), much less has been done toward the understanding of the dynamics process of air traffic controllers' activities.

4.1.1 The Spatial Behavior of the Controllers

In fact, the process of managing traffic is the information diffusion process by the controller. In order to manage the traffic, controller has to gather and spread information to the aircraft to avoid traffic conflict, ensuring aircraft can reach their destinations successfully. Both the types of information and the sources for accumulating information are generally clear (see Section 2.2.2.1). However, little is known about the way how controllers diffuse information. As aircraft are moving in the sector at high speed, the physical relationships between aircraft change quickly. Many of the complexity metrics are based on the measurements of such physical relations. Rather, we believe that the spatial distributed aircraft in the sector are not exactly the same as that in controllers' minds. Although some complexity measures account for the cognitive parts of the controllers, such measures cannot predict complexity correctly largely due to the dynamical changes in controllers' cognitive processes.

The spatial behavior we defined here captures two aspects of controllers' cognitive activities:

(1) The layout of the traffic in controllers' mind, i.e. the relationships between the flights recognized by controller after processing of current traffic situation.

(2) The dynamical process occurring on the layout for the information propagation.

4.1.2 Motivations

The impetus to study the spatial behavior of controllers is multifaceted. First, the spatial behavior can provide a fundamental understanding of information process at a macroscopic level, and consequently will contribute to a more accurate understanding of workload since both workload and spatial behavior are depending on the cognitive activities. Second, it is expected that revealed spatial patterns are related to the physical position of aircraft in the sector to some extend, thus it will give insights into the airspace design and air traffic flow planning. Also, it will leverage the development of the artificial intelligence systems that alleviate controller's taskload. Last but not the least, it may be beneficial to our knowledge beyond the ATC domain through the investigation of the spatial behavior of controllers.

4.1.3 Objectives

Like human dynamics, the research on human mobility indicates that there is a simple and general rule which governs our spatial activities (see Section 4.1.4.2). Here raise the question about air traffic controllers' activities. Whether or not there exist the similar patterns among controllers in selecting aircraft to control, and that phenomena can be explained by a simple mechanism? Our principal intention was not to find the specific threshold of mental workload; rather, it was to provide a novel method to reveal the underlying patterns. On the analogy of the human mobility, the air traffic controllers' activities problem can be described as the follows. Each flight can be denoted as a place or node with a validated time frame, and controller has to visit these nodes in order to transmit the information that is regarding on changing flights' motions, so that each one of the flight can reach its destination without involved in a conflict.

Our analysis of air traffic controllers' spatial behavior will be performed on the temporal sequences of the voice communication data. The time series of controllers' voice communication events contain rich information about how controllers manage traffic, since voice communication is the only way for the information flow between controllers and pilots in the air traffic control centers without data communication (see Section 2.2.4 Information diffusion via voice communication). Therefore, the sequence of controller's communication can be seen as controller's trajectory of visiting the flights, i.e. the information diffusion trajectory. One of our main objectives here is to identify the spatial related patterns in the controllers' communication. The information propagation process is also interesting to us.

4.1.4 Related work

4.1.4.1 Structure-based Abstraction

Although contextual factors such as airspace configurations and traffic distribution will influence controller's activities, cognitive analyses have unrevealed the common strategies employed by controller while controlling traffic (Histon and Hansman Jr 2008). Histon and Hansman have shown that how air traffic controllers use structure information, which is defined as the physical and informational elements in the working context, to mitigate cognitive complexity. Four types of structure-based abstractions are summarized below based on their report.

- Standard Flow

Standard flows are formed by many aircraft that orderly fly in the same lateral paths. Controllers concerned that the standard flows are a key structural feature of the sector. The standard flow abstraction captures the common spatial trajectories, and reduces the core cognitive tasks of the controllers. For example, aircraft in the standard flow normally have the same attributes, such as aircraft altitudes, speeds, the events requests from pilots etc, and it will facilitate to project aircraft trajectory or to predict potential conflicts. The most powerful mechanism by which standard flow simplifies the mental workload model is reducing the degrees-of-freedom of the aircraft.

- Critical Point

Critical points are the high priority regions that have been identified by the controllers in the sector during daily operation. Air traffic controllers will pay much attention to the aircraft that are near critical point. A navigation aid where two different traffic flows merge into a sing one is an example of critical point.

- Grouping

Grouping abstraction is a kind of aircraft/weather clustering by the controllers. Aircraft flying with the same route, or aircraft that have the same performance, are the basis of grouping abstractions. Formulation of these groups also reduces the mental workload model in that represent the aircraft in the group by the group properties.

- Responsibility

By delegating the tasks to the downstream controller or pilots, controllers can limit their scope of monitoring, evaluating, and projecting processes.

The above four types of structure-based abstractions describe the powerful mechanisms that mitigate cognitive complexity and simplify mental workload. Note that all of them are based on the spatial distributions of aircraft. Quantitatively capturing such mechanisms are still lacking.

4.1.4.2 Human Mobility

In the past few years there has been a surge of interest in both empirical studies of human daily activities and development of models to explain the observed phenomena (Barabasi 2005; Oliveira and Barabasi 2005; Malmgren, Stouffer et al. 2009). We have presented the existing results on temporal patterns of human actions in Section 3.1.1. This section will devote to the research on anther side of human activities, i.e. human mobility.

The dynamic spatial distribution of individuals is fundamental to the successful design and management of human-driven systems, such as epidemic diseases control (Colizza, Barrat et al. ; Vespignani ; Song, Koren et al.), transportation engineering (Song, Koren et al.), and economic forecasting (Song, Qu et al.). Scientists have drawn attention to characterize and model the trajectories that humans follow during daily activity the in the past few years. Quantitative assessments from the circulation of bank notes (Brockmann, Hufnagel et al.), and mobile phone data sets (Gonzalez, Hidalgo et al. 2008), demonstrate that the human trajectories show a high degree of temporal and spatial regularity. The overwhelming results indicate that the aggregated jump-size which is the distances covered by an individual between consecutive movement, and waiting time – the time spent by an individual at the same location, are fat-tailed. Both of the two properties can be well described by the power law form. In (Song, Qu et al. 2010) the limits of predictability in human mobility has been studied by measuring the entropy of human trajectory. It was found that there is a 93% potential predictability in human mobility across the whole data. The underlying similarity among human actions indicates that there exists the same law, which governs human activity.

Models based on Lévy flights and Random Walk have been proposed to explain the mechanisms which lead to the scaling law of human trajectories (Colizza, Barrat et al. 2007). While Zhou et al. (Han, Hao et al. 2011) considered the hierarchical organization of traffic systems as an important factor in their model to mimic the scaling properties of human mobility. Song et al. (Song, Koren et al. 2010) added two principles that govern human trajectories into traditional random-walk models. The first one is exploration that is the slowing down trendy of exploring a new locations; the second principle is preferential return to the locations visited frequently before.

4.2 Method

4.2.1 A Network Approach

To trace the trajectory of controller visiting flights, we turn to network approach. Network is widely used to represent the patterns of connections between the components of complex system. A plausible representation of the relational information transmitting in dynamic systems such as a social community is stochastic network or temporal network that is topologically rewiring and semantically evolving over time (Ahmed and Xing 2009).

Recently, there is increasing interest in the study of temporal networks that encode the time-dimension into the classic network analysis (Chechik, Oh et al. 2008; Ahmed and Xing 2009; Holme and Saramäki 2011). For example, it has been used to study the information spreads on the social network (Liben-Nowell and Kleinberg 2008; Rocha, Liljeros et al. 2010), or extracting the information from the posts on the Web community to build the temporal networks to analyze the prostitution activities (Rocha, Liljeros et al. 2010), etc.

4.2.2 Mapping Time Series to a Network

In order to study the spatial behavior of controllers' activities through a network approach, we have to construct the network from their activities. To unmask the hidden dynamics from the time series, techniques that convert time series into a graph following with network analysis are being widely reported (Zhang and Small 2006; Xu, Zhang et al. 2008; Gautreau, Barrat et al. 2009; Haraguchi, Shimada et al. 2009; Vassilis 2009). Methods that transform time series into complex network can be roughly classified into the three classes (DONNER, Donges et al. 2010):

- Mutual proximity of different segments of a time series. For example, in the recurrence plot approach, nodes are defined from the phase space trajectory and a link between two cycles when two nodes are rather similar (Marwan, Donges et al. 2009);
- Convexity of successive observations (i.e. visibility graphs). Algorithm for converting time series into a graph can be found in (Lacasa, Luque et al. 2008);
- Transition probabilities between discrete states (transition networks). See(Campanharo, Sirer et al. 2011).

We propose a novel method for the transform of the temporal activities data into an undirected weighted network. The assumption is that each controller's communication is related to a flight, disregarding the events that are not related to the flights (e.g. communication with the assistance controller).

4.2.2.1 Definition of the Nodes

The nodes of the network are the flights traversing the sector. Each node will have a validated time period that accounts for its flying time in the sector, so that controller cannot visit the flight before the flight entering or leaving the sector. In the current study, the communications with other controllers are not considered yet.

4.2.2.2 Determination of the Edges

The edges between the nodes should indicate the relationship between the two flights. A practical algorithm that transform the time series into a network is the visibility graph (refer to (Lacasa, Luque et al. 2008)), Given a series of time data, a connection between two arbitrary data values (t_a, y_a) and (t_b, y_b) if any other data (t_c, y_c) placed between them fulfills the criteria that

$$y_c < y_b + (y_a - y_b)\frac{t_a - t_c}{t_b - t_a}.$$

Figure 4-1 shows an example of transferring the random time series data into a graph.

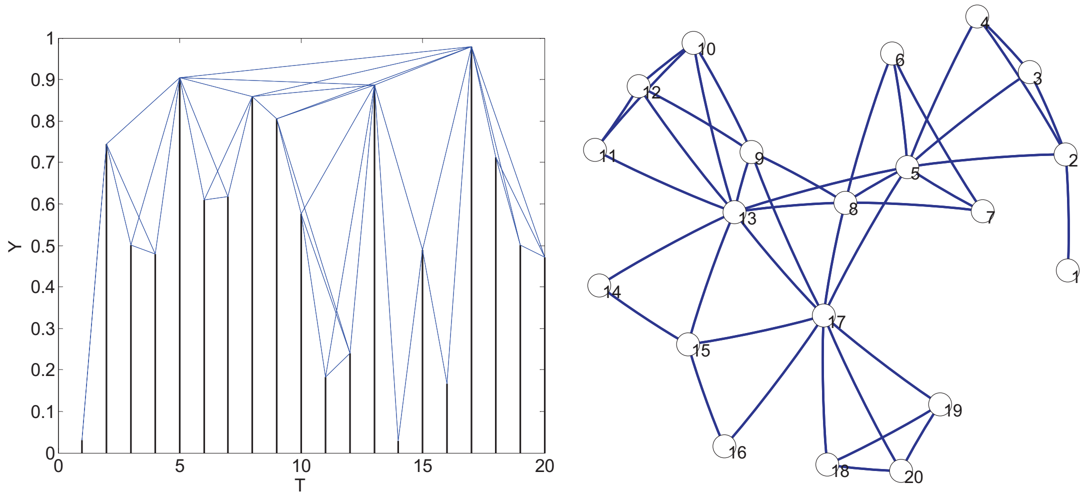


Figure 4- 1 The visibility graph algorithm. (a) Each of the vertical bars stands for a data point in the time series with the horizontal denoting the time and Y representing the value of the data. It is obviously that scaling in both dimensions has no influence on the connectivity of the nodes. (b) the associated network construct by the visibility graph algorithm.

The visibility graph algorithm is efficient for large datasets analysis. However, to determine the connectivity between the flights we must take controllers' behavior into account. We can determine the linkages from the physical relationships of flights, for instance the distances that have been used to calculate the traffic complexity. Rather, we prefer to link the nodes using the temporal communication data on the hypothesis that these relations are mapped from the physical relations by the controller. As we know, it is obviously that the two flights have no relationship if all of their communications were separated by a long period of time. On the contrary, they should have some kind of relation if they were called in the short time span.

To determine whether two nodes are connected or disconnect, we first calculate the temporal distances $\delta(i, j, t) = t_j - t_i - l_i$ between flight i and flight j at the time (t_i) when flight i was called, where t_j is the time when flight j was called and l_i is the communication duration of event i. Since there will be no relations between flight i and the later incoming ones after i has been transferred out to the downstream sector, therefore we define service time s_i, as the time window when flight i is staying within in the sector. Below we describe the methods to build an aggregated network and a temporal network.

4.2.2.3 Time Aggregated Network

A predefined time window $\tau_{\min}$ is used to determine the connectivity between the nodes. If $\delta(i,j,t)$ is smaller than $\tau_{\min}$, 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 A of the network G can be obtained as

$$A(i,j)=\begin{cases}1, & \text{If } \delta t(i,j,t)<\tau_{\min},\ \text{and } s_i\cap s_j\neq\varnothing \\ 0, & \text{otherwise.}\end{cases}.$$

Especially, we define $A(i,i)=0$. Note that there may be more than one links between flight i and flight j, we define another two matrices N and W along with the adjacency matrix A. While $N(i,j)$ records the number of link $A(i,j)$ occurred across the whole time span, $W(i,j)$ indicates the strength of the relation between the two flights. There are certain circumstances that controller has to read back to the pilots, or to send acknowledgements transmission. To filter the noise like that, we use $N_{\min}$ as the threshold for the determination of edge-stability. Based on $\delta(i,j,t)$ and $N(i,j)$, the relational distance, $W(i,j)$, is calculated as

$$W(i,j)=\left(\frac{1}{N(i,j)}\sum_{\substack{\delta t(i,j,t)<\tau_{\min}\\ N(i,j)>N_{\min}}}\frac{1}{f(\delta t(i,j,t))}\right)\exp^{N(i,j)}$$

where $f(x)$ is the function to calculate the weight given the parameter x. In the paper we use $f(x)=x$.

For illustrative purpose, in Figure 4- 2 and Figure 4- 3 we present a scheme of the communication time series and its associated network.

4.2.2.4 Temporal Networks

The network G constructed above contains much information about the controller's communication activities. It is expected that the network properties can recover controller's behavior dynamics. The time ordered behavior, i.e. the sequence of communications, is however excluded. For instance, the degree of flight AC7 in Figure 4- 4 is five which tells that there were five flights have been involved with AC7. From the snapshots, we can see that the neighbors of AC7 change with time, and the most frequent degree of AC7 is actually two. In order to capture this, we refer to (Pan and

Saramäki 2011) and define the temporal network $G(t)$ by a set of quadruplets $e=(i,j,t,\delta t)$ indicating the connecting flight i and flight j at time t with the cost of δt. Similarly, there will no relation between flights i and j if the service times s_i and s_j are not intersected. Thus, we have

$$e(i,j,t,\delta t)=\begin{cases}1, & \text{If } \delta t(i,j,t)<\tau_{\min}, \text{ and } s_i \cap s_j \neq \varnothing \\ 0, & \text{otherwise.}\end{cases}.$$

To analyze the local temporal dynamics, we introduce the observation time window τ_{tw}. The temporal network will then be split into $n=(T_{\max}-T_{\min})/\tau_{tw}$ network snapshots.

4.2.3 Network Analysis Techniques

4.2.3.1 Classic Techniques

We first focus on the analysis of the network aggregated at different time scales. Topological changes of the network were measured with characteristics that focus on the degree distribution which have been used in prior research on network dynamics. The degree k_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

$$k_i=\sum_{j,N(i,j)>N_{\min}} A(i,j).$$

The degree distribution of a graph is defined as a discrete probability distribution that expresses the probability of finding a node with degree k. By construction, one can tell that there is high probability for a flight i with a bigger degree if there are more flights in the sector when flight i traverses. To give a general description, we introduce the normalized degree, which is defined as

$$\hat{k}_i=\frac{k_i}{N^i_{traffic}}$$

where $N^i_{traffic}$ is the number of flights in the sector when flight i traverses the sector.

4.2.3.2 Community Detection

A community is the dense sub-network within a larger network. The community is of particular interest because it may not only correspond to the functional unit of a complex system, but also can tell the properties of the individual community structure.

The community here, i.e. a group of flights, can be seen as certain functional component as traffic evolves. For instance, the aircraft flying along the same route with same flight level during the same period could be seen as a community in the sector. The investigation on the community and its structure is a way to understand how air traffic controllers clustering aircraft.

Algorithms for detecting communities in complex network being classified into three groups, hierarchical clustering, optimization methods, and block models, were critical reviewed in a recent article (Newman 2012). Given the fact that flights in the sector are changed with time, overlapping community is likely to occur in the network. Hence, we choose stochastic block models for the community detection. In brief, the block model is based on the idea of generating networks that contain community structure with the stochastic process for linkage creating between nodes. Let G be an undirected network with n nodes, and c_i represents the community to which node i belongs to. Denote p_{rc} the probability that there will be an edge between a node in group r and a node in group c. Again $A(i,j)$ is the element of the adjacency matrix. To identify the communities in the network that has been generated by the block model, one can simply maximize the following quantity over p_{rc} and c_i ,

$$L = \prod_{i<j} p_{c_i c_j}^{A(i,j)} (1 - p_{c_i c_j})^{1-A(i,j)} .$$

Since our purpose is to uncover the communities in the network, rather than the development of the algorithm for community detection. In this article we use an existing algorithm presented in (Lancichinetti, Radicchi et al. 2011) to find communities in the time aggregated network G .

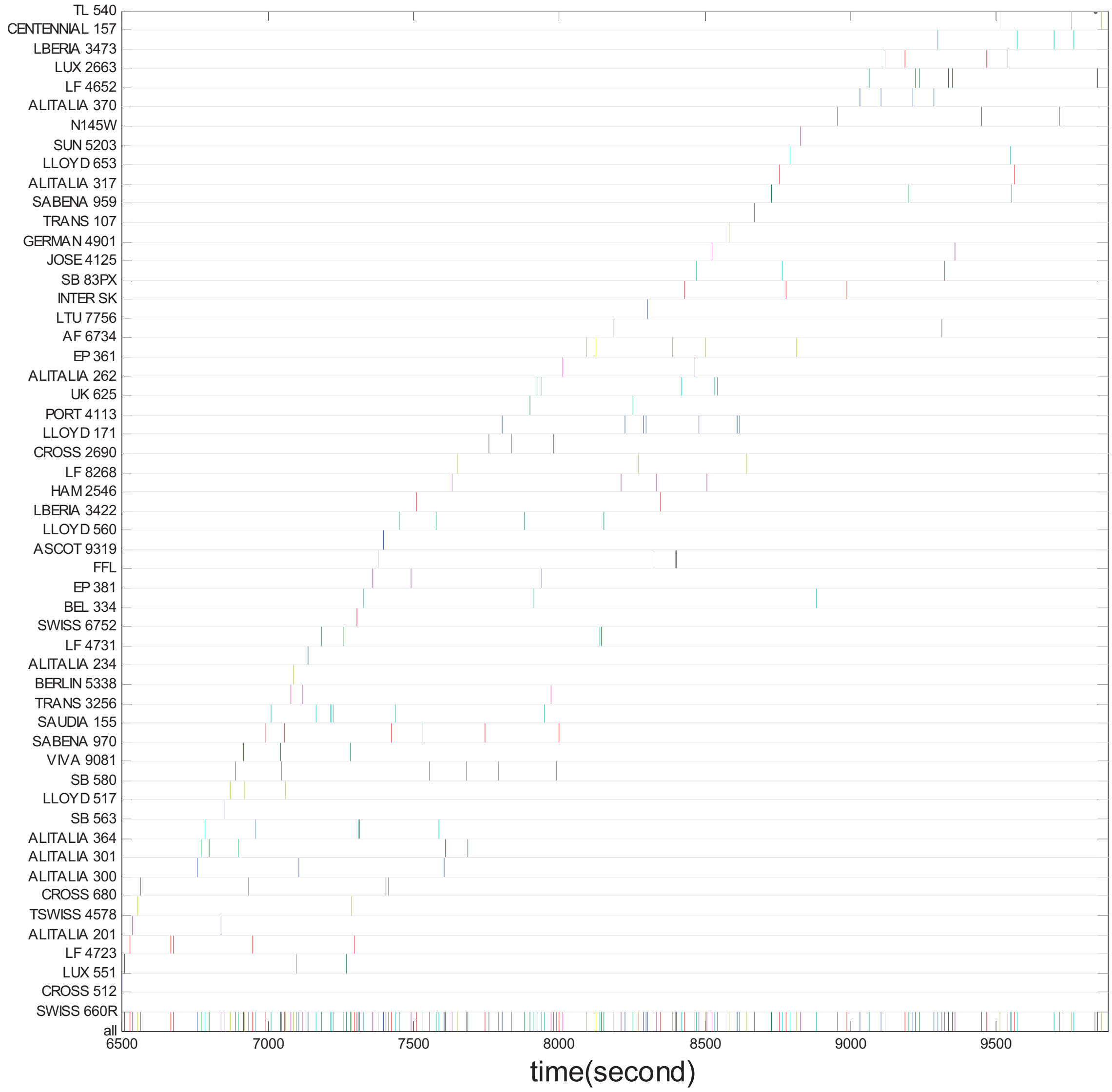


Figure 4- 2 Example of a series of communication data. Historical communication activities constructed from controller speeches. The upper displays communication events of the aircraft. Each horizontal grey line stands for a different aircraft, with each vertical line corresponding to a communication event. The down side gives the succession of communication activities of controller, with each vertical line represents a communication event over time.

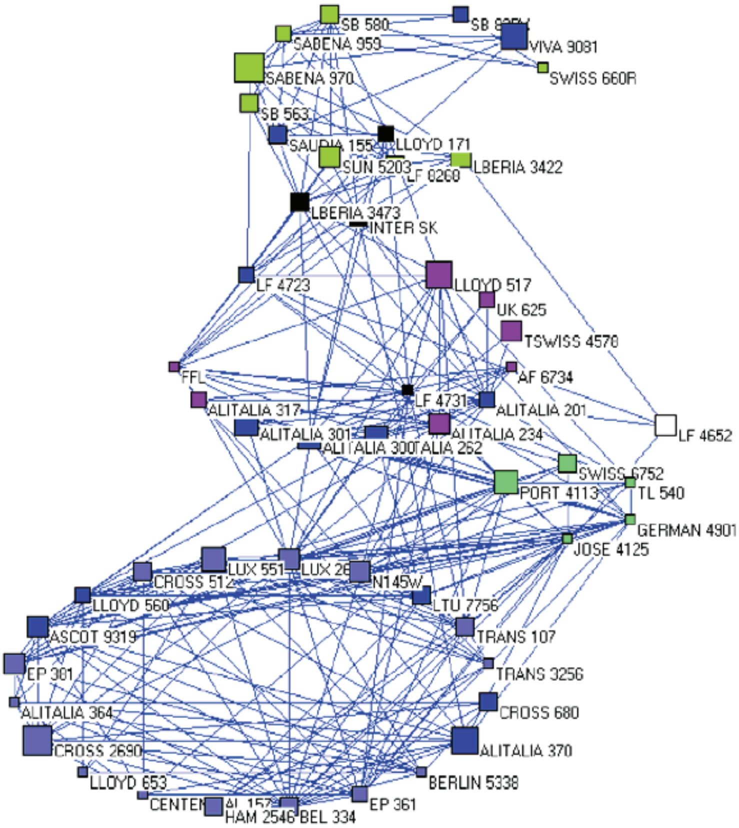


Figure 4- 3 The associate network of the communication events in Fig. 4-1. Each node corresponds to a flight, and the size of the nodes corresponds to the frequency of communication with controller. Colors represent the different communities that have been identified using the algorithm in (Lancichinetti, Radicchi et al. 2011).

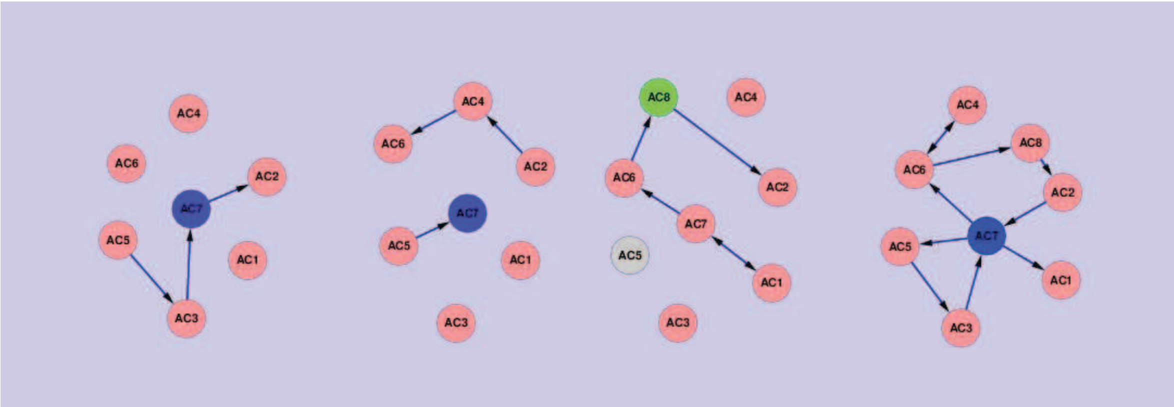


Figure 4- 4 An example of a sequence of communication networks. Each frame of the first three corresponds to a time interval of duration τ_{tw} and the last one is the network aggregated from the first three. Each node in the sub panel stands for a flight on the sector frequency. A link between nodes indicates the communications to the two flights are related.

4.2.3.3 Motifs Detection

At a level between nodes and network community, a most investigated network structure is the network motifs. A network motif is the equivalence class of sub-graphs or patterns that recur much more often than at random. It was thought that motifs can be related to the function of the system that networks are built from. Thus, the detection of network motifs will uncover the information-processing that carry out on the network.

From the air traffic controller's perspective, it is most likely that controller will shift attention over the flights according to the flights' position in the sector. In other word, route structure and other airspace factors, as well as traffic flow will shape controller's communication patterns. Both theoretical and practical studies have found that route structure (e.g. critical points formed by the merging of two traffic flow) is an important factor for managing traffic. Our focus on the temporal network motifs takes a first step to characterize the shape of controller's communications, thus to capture the information propagation process.

Given that fact that the maximum number of flights that are in the sector at the same time is limited, we define the following three basic motifs similarly to the social communications (Zhao, Tian et al. 2010). The three types of motifs are (i) *Chain*: That is to communicate with different flights consequently; (ii)*Loop*: After calling few flights, controller talk to the first flights; (iii) *Star* : It is obviously because the central flight is very important so that controller has to select it frequently. **Figure 4- 5** shows all three types of motifs. Again, because the maximum number of flights in the sector is limited, thus the temporal networks will have finite number of nodes. In the result section, we shall vary the size of motifs and test the frequency of each type of motif that has occurred in the datasets.

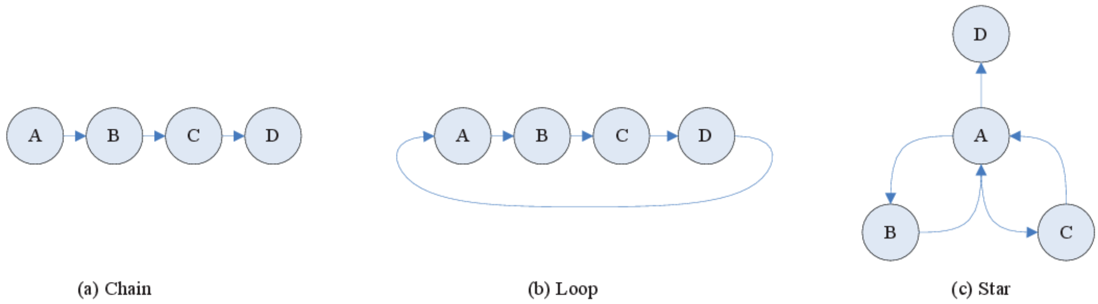


Figure 4- 5 Three types of motifs, chain, loop, and star.

4.3 Data

In this chapter, we have tested our method on three datasets. The first two datasets, D_1 and D_2, are the ATCOSIM corpus dataset and Paris TMA datasets that have been described in Section 3.2, whereas the D_3 dataset was created from Paris TMA dataset.

Both traffic information and communication information of D_1 dataset was given in Table 3- 2. Flight information was decoded from the text of the dataset. Overview of traffic and communication of D_2 dataset is reported in Figure 4- 6. Since it cannot extract flight information from radio communication data, our analysis of D_2 dataset was based on the Pilots manipulating data.

We constructed D_3 dataset from Radio communication, pilots' manipulating data, and transfer information data in the D_2 dataset. Briefly, we match the communication with flights using the following algorithm.

- Step 1. Sort the communication events, transfer data, and pilots' manipulate data in the ascending order. Denote $[t_0, t_{\max}]$ the considered time span for analysis. According to the transfer information and pilot's manipulate data, select the nearest controller's communication and mark it with the associated flight's call-sign.

- Step 2. Let $t_1 = t_0$, do the following.

- Step 2.1. If $t_1 > t_{\max}$, then terminate the algorithm. Otherwise, locate the next transfer event T_{next} in the transfer data, and let $t_2 = T_{next}$. Identify all the flights that are on the sector's frequency during time $[t_1, t_2]$, and denote the flights set as F^t. Let C^t be the set of communication events during the time $[t_1, t_2]$.

- Step 2.2. For the communication events in the C^t without flight' call-sign, randomly select a flight in the F^t to be the flight's call-sign, and delete the flight in F^t. Repeat doing this until all the communication events are assigned with flights' call-signs. Then let $t_1 = t_2$ go the Step 2.1.

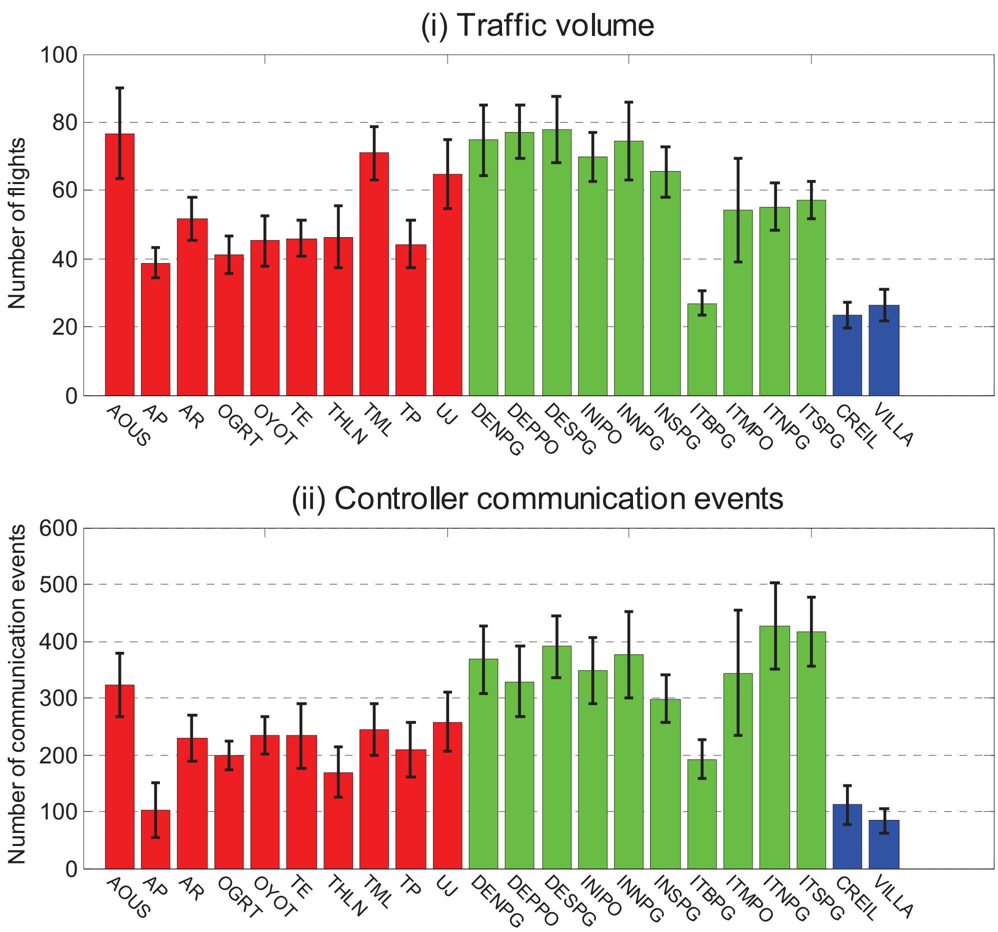


Figure 4- 6 Overview of traffic activities and controller communication activities in Paris TMA data. The height of the bar represents (i)the average number of flights ((ii)controller communication events) in each sector, while error bar shows the standard deviation across all the exercises. Red bars are the en route sectors, while green bars are the approach sectors. Military sectors are filled with blue.

4.4 Results

In the section, we present the results and provide an avenue for discussions of our techniques. Recall that the minimum distance $\tau_{\min}$ is used to determine the connectivity between two flights based on their temporal communications' information. If $\tau_{\min}$ is big enough that every flight i is able to link with the flights that are in the sector during time period s_i, whereas the small $\tau_{\min}$ places a hard constraint on the connectivity between flights. It is therefore expected that the value of $\tau_{\min}$ has impact on the network structure. To test this hypothesis, we selected the value of $\tau_{\min}$ from 1 minute to 5 minutes with a 10 seconds growth rate. Consider that most of flights were called less than three times by the controller, the minimum weight thresholds $N_{\min}$ were chosen from 1 to 5. Table 4-1 presents general information about the networks constructed by our algorithms.

Table 4-1 Summary of the main features of the networks obtained over a minimum weight of link $N_{\min}$

		D1 (ATCOSIM)		D2 (Paris UM)		D3 (Paris M)	
		average	variance	average	variance	average	variance
$N_{\min}=1$	#of networks	1250.0	0.0	7681.0	1.1	7000.0	0.0
	# of nodes	62.0	5.9	49.1	18.1	53.1	18.3
	# of edges	597.2	155.0	194.2	117.7	270.8	162.1
$N_{\min}=2$	# of networks	1250.0	0.0	7650.0	0.9	7000.0	0.0
	# of nodes	62.0	5.9	49.2	18.0	53.1	18.3
	# of edges	313.1	141.7	139.0	91.8	207.4	130.4
$N_{\min}=3$	# of networks	1250.0	0.0	7612.0	2.8	7000.0	0.0
	# of nodes	62.0	5.9	49.4	17.8	53.1	18.3
	# of edges	168.0	105.0	98.9	74.1	157.6	106.7
$N_{\min}=4$	# of networks	1249.0	0.2	7518.0	2.7	6996.0	0.5
	# of nodes	62.0	5.9	49.9	17.4	53.2	18.3
	# of edges	89.3	68.8	72.5	61.5	120.4	88.8
$N_{\min}=5$	# of networks	1234.0	2.0	7414.0	7.4	6975.0	2.3
	# of nodes	62.0	5.9	50.2	17.2	53.2	18.2
	# of edges	48.0	43.1	53.7	52.3	92.2	73.9
	# of networks (total)	6233		37875		34971	

4.4.1 Time Aggregated Networks

4.4.1.1 Degree Distribution

Figure 4- 7 plots the normalized degree distribution in D_1 dataset. To our surprise, the degree distributions have quite similar shapes across all the sectors. With $\tau_{\min}$ fixed and $N_{\min} \leq 3$, instead of randomly distributed, most of data can be described as a Poisson distribution or Normal distribution. Such trends appear commonly in the random

network studied by Erdos and Renyi (Erdös and Rényi 1959) with each edge is present or absent with equal probability. This suggests that the pairs of flights are uniformly selected. With $N_{\min}$ 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 $N_{\min}$ exceed 3. Most flights have a small degree, while very few flights still have more neighbors.

To examine the effects of minimum temporal distance $\tau_{\min}$ on the network structure, we grouped the degree in each dataset. In Figure 4- 8 we can see that there is a clear trend that both the degree and normalized degree growing as $\tau_{\min}$ increases. It is not surprise because the probability to link more flights will be higher when $\tau_{\min}$ become longer. It should be noted that the gap between the degree with the same temporal distance but with minimum weight value at $N_{\min} = 1$ and $N_{\min} = 2$ are much bigger than other differences. We are acknowledged that most of the flights are probably flying without controller's extra intervention that is they are not involved in a conflict. For example, most of the flights in en route sector receive one transfer in message and one transfer out message if the flight doesn't need to change the speed or altitude. When we increase the threshold of minimum number of links, such noise was filtered away.

While the analysis of time aggregated network show a general picture of how controller communication with flights, the dynamical patterns, such as how the controller's attention is paying to, is cannot be identified. Therefore, we will need the time ordered networks to investigate the time evolving behavior.

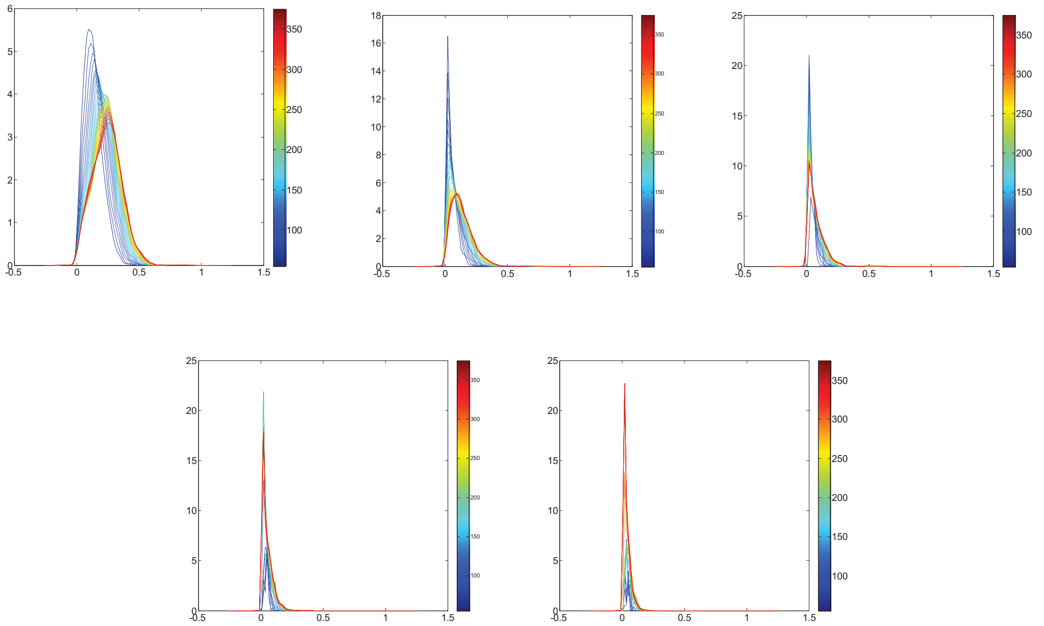


Figure 4- 7 Normalized degree distribution in k_i dataset. X-axis denotes the normalized degree of a flight, with y-axis is the probability density. Colors of the lines represent the minimum distance $\tau_{\min}$ indicated by the colorbar

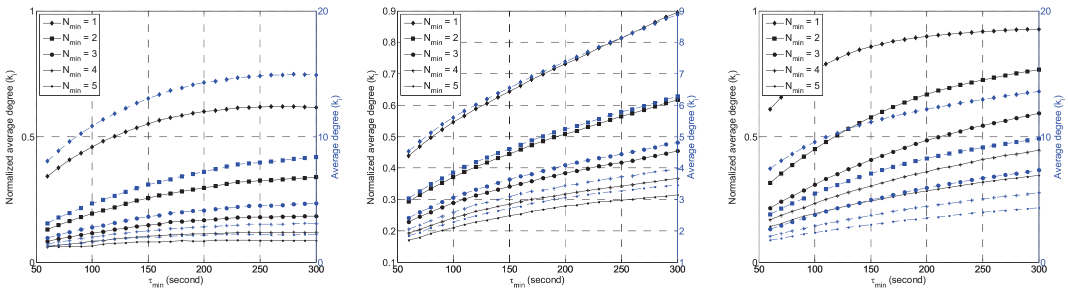


Figure 4- 8 Effects of minimum temporal distance $\tau_{\min}$ on the aggregate degree distribution. Blue markers are the average degrees of the nodes k_i , while black markers are the normalized degree $\hat{k}_i$

4.4.1.2 Correlations between Network Community and Air Traffic

To recover the detailed picture of traffic from the controller's communication is of great interest and with much difficulty. The physical relations between aircraft in the sector are not exactly the same as that in controller's mind. To find out the abnormal in the controller's communication that correlates to the severe traffic situation such as conflict will help to prevent such events occur. Here gives our initial attempt to link controller's communication activities to the traffic activities. One way to reoccur the traffic from the network that generated from controller's communication is the use of community detection technique. We chose the algorithm that was developed in (Lancichinetti, Radicchi et al. 2011) for community detection. The analyses were performed on W matrix.

We found that the correlations between average community size and the number of traffic in the sector depend on sector types (see Table 4- 2). Most of the en route sectors were found to be better correlated than the approach sectors. The p-values of the approach sectors, for instance ITBPG, ITMPO ITNPG, are approaching zero. It is possibly that the communications in these sectors are different from the others, and the time aggregated network is incapable of unmasking the behavior.

Table 4- 2 Correlation coefficients of average community size and number of flights in the sector

Sectors	Corrcoef	P	Sectors	Corrcoef	P
AOUS	0.1063	0.7175	ITMPO	0.9451	0
AP	0.9653	0	ITNPG	0.9924	0
AR	0.4314	0.1235	ITSPG	0.9871	0
CREIL	0.9272	0	OGRT	0.5729	0.0323
DENPG	0.7971	0.0006	OYOT	0.5769	0.0308
DEPPO	0.7443	0.0023	TE	0.4568	0.1006
DESPG	0.424	0.1308	THLN	0.7919	0.0007
INIPO	0.667	0.0092	TML	0.8194	0.0003
INNPG	0.5954	0.0247	TP	0.6681	0.009
INSPG	0.4672	0.0921	UJ	0.8643	0.0001
ITBPG	0.9811	0	VILLA	0.7268	0.0032

4.4.2 Temporal networks

It is with no difficulty to calculate the quadruplets $e=(i,j,t,\delta t)$ from controller's communication data. With the quadruplets and the window τ_{tw}, we can have $n=T/\tau_{tw}$ sets of snapshots of network $G_3^w(t_{\min},t_{\max})$, where $t_{\min}$ is the staring time and $t_{\max}$ is the ending time, such that $T=t_{\max}-t_{\min}$. The following presents the information dynamics unmasked by the time respecting network properties. While there is an abundance of measures for characterizing the topological structure of static networks, measures proposed for the temporal networks are still lacking, with many of which are built on the concept of time-respecting paths that define which nodes can be reached from which other nodes within some observation window. Such measures include reachability ratio, connectivity, distances, and latencies etc(Holme and Saramäki 2011). In the context of air traffic control, we select the time dependent degree, and motifs to study the temporal network.

4.4.2.1 Time Dependent Degree Distribution

Time dependent degree of a node can be seen as the number of links activated within a time window τ_{tw} . Frequently appeared links suggest strong relationships between the nodes. Plotting in the Figure 4- 9, the climax of each hill shows the time dependent degree distribution of each flight in an exercise in D_1 dataset. It can be seen from the figure, most of flights have degree of two, rather than six which was found out in the time aggregated network (see Figure 4- 7). This indicates that the flights are dynamical grouped by the controller according to the traffic.

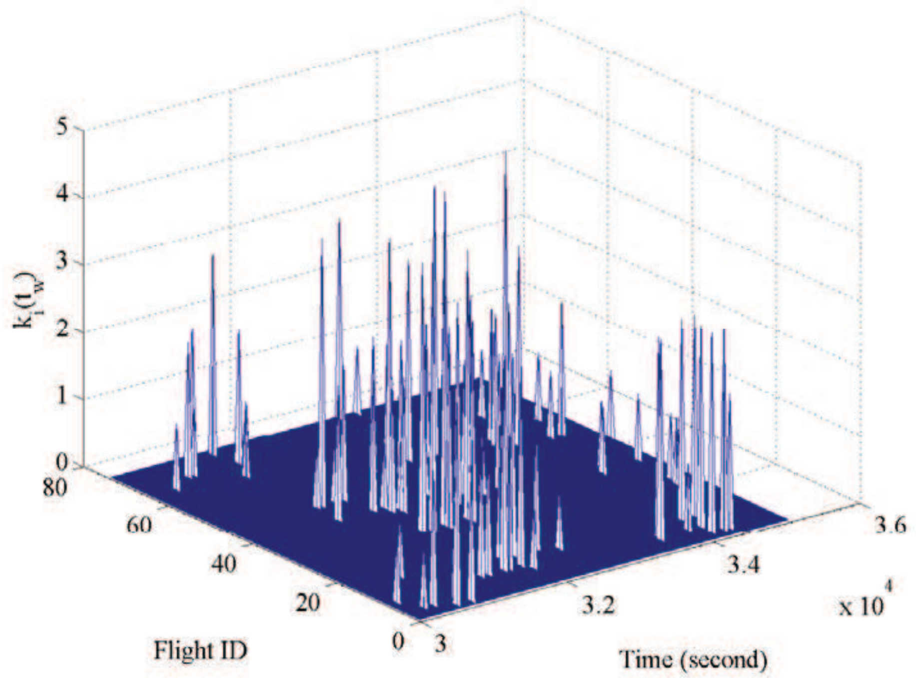


Figure 4- 9 Time dependent degree of each flight in a sector with $\tau_{\min} = 60$ seconds.

We expected that airspace structure may have effect on the communication dynamics that was not uncovered by the time-aggregated network. The studies on the controller's cognitive activities have found that airspace structure plays an important role while controller control traffic (Histon and Hansman Jr 2008). To test this hypothesis, we calculate the empirical distribution of time-dependent degree of each sector in every dataset. To our surprise, the probability distributions of the degree have quite similar shapes, which suggest that airspace structure has little effect on the communication. Meanwhile, we didn't see much difference in the distributions across the entire time window τ_{tw} (Figure 4- 10 shows the empirical distribution of degree in D_2 dataset with τ_{tw} varying from 60 seconds to 110 seconds). Interestingly, the statistical results reveal that most of flights have two neighbors. The reason for such could be the orderly communicating with flights as shown in the Figure 4- 4. To examine this hypothesis, in the following we investigate the network motifs.

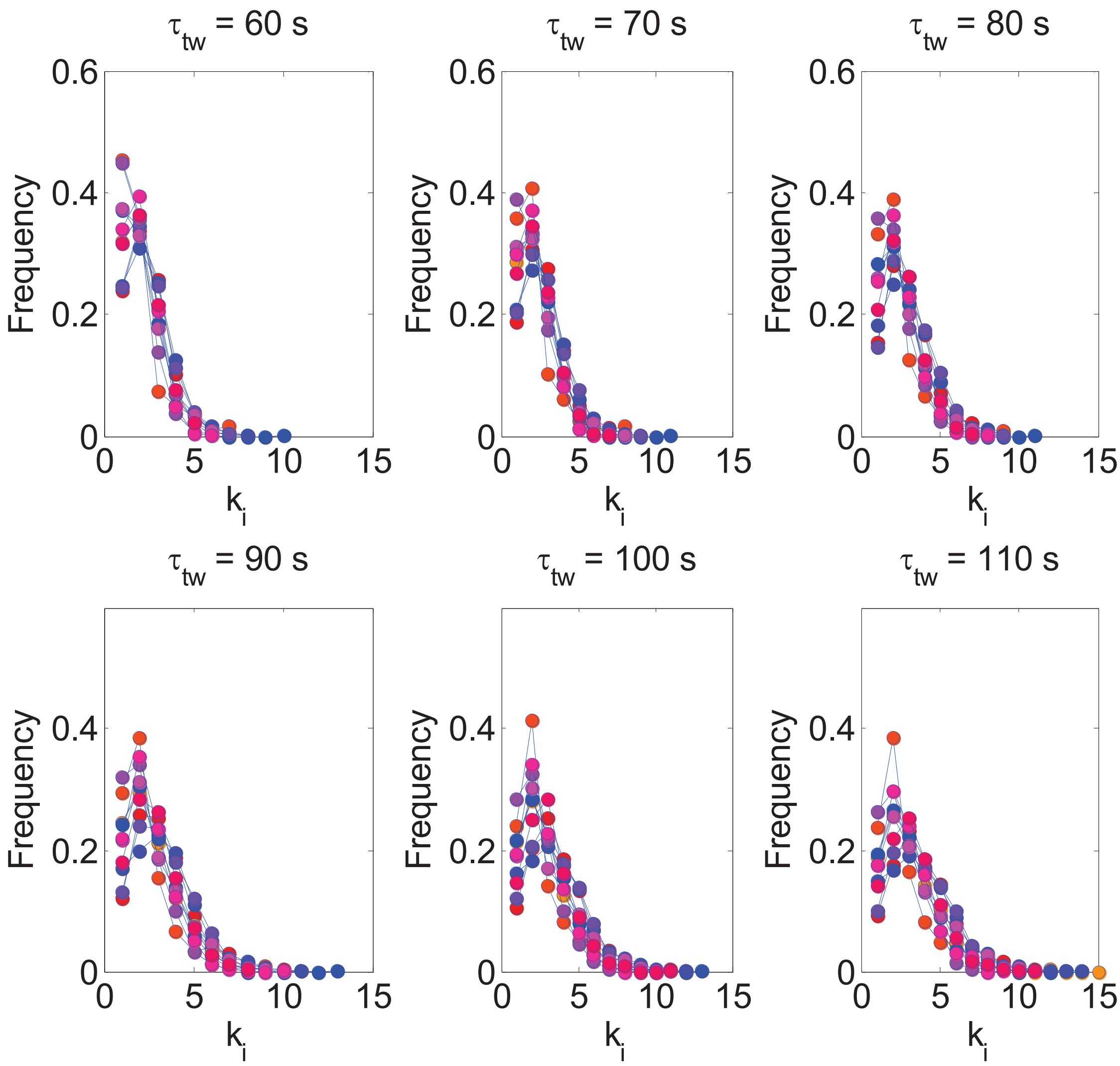


Figure 4- 10 Frequency of degree in each sector in D_2 dataset.

4.4.2.2 Network Motifs

In contrast to the commonly used network motifs detection, what we are trying to analyze is the most frequently occurred patterns in the controllers' communications. Therefore, we will calculate the motifs for the temporal network snapshot with observation window τ_{tw}.

Figure 4- 11 shows the frequency of three types of motifs as a function of time window τ_{tw} .Clearly, the chain topologies are the most occurred patterns. With the increase of τ_{tw} , both the loops and stars grow quickly. As we know that if we increase the length of τ_{tw} , the possibility of higher number of flights will increase. Therefore, there might be high probability for loops and stars occurring. We can see that there is a changing point at $\tau_{tw} \approx 150$ seconds in all the three datasets, where the possibility to have chains and loops are almost the same. Compared to the loop motifs, star motifs grow much slower. Even the observation time window reaches five minutes, the percentage of star motifs are less than 20%. Meanwhile, we note that percentage of loop motifs seems to reach its climax at 60%.

One would expect that controller will return to a flight that is previously communicated with. However, results obtained here suggest it is not the case. Chains and loops are the most frequently motifs in the controller's communication, such topological characteristics have been reported in the information propagation in other human social communication (Zhao, Tian et al. 2010).

In the time aggregated network analysis, we brought forward our hypothesis that the probability to select an aircraft to communicate is uniformly distributed in the whole time span. Rather, the temporal network reveals that chain and loops patterns are the most common patterns at the local temporal dynamics.

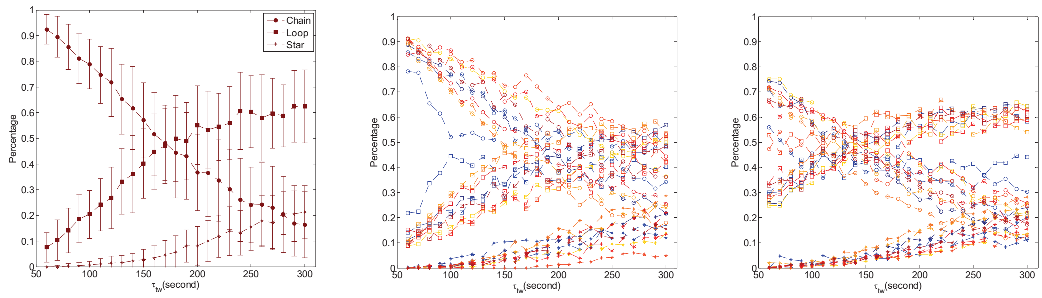


Figure 4- 11 Percentage of three types of motifs detected in the three datasets. Circles show the percentage of chains; squares represent the loops and stars stands for the star motifs. Sectors were plotted with different colors in (b) and (c).

4.5 Chapter Summary

A network perspective is extremely useful for understanding the information propagation process. In this chapter we have presented a temporal network approach to analyze air traffic controller’s communication activities. Our analyses on network properties provide the evidence that the probability to select an aircraft to communicate with are uniformly distributed. The correlations between network communities' sizes and traffic volume reveal that the communication network do preserve traffic information. Motifs being a good measure is capable of uncovering the information process on the temporal network. Our observation suggests that chains and loops are the most frequently occurred patterns in controller’s communication. To trace information dynamics solely relying on air traffic controller’s communication data is able to identify the general information flow patterns. However, information diffusion investigated with airspace route structure may help to detect more clear characteristics that depend on the airspace such as the final approach sectors, since network structure may shape information dynamics. Local temporal dynamics of controller’s communication deserves further consideration because it contains information about the microscopic dynamics of controller’s attention.

In the light of network science, there are still open topics for further investigation. With regard to the future air traffic management operation, the studies of information diffusion would be an important step. We must note that air traffic controller in the current system acts as a role to deliver the information to the flights, while in the future there would be automation systems to do that. The underlying mechanisms uncovered by the controller’s communication not only help us to the understanding of human activities but also provide the support to the development of such automation systems.

CHAPTER 5 FLUCTUATION SCALING IN THE CONTROLLERS' COMMUNICATION

This chapter introduces the fluctuation issues in the air traffic controllers' activities. In general, air traffic controller is assigned to a sector where he/she will work for a long time. If controller has been changed to a new sector, further training, acquisition and checkout of expertise are necessary. Although the route structure in the sector does change very often, controllers have to be prepared to face the unexpected traffic situations that can not be predicted due to uncertainty. Thus, their activities will exhibit variety during repeated operations or simulations. Here, we report the fluctuation scaling of controllers' communication activities. Then the associated model to explain observed phenomena is developed. Several implications are discussed.

5.1 Introduction

Complex systems consist of large amount of interacting elements that are hierarchical linked. Dynamics at low level elements may result in the emerge of collective behavior at high level, which is referred as "complex". Activities at an element of the system will fluctuate within certain range while the whole system operates normally. Take air traffic control system as an example, a predefined maximum number of aircraft that can be accepted in the sector is set, in order to avoid high workload that may lead to unsafe event occurring. Traffic volume in each sector can fluctuate under the maximum value.

Human activities are the results of the stochastic process of the cognitive activities. Even facing the same traffic situations, controllers' strategies may be not exactly the same. As we know that both traffic dynamics and controllers' cognitive process are full of stochastic, controllers are able to adaptive to this environment to control the traffic.

To character the relationship between the fluctuation in the activity of an element and the average activity in a complex system, Taylor's power law have been widely reported in many disciplines, ranging from ecology(Taylor 1961; Taylor and Taylor 1977; Taylor, Taylor et al. 1983; Grenfell, Wilson et al. 1998; Sæther, Tufto et al. 2000; Bjørnstad and Grenfell 2001), river flow(Sadegh Movahed and Hermanis 2008), through human gait (Hausdorff, Purdon et al. 1996; Cai, Zhou et al. 2007), to financial markets(Gopikrishnan, Plerou et al. 2000; Sato, Nishimura et al. 2010; Bolgorian and Raei 2011), and social activities(Onnela and Reed-Tsochas 2010). The Taylor's power law, which was named after L. R. Taylor in recognition of his paper in 1961(Taylor 1961), is usually in the following form:

$$fluctuation \approx const. \times average^{\alpha}, \text{ where } \alpha \in [1/2, 1].$$

Our interest is to capture the adaptive phenomena of air traffic controller's activities using controller's voice communication activities as a proxy. First, a brief review on fluctuation scaling methods is summarized in Section 5.2. Then in Section 5.3, we list two communication datasets that have been investigated. Consequently, Section 5.4 presents the empirical results, and a model was developed in Section 5.5. The chapter ends with conclusion remarks in Section 5.6.

5.2 Fluctuation Scaling

Here we briefly depict the summary of fluctuation scaling (FS). For a detailed discussion and the example of using FS to study the effect of social influence, refers to (Eisler, Bartos et al. 2008; Onnela and Reed-Tsochas 2010).

5.2.1 Temporal Fluctuation Scaling

Let us consider a complex system with many nodes i. For any time block $[t, t+\Delta t]$, the quantity f_i that measure the activities of node i can be decomposed as the sum of all the constituents which contribute to f_i during the time interval, that is

$$f_i^{\Delta t}(t) = \sum_{n=1}^{N_i^{\Delta t}(t)} V_{i,n}^{\Delta t}(t),$$

where $N_i^{\Delta t}(t)$ is the number of constituents, and $V_{i,n}^{\Delta t}(t) \geq 0$ is the value of nth constituent in the time block.

Then the time average activities f_i during observed interval [0,T] can be obtained as

$$\left\langle f_i^{\Delta t} \right\rangle = \frac{1}{Q}\sum_{q=0}^{Q-1} f_i^{\Delta t}(q\Delta t) = \frac{1}{Q}\sum_{q=0}^{Q-1}\sum_{n=1}^{N_i^{\Delta t}(q\Delta t)} V_{i,n}^{\Delta t}(q\Delta t),$$

where $Q = T/\Delta t$. The variance can be calculated as

$$\sigma_i^2(\Delta t) = \left\langle \left| f_i^{\Delta t} \right|^2 \right\rangle - \left\langle f_i^{\Delta t} \right\rangle^2 .$$

Since $\left\langle f_i^{\Delta t} \right\rangle \equiv \Delta t \left\langle f_i \right\rangle$, when one varies the node i while keeping Δt fixed, the relationship between the standard deviation and the mean of f can follow a power-law relationship

$$\sigma_i(\Delta t) \propto \left\langle f_i \right\rangle^{\alpha_T} .$$

Normally the exponent α_T is in range [1⁄2, 1]. This power-law relationship is known as fluctuation scaling, or Taylor's law.

5.2.2 Ensemble Fluctuation Scaling

Because the above calculations were based on temporal average, it is referred as Temporal Fluctuation Scaling (TFS). Empirical results on TFS were reported in complex networks(de Menezes and Barabási 2004), stock markets(Eisler and Kertész 2007), human dynamics (Eisler, Bartos et al. 2008) etc.

If there is a well defined size-like parameter S for all the nodes, for instance the linear extend (L), area (A), or a fixed constituents (N), and the i-dependence of $\langle f \rangle$ and σ is only manifested via S, then we can obtain the Ensemble Fluctuation Scaling (EFS) by the following steps. First, the ensemble average of f within S can be calculated as

$$\overline{f_S^{\Delta t}} = \frac{1}{M_S} \sum_{\forall i: S_i = S} f_i^{\Delta t}(t),$$

where M_S is the number of the nodes which have a size $S_i = S$. Then the standard deviation is given by

$$\overline{\sigma_S^2(\Delta t)} = \overline{\left[f_S^{\Delta t} \right]^2} - \overline{f_S^{\Delta t}}^2.$$

Fluctuation scaling can also arise as

$$\overline{\sigma_S} \propto \overline{f_S}^{\alpha_E}.$$

The classic study of EFS is the given by Taylor(Taylor 1961). The author measured the means and the variances of the natural populations in the different size of area A. With increasing the size of area both the mean and the variance of the population grew, with a power law relationship between the two quantities.

5.3 Data

Two empirical datasets were analyzed in this chapter. The first one is Paris TMA simulation data, and the second one is ATCOSIM Corpus Data.

Descriptions on the Paris TMA simulation dataset are given in the Chapter 3 and Chapter 4. To capture the fluctuation scaling, we will need both controllers' communication data and traffic data. To measure the average activities and the standard deviations of the activities needs a series of observations of the same controller (or sector). Paris TMA simulation data provides fourteen observations on twenty-two sectors. Information about the sectors in the ATCOSIM dataset is not available. However, we add the ATCOSIM dataset to examine whether this dataset shows the same phenomena. If the observations of the two datasets fall into the same range, then the results will be more promising. Sector relationships of Paris TMA data is shown in Figure 5- 1.

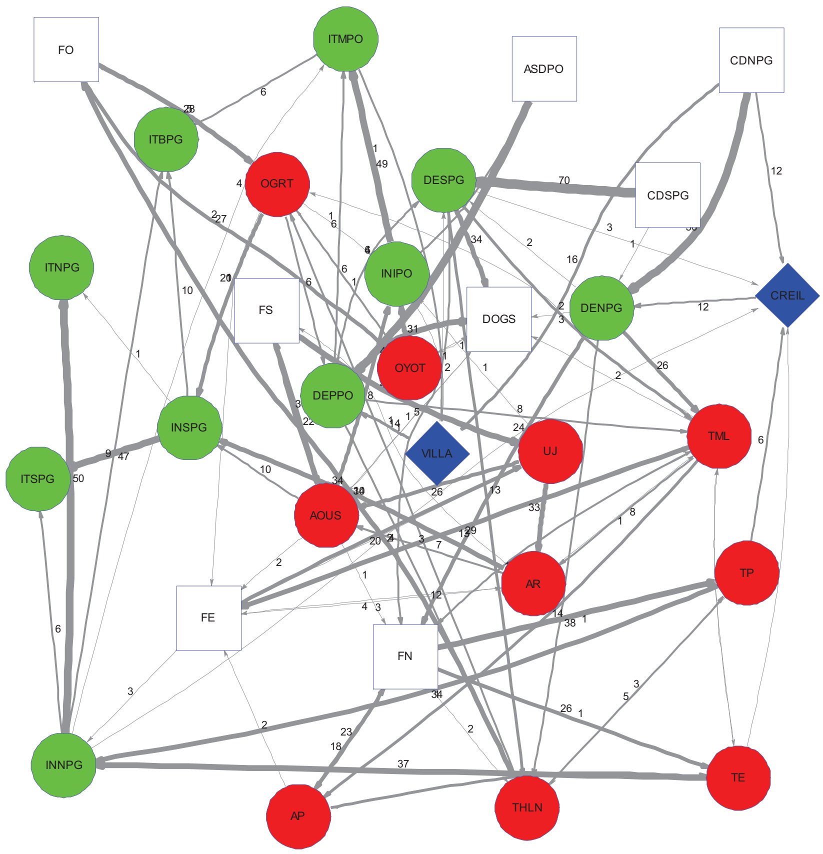


Figure 5- 1 Traffic flow between Paris TMA sectors. Each node corresponds to a sector, and the square ones are the feeding sectors which were used for traffic initialization and finalization. The widths of line arcs are proportional to the traffic volume for the two sectors with arrow indicates the direction of flow. Data was from exercise 100618A.

5.4 Results

We are acknowledged that air traffic patterns, say input/output flow rate, can influence air traffic controller's communication activities. In our previous work, we did find the strong correlations between air traffic activities and communication activities. Therefore, it is naturally to analyze the traffic characteristics before looking at controller's communication. One of major traffic factors that influence controller's communication is the service time τ , which is defined as the duration of a flight stays in the sector. The longer the service time is, the higher probability of receiving more communication is. Traffic configurations in terms of traffic complexity or input/output flow rate, together with the air route structures are heterogeneous in the Paris terminal area. Figure 5- 2 shows the empirical distributions of inter-arrival rate and service times in each sector. From the shapes of the curves, we could propose the normal distribution to fit the empirical data of a sector. However, it cannot find a universal distribution function for all the sectors.

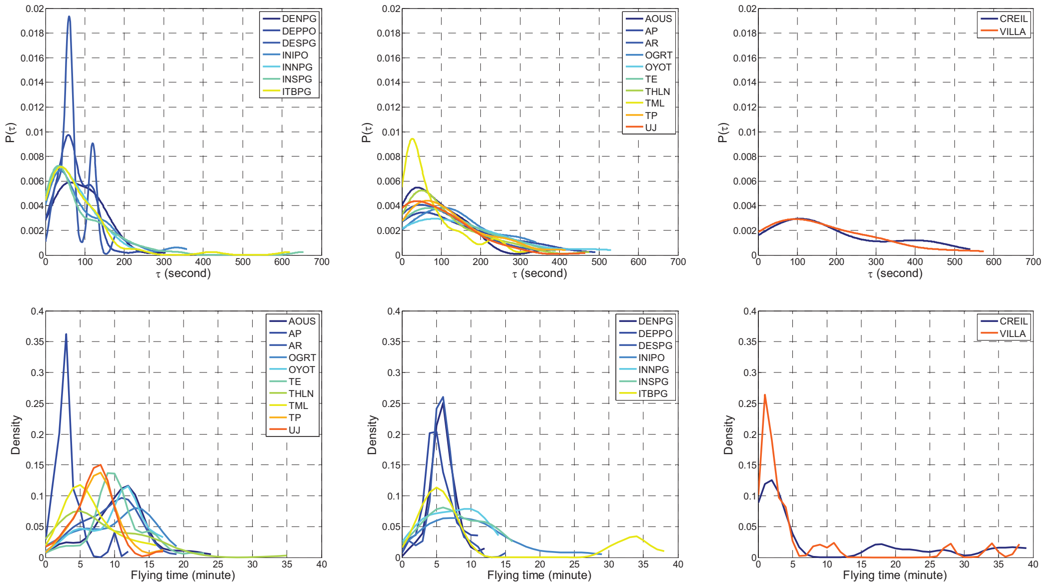


Figure 5- 2 Empirical distribution of inter-arrival rate ($a \sim c$) and service times ($d \sim f$) in the sectors. Results were constructed from Exercise 100618A

Another question arising is that whether there is fluctuation scaling in the traffic-arrival rate as other transportation systems exhibit Fronczak and Fronczak(Fronczak and Fronczak 2010). As shown in Figure 5- 3, the number of aircraft in the sectors during the observation time window (Δt) and the associated standard deviations are plotted. There is a trend in the linear relationships between the two quantities in the log-log plane. However, we could not give a conclusive remark due to the limited number of sectors and traffic volume. The sectors' network in Paris terminal area consists of around twenty-two sectors, and the Paris TMA simulation traffic data were prepared with only two peak hours. Comparing with the five years' traffic data in the Minnesota transportation network, it is not surprise that the fluctuation scaling didn't emerge in our data.

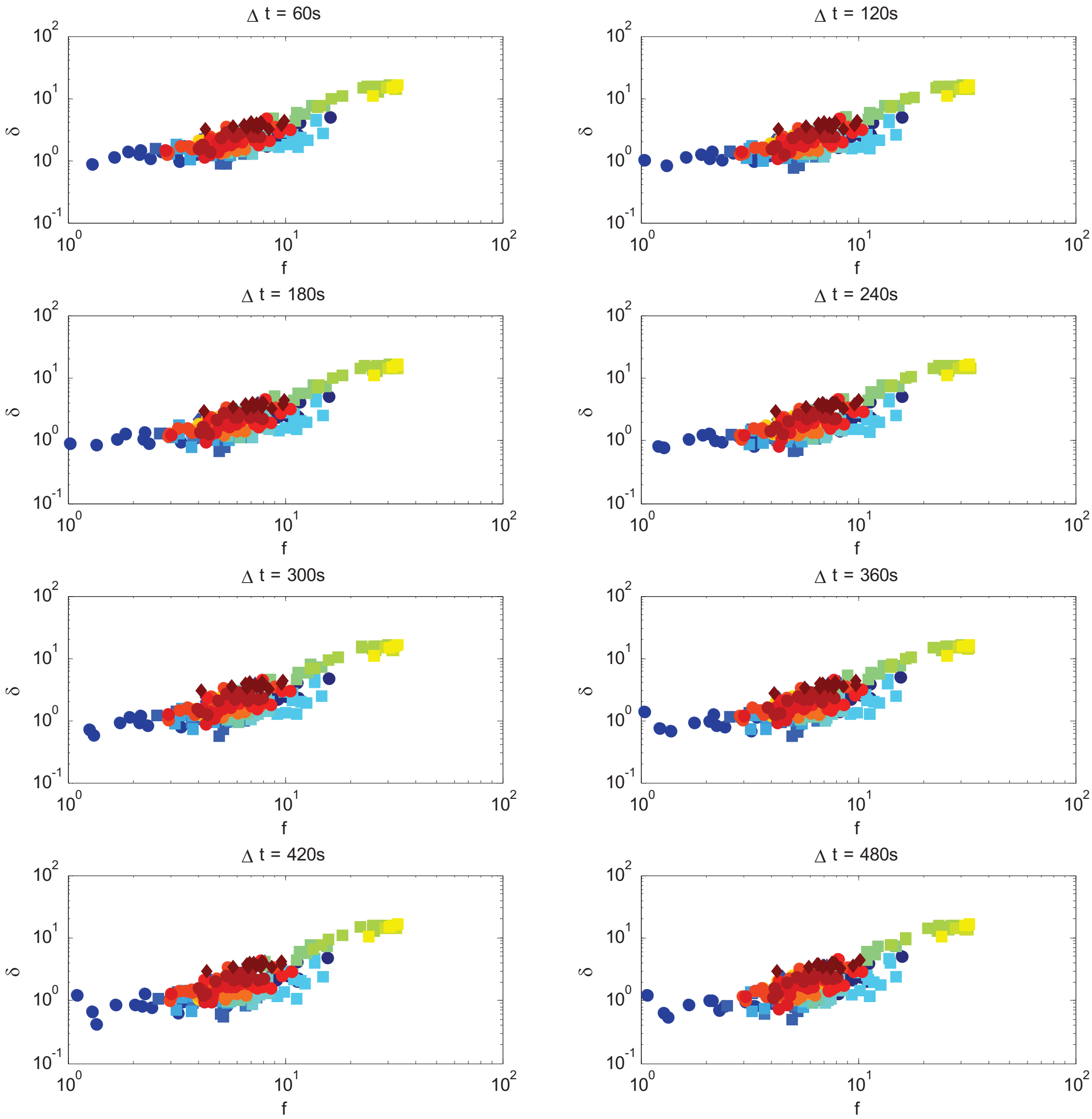


Figure 5- 3 Fluctuations in traffic activities in the sectors. Sectors are represented with colors.

5.4.1 Temporal Fluctuation Scaling

Given the heterogeneity of traffic in each sector, controllers' communications could be heterogonous too; simple reason is that controllers' communications are depending on the traffic activities. To examine the temporal fluctuation scaling in the controllers' communication activities, we plot the average communications and the standard deviations in the log-log figures. Reported in the Figure 5- 4, the relationships between the average f and the standard deviation σ cannot be described by a single equation.

The sector with high traffic volume has higher communications. It indicates that the temporal distributed traffic has significant impact on the controllers' communication.

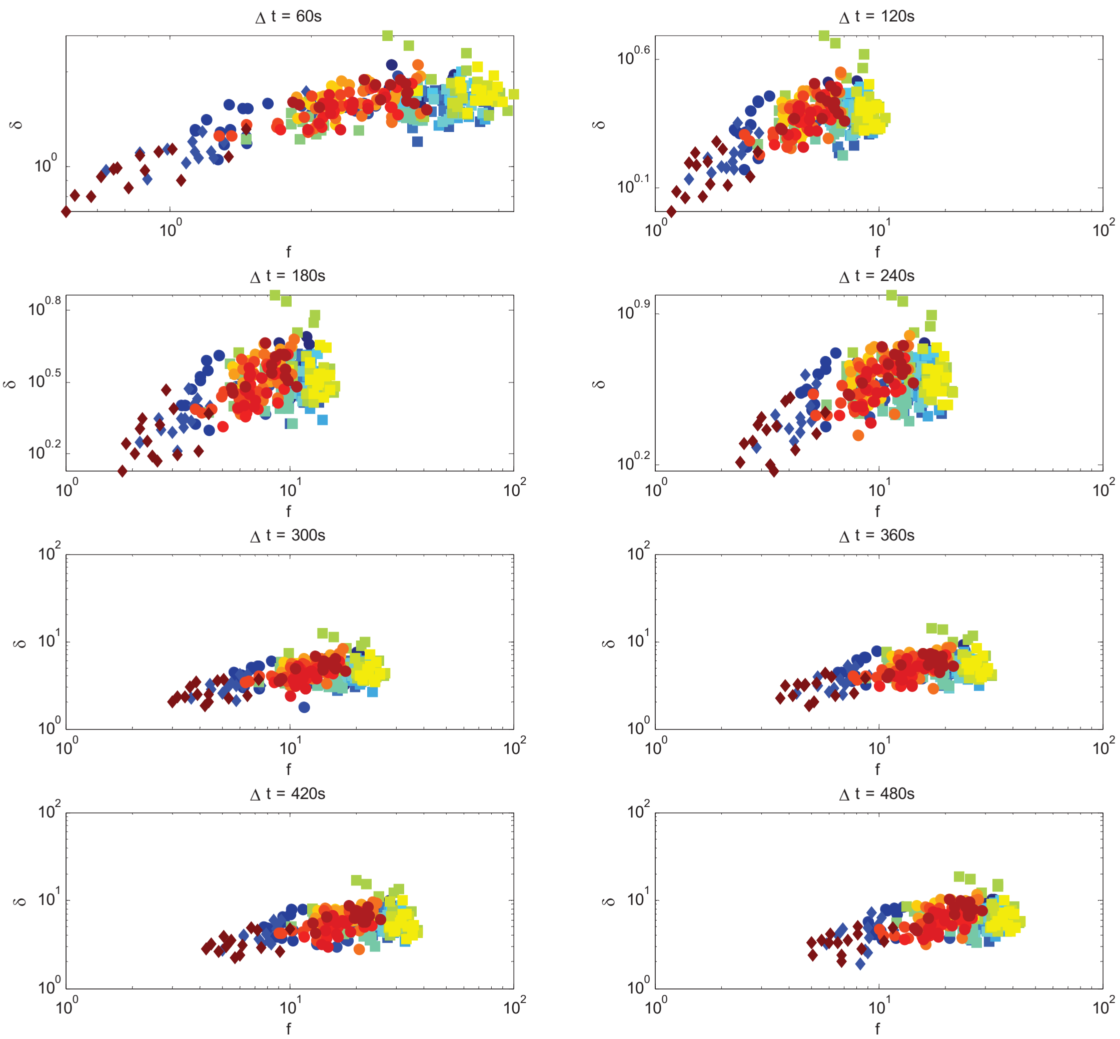


Figure 5- 4 Temporal fluctuations in the controllers' communications. Markers with the same color stand for the same sector.

5.4.2 Ensemble Fluctuation Scaling

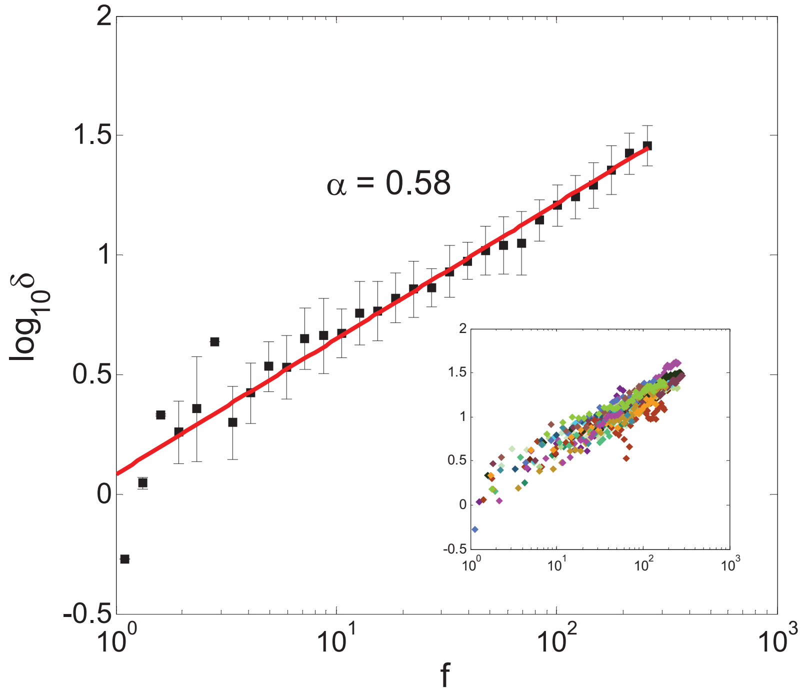
To minimize the above factors' effects on the controller's communication activities, we perform the ensemble fluctuation analysis following the steps depicted in 5.2 . Similarly to Taylor's work, we calculate the average of controller's communication activities $\overline{f_i}$ and the standard deviation $\overline{\sigma}$ according to the different volume of the flights entering the sector. When a flight flies into the sector, controller will give several control instructions and clearances to avoid conflict and hand flight out to the next sector. Thus, the communication activities can be obtained by

$$f_i = \sum_{n=1}^{N_i} V_{i,n},$$

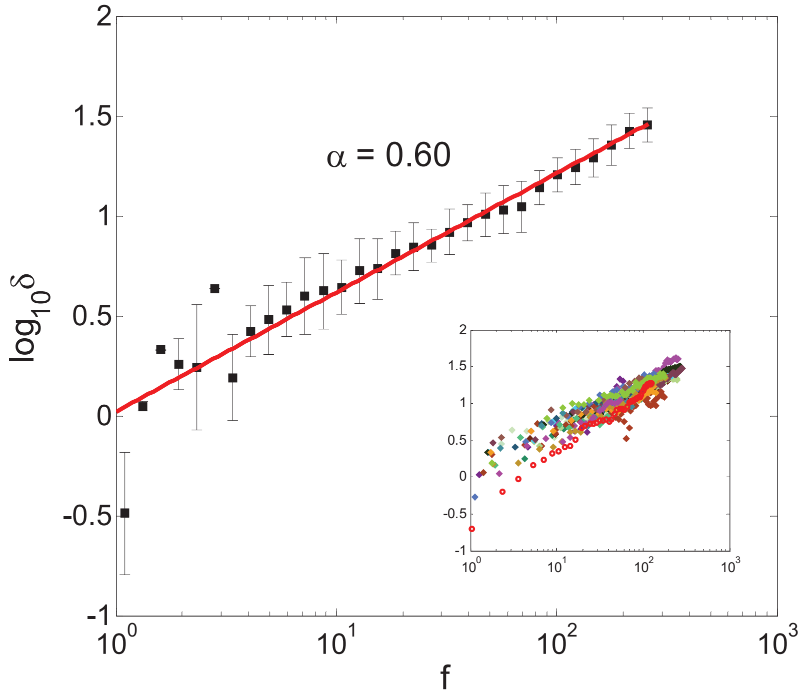
where N_i is number of flights entered the sector i, and $V_{i,n}$ is the number of communication activities with flight n. The calculation can be done through all the sectors with different amount of entering flights.

It found that both the average and the standard deviation of the communication activities grow quickly as the number of flights increases. Then we plotted the standard deviation according to the average of the communication activities in Figure 5- 5. In spite of the heterogeneities of traffic patterns and airspace configuration, we can clearly observe a linear fit of the empirical data in the log-log plot (solid red line), which indicates that the standard deviation of the activities and the average activities do exhibit a clear Taylor's power-law relationship with $\alpha \approx 0.58$. Because of the initialization of traffic for the first few flights, there are strong fluctuations at the beginning of few data points. When we add another dataset, ATCOSIM data, into the figure, the slope of fitting line changed slightly. The whole dataset still can be described by $\sigma = \langle f \rangle^{\alpha}$ with $\alpha \approx 0.60$. We emphasize that ATCOSIM dataset and Paris TAM dataset were recorded in 1997 and 2010 respectively. In total, fifty-five controllers' communication data were included. Here we have showed that their behaviors can be characterized by the similar fluctuation scaling patterns.

It is possible that air route structure and sector type (en route, approach, tower, and ground) may have particular influence on the controller's communication. To examine this, we repeat the scaling plot for all the sectors (see Figure 5- 6). We can see that the fitting α does differ from sector to sector, and most of them vary between 0.50 and 0.64. Few sectors, AP, CREIL, INSPG, and VILLA exhibit abnormally, which could be the results of low traffic volume and short service times. To interpret these α is limited due to the fact that there are only fourteen exercises communication data for a sector (few sectors with less).



(a)



(b)

Figure 5- 5 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 ¡À0.04 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.

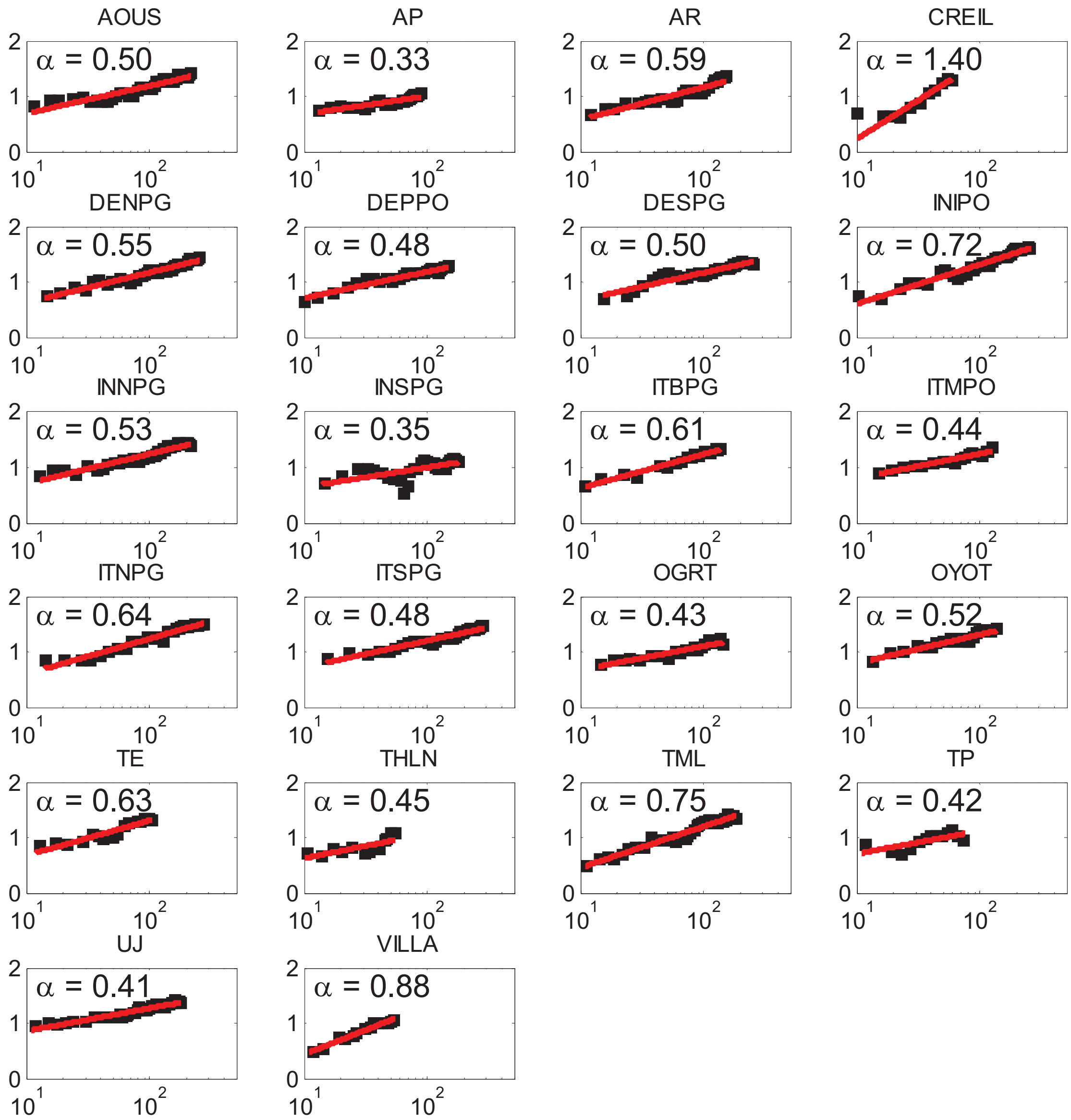


Figure 5- 6 Fluctuation scaling in all sectors. X-axis is the average of communication activities, while y-axis is the logarithmic standard deviations.

5.5 Model

To explain the observed behavior, one might suggest the hypothesis of tossing coins process Eisler et al. (Eisler, Bartos et al. 2008), Onnela and Reed-Tsochas(Onnela and Reed-Tsochas 2010). Consider the following two systems S_1 and S_2 both with n elements. The *ith* element of S_1 consists of i coins. One side of the coin is marked with zero while the other side is one. The activity of *ith* element f_i is defined as the sum of coins' value when tossing them independently. Obviously, $\langle f_i \rangle \propto i$ and the variance $\sigma_i \propto \sqrt{i}$, then it will lead to $\alpha = 1/2$. For S_2, the *ith* element has a single coin that one side is zero while the other side is i. That is equal to toss i fully coupled coins. Then we have $\langle f_i \rangle \propto i$ and $\sigma_i \propto i$, thus $\alpha = 1$. One example of using such process is to model Facebook users' decision behavior on application adoption, in which the coins are biased and tosses are coupled via local and global signals(Onnela and Reed-Tsochas 2010).

From air traffic control perspective, we shall take the following two factors into account. (i) Sector capacity (C_a). Sector capacity is the nominal maximum number of flights that can be in the sector. Air traffic controller will not accept flight coming into his/her sector when the flights under control are going to reach sector capacity. (ii)Grouping (G_m). Histon and Hansman Jr (Histon and Hansman Jr 2008) have identified four types of strategies that controller use to mitigate cognitive complexity, among which grouping is the most common one. According to the characteristics of flights, air traffic controller keeps several flights (G_m) as a group together to control. In such case, the communications with these m flights are coupled. For example, if there are m($m \geq 2$) flights that are predicted to be involved in a conflict, then controller will communicate with these m flights alternately to solve the potential conflict.

While taking sector capacity and grouping behavior into account, we develop the following model to reoccur the observed phenomenon. First, we define a grouping factor g_f as $g_f = G_m / C_a$, which tells the percentage of flights that will be grouped. Then we change the rules of tossing in the "coins system" above as that there will be $g_f \times s$ coins fully coupled when the system size is s. We perform 1000 Monte Carlo simulation runs with g_f from 0.01 to 1.0. Test results are shown in Figure 5- 7. It can be seen from the figure, the exponent lies between 0.58 and 0.65, when $g_f \in [0.08, 0.15]$. α nearly reaches 1 when the grouping factor is over 0.8. Due to the nonlinear fitting, there are few points with α slightly fluctuating around 1. Therefore, a conclusion can be drawn that there are around 10% flights are grouped when air traffic controller manage traffic. Our model can capture the overall grouping behavior of air traffic controller.

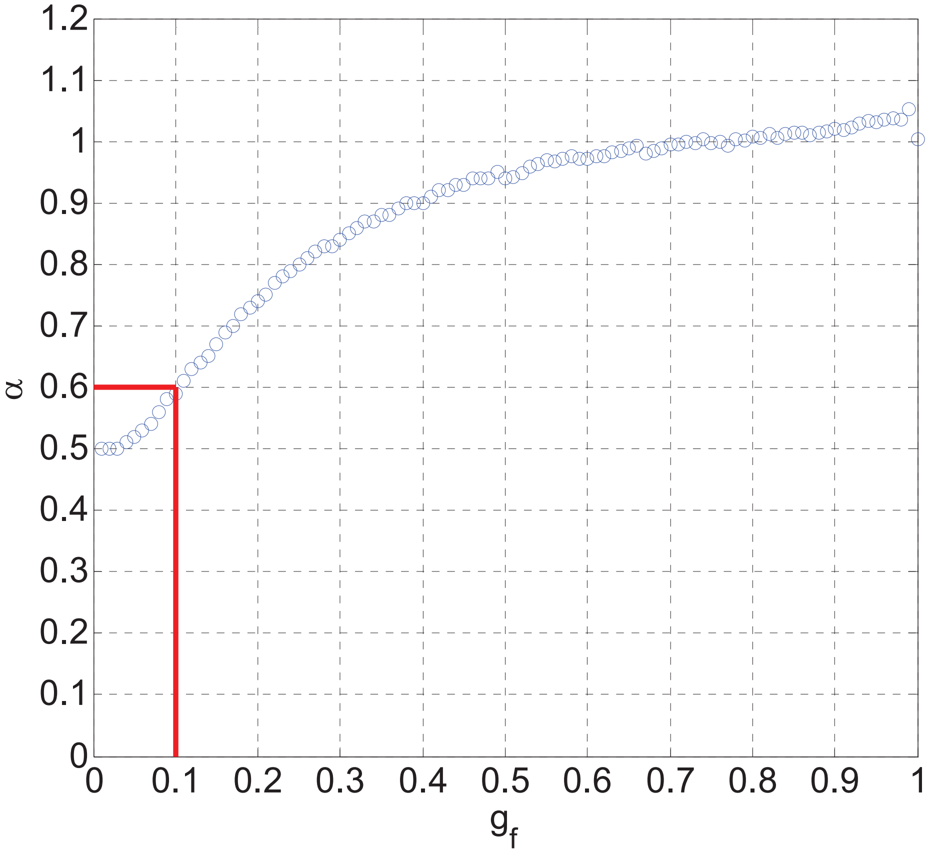


Figure 5- 7 Simulation results on the α as a function of g_f

5.6 Chapter Summary

We have shown that air traffic controller's communication activities can be characterized by the Taylor's power-law. we present a basic model to simulate the observed behavior. Although our model cannot identify the dynamics of grouping behavior of air traffic controller, it is nevertheless useful to characterize the overall controlling pattern. 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. To allow the activities of an element fluctuate within certain range, is very important to system's safety. With the system continues to evolve, such complex phenomena are critical to our understanding of the dynamical aspects of the evolution.

CHAPTER 6 IMPLICATIONS OF AIR TRAFFIC CONTROLLERS' DYNAMICS

The filed of air traffic management has a strong interdisciplinary nature, combining of technological, economic and regulatory aspects. A great number of contributions have emerged from the interactions between scientists trained in different fields, ranging from computer science, through mathematics, to psychology. Researchers and operation experts have contributed to our understanding of air traffic controllers' behaviors for several decades. There are still unanswered questions. Either psychologists or air traffic control specialists only give the descriptive properties of controllers' activities. So far, the main obstacle being the difficulty of capturing controllers' activities is the inadequate knowledge of human adaptive nature.

The recent surge of physicists into the realms of social science and human behaviors has been fuelled largely by the availability of huge empirical data. The combination of the statistical mechanics theory and the observations of human activities have arisen in part to fulfil the particular need of quantitative illustration of human dynamics. Both collective behavior and individual behavior being unmasked have scientific value and potential applications.

In this thesis, we have investigated air traffic controllers' activities from a complex system perspective, providing a physical understanding of controllers' activities. Investigations on the controllers' activities at a microscopic level have revealed critical aspects relating to the operators' performance. Here, we address the promising applications of using controllers' dynamics to the ATM system and other human-driven systems.

6.1 Implications for a Model-based Simulation for the ATM System

To improve the performance of the air transportation systems, both NextGen in the U.S. and SESAR in the Europe have entering the deploying stages. Advanced technologies have being applied into the new system, and new operation concepts, e.g. Trajectory Based Operation (TBO), 4D Trajectory (4DT) management, are proposed and are under test. There is no doubt that the system will be safer and more efficient. The technologies and the methodologies not only improve the system capability but also increase the system complexity. Model the ATM system from a complex system modeling approach may be an efficient way to analyze the whole system and the subsystems. Due to the limitation of common understanding of the mechanisms of ATM system, realistic analytical modeling of system has been unfeasible.

As a matter of fact, model-based simulations in ATM have been reduced to fast-time simulations with approximated representations of controllers' task-loads. The gap between low-degree of realism fast-time simulations and high-fidelity real-time human-in-the-loop simulations has been wide, and validation exercises become extremely costly to R&D since in many cases, real-time simulations have been required instead of model-based simulations for their validation tasks. For SESAR validation exercises, NCD/COE Validation Infrastructure Unit is fostering its effort to develop a suitable model-based simulation tools. Besides the development of a model-based simulator that shall be flexible enough to accommodate the highest degree of realism necessary for SESAR concepts, an exploratory effort is deployed to investigate the possibility to perform ATM model-based analysis from theories of complex systems involving cognitive sciences and system sciences.

Air traffic controllers as the core component of is deeply embedded in the ATM system. It may result in inappropriate conclusions if analyzing controllers' behavior by separating them from the system. We have shown our methods to capture the controllers' behavior in the continuous environments. The similarity of their behaviors can be easily adapted into a model-based simulator acting as the role of controller.

6.2 Implications for the Study of Cognitive Activities

Like many other human activities, air traffic controller' activity is cognitive-guided activity which can be modeled by a full information process, from the receipt of information, information selection and search, through information integration, decision-making, to the information communication and providing feedback (Kallus, Van Damme et al. 1997). Tasks analysis of air traffic controllers' cognitive aspects revealed the main activities that have been illustrated in the **Figure 6- 1**.

Instead of looking at the top-down activity focusing on the core process of air traffic control, we took air traffic controller as a complex system. Air traffic, airspace, physical systems, and regulations all can be seen as the input of this complex system. From the system point of view, the underlying process of controlling traffic is complicated and stochastic. As many workload studies show, the output of controller is the control strategy that will be input into air traffic management system. Research based on psychology, cognitive science, etc., are trying to analyze the detailed dynamics of this human system. The bottom-up approach has encountered difficulties when the environment is changed. It mainly because that the interaction dynamics between the large elements is unknown. In contrast, our up-down approach starts from the observation of the output of controller, then followed with the model to simulate the dynamics process, so that it can be adjusted to the most of the situation.

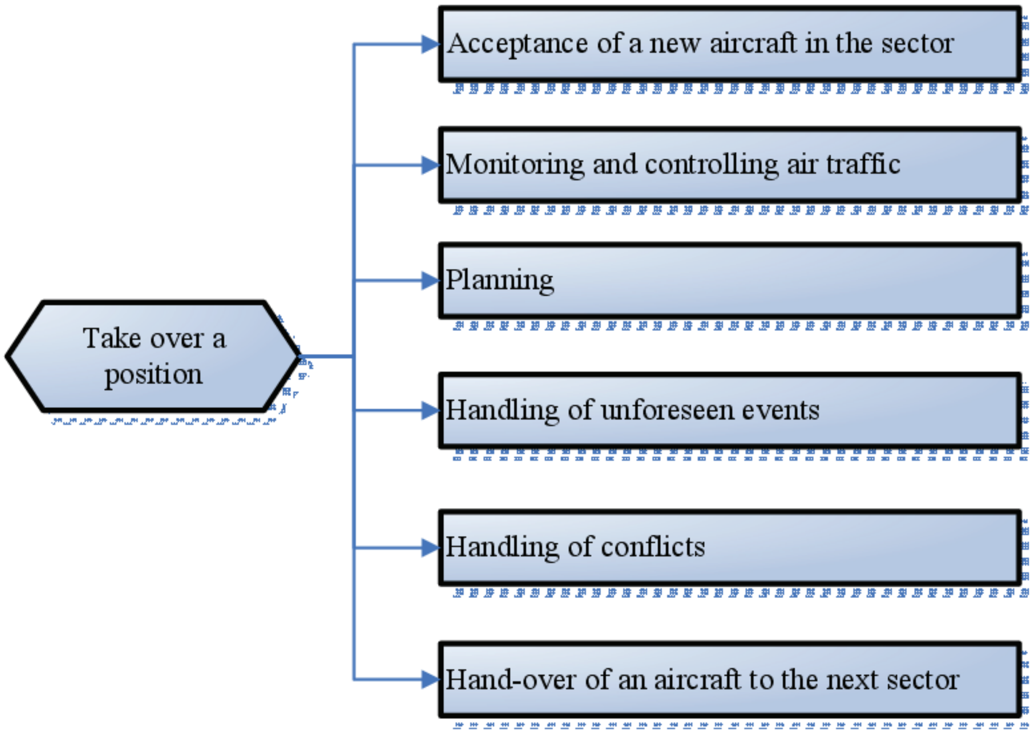


Figure 6- 1 Cognitive tasks of air traffic controller

6.2.1 Implications for the Resource Allocation

One of the basic messages of the temporal characteristics of controllers' communication is that the internal dynamics of air traffic controllers may be the followed the same rules, supporting the hypothesis that controllers are acting proactively according to the preformatted plans, rules, and mental pictures of the traffic situation (Kallus, Van Damme et al. 1997). Models of controllers' behavior are crucial for better resource allocation. The resource here refers to both the airspace and controllers' attentions. One of the key gradients of the future ATM system is the 4D trajectory planning and management. There are ongoing efforts in the modeling and predicting the uncertainty and complexity of the 4D trajectories in the sector from mathematics perspective.

Then the question will be raised about the role of air traffic controller in the new system. How the air traffic controller adapts to the new control environment, such as under the trajectory management with data-communication? Obviously, air traffic controller will change the communication behavior from radio-communication to data-communication. Under the 4DT or TBO, the strategies for conflict detection and resolution will also different from current radar surveillance control. We should note that the decision dynamics, deep within the cognitive activities, will change slowly.

Considering the human correspondence and email communication for example, although the technology facilitating our communication have been enhanced and the communication dynamics patterns are different (the exponent α for correspondence is 1.5, while for the email is 1 (see(Barabasi 2005)), the underlying rule governs actives seems universal. So far there is a lack of evidence from a task-specific activity with urgency and high pressure. Our work not only provides a first attempt to investigate the controller's activities, but also complement to the human dynamics study.

6.2.2 Implications for the Systems Design

When designing a system, one must balance the system predictability and flexibility. Flexibility is the ability of the system to respond to uncertainty in a manner to sustain or increase its value delivery. The ATM system must have the ability to resistant to the change of the system, such as unforeseen weather or events, ensuring the air transportation safe. In the ATM system, there are too many sources of the uncertainty. Automation systems have significantly improved the performance of the ATM system. Under normal conditions, these tools work well. However, most of them are unable to deal with the unexpected situation, such as emergence events. Controllers have to be involved during such situations, either modifying the automation systems' input or controlling the traffic directly.

With the growing technological possibility, automations and decision support tools are release human parts of the system from the role of decision maker and operator to the role of monitor. The long time monitoring may cause controller loose the traffic picture. There is one big concern that in case of system failure, whether or not controller can quickly take over.

The fluctuation scaling observed through controllers' activities reflects the flexibility of the system to certain extent. When there are large fluctuations either in traffic or in the airspace, controllers' or supervisors should be attention. Traffic management initiatives have to be implemented if necessary.

6.3 Implications for other Human-Driven Complex Systems

Despite the potential applications of this study in the air traffic management domain, there is also a fundamental angle from which to address these questions.

CHAPTER 7 CONCLUSIONS AND PERSPECTIVES

In this final chapter, we summarize the work presented in this dissertation and outline some future directions.

7.1 Summary

Air traffic controller is a one of the components of the ATM systems. The behaviors of controllers are directly related to the system performance and safety. Thus, the understanding of air traffic controllers' activities is critical to the analysis of ATM system. Duo to the complex interaction and uncertainty in the ATM system, air traffic controllers' activities are difficult to be measured and predicted through the classical methods. In this dissertation, we have presented the investigations on the controllers' communication behaviors from the complex system and human dynamics approach. More precisely, we took air traffic controller as a complex system, and have examined their temporal, spatial, and fluctuation behaviors.

To examine the effects of air traffic factors on controllers' communication activities, we have calculated the dynamics density and the complexity based on the dynamical system modeling from the empirical traffic data. The correlations results suggest that air traffic complexity has little impact on the controllers' communication.

To test the hypothesis that whether controllers' activities exhibit the same heavy tailed patterns as other human activities, we have investigated the inter-communication behaviors of controllers. We found that controllers' communications do have heavy tailed features. The overall inter-communication events are fitted into Inversed Gaussian distributions, can well interpreted by the psychological model, the diffusion model. When we focus on the inter-communication activities, i.e. restrict the communication transmissions regarding on the change of flight motions, the collective behaviors are well described by a power law form, whereas the individuals show much more heterogeneous. Note that the inter-activities times of controllers decay much faster than the interval times in other human activities, suggesting that the stress and time pressure push controllers' activities one follows one quickly.

To capture the traffic dynamics evolution in the controllers' cognitive activities, we have analyzed the spatial behavior of their communication activities. We proposed a temporal network approach to trace and quantify controllers' communication trajectories. Time aggregated network analysis revealed that controllers randomly select flights to talk, whereas time dependent network analysis shows the dynamics of grouping behaviors. By leveraging the motifs detections algorithms, we have identified the loops and chains are the most popular communication patterns.

To explore the adaptive property of controllers' activities, we analyzed the fluctuation scaling behavior of controllers' communication. Throughout the datasets, we observed an ensemble fluctuation scaling phenomena, leading to uncovering of grouping behavior. Based on the empirical results, we presented a model to explain the origin of the fluctuation scaling. It was found that 10% of flights were being grouped for communication which can result in a fluctuation decay exponent of 0.60.

This thesis contributes to both the field of air traffic management and the filed of human dynamics. Our work have been presented at international conferences in the domains of air traffic management and publications in the journals, including

Published articles:

- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Vu Duong, "Empirical Analysis of Air Traffic Controller Dynamics", Transpiration Research Part C, doi:10.1016/j.trc.2012.04.006;
- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Patrick Bellot, and Vu Duong, "Spatial, Temporal, and Grouping Behaviors in Controller Communication Activities", Ninth USA/Europe ATM R&D Seminar, Berlin, Germany, June 14 - 17, 2011;
- **WANG Yanjun**, Minghua Hu, Vu Duong, "Fluctuation Scaling in the Air Traffic Controller Communication Activities", 2nd ENRI International Workshop in ATM/CNS, Tokyo, Japan, Nov 10-12, 2010;
- **WANG Yanjun**, Hu Minghua, "Analysis of Air Traffic Controller Dynamics based on Data Driven Approach (in Chinese)", First National Conference in CNS/ATM, 2010;
- **WANG Yanjun**, Frizo Vormer, Minghua Hu, Vu Duong, "Empirical Analysis of Air Traffic Controller Dynamics", 4th International Conference on Research in Air Transportation, Budapest, Hungary, June 1-4, 2010;

Paper being prepared or submitted:

- **WANG Yanjun**, Vlad Popsecu, Chenping Zhu, Minghua Hu, Patrick Bellot, Vu Duong, "Fluctuation Scaling in the Air Traffic Controller Communication Activities", will be submitted to the Proceedings of the National Academy of Sciences (PNAS), 2012;
- **WANG Yanjun**, Minghua Hu, Patrick, Bellot, and Vu Duong, "A Temporal Network Approach for the Study of Air Traffic Controller's Activities", prepared for PLoS ONE;
- **WANG Yanjun**, Minghua Hu, Patrick Bellot,Vu Duong, "Rapid Decay in the Heavy Tailed Human Dynamics", will be submitted to Physica A: Statistical Mechanics and its Applications;

7.2 Perspectives

Although the presented work was based on the controllers' voice communication activities under radar surveillance context, this work however opens a variety of perspectives. In what follows, we present two distinct directions.

(i) The understanding of human activity:

Psychology analyzes human mind via the study of external behaviour aiming at understanding individuals and groups by both establishing general principles and research specific causes. Psychologists explore the role of mental functions, physiological and neurobiological processes underlying the cognitive functions and behaviours. With the growing technologies, there is a trend that scientists from physics, mathematics, computer science, and other disciplines as well are rushing into the realms of understanding human activity. The emerged human dynamics is an example of study human activity in the physicists' interest.

Out of its important to the ATM system, the study of controllers' behaviour also stems possibility of combining the cognitive science and physics to realize a computational cognitive model. In the system that safety is at the first priority, such as ATM system and nuclear power plant, the operators' capability is most important to the system's performance. The determination of the limitation of human cognitive capability is therefore of both scientific value and applied potential.

(ii) The modelling of complex system

Complex system has been studies through its structure and the dynamics occurring on the structure. While network science provides an efficient perspective for the description of the structure, network dynamics has however reached the bottleneck. Furthermore, it will be more difficult when human is involved in the system. This thesis only focuses on the controllers' dynamics at the intermediate level, how to model the ATM system at a macroscopic level taking the controllers as the components is to be studied. Especially in the 4D trajectory management, the model of the system help to understand and predict the critical aspects of the system, such as uncertainty prorogation, system flexibility. In fact, the ATM can be represented as a bipartite complex system with controllers as one part and aircraft flow as the other part. Analysis of the bipartite network could lead us to a new view of the whole system.

REFERENCES

(ICAO), I. C. A. O. (2007). Manual of radiotelephony, International Civil Aviation Organization (ICAO).

@misc{, title = {Doc 9750 Global Air Navigation Plan (3rd Edition)}, et al.

Academies, N. R. C. o. t. N. (2010). Air Traffic Controller Staffing in the En Route Domain: A Review of the Federal Aviation Administration's Task Load Model. Washington, D.C., Transportation Research Board.

Ahlstrom, U. and F. J. Friedman-Berg (2005). Subjective workload ratings and eye movement activity measures, Federal Aviation Administration.

Ahmed, A. and E. P. Xing (2009). "Recovering time-varying networks of dependencies in social and biological studies." Proceedings of the National Academy of Sciences **106**(29): 11878-11883.

Arad, B. A. (1964). "The controller load and sector design." Journal of Air Traffic Control: 12-31.

Athenes, S., P. Averty, et al. (2002). ATC Complexity and Controller Workload: Trying to Bridge the Gap. Proceedings of the International Conference on HCI in Aeronautics.

Averty, P., S. Athenes, et al. (2002). Evaluating a new index of mental workload in real ATC situation using psychophysiological measures. Digital Avionics Systems Conference, 2002. Proceedings. The 21st.

Baart, D. (2001). An Evaluation of Dynamic Density Metrics Using RAMS.

Barabasi, A.-L. (2005). "The origin of bursts and heavy tails in human dynamics." Nature **435**(7039): 207-211.

Bedny, G. and D. Meister (1997). The Russian Theory of Activity: Current Applications to Design and Learning. Mahwah, New Jersey, Lawrence Erlbaum Associates.

Bjørnstad, O. N. and B. T. Grenfell (2001). "Noisy Clockwork: Time Series Analysis of Population Fluctuations in Animals." Science **293**(5530): 638-643.

Bloem, M., C. Brinton, et al. (2009). A Robust Approach for Predicting Dynamic Density. 9th AIAA ATIO Conference, Hilton Head, USA.

Bolgorian, M. and R. Raei (2011). "A multifractal detrended fluctuation analysis of trading behavior of individual and institutional traders in Tehran stock market." Physica A: Statistical Mechanics and its Applications **In Press, Corrected Proof**.

Brockmann, D., L. Hufnagel, et al. (2006). "The scaling laws of human travel." Nature

439(7075): 462-465.
Bruce, D. S., N. E. Freeberg, et al. (1993). An explanatory model for influences of air traffic control task parameters on controller work pressure. Proceedings of the Human Factors and Ergonomics Society 37th Annual Meeting, Human Factors Society.
Busing, H. G. and R. J. Hansman (2005). Air Traffic Control Operating Modes and the Management of Complexity. Cambridge, ICAT.
Busing, H. G. and R. J. Hansman (2006). Air Traffic Control Operating Modes and the Management of Complexity.
Cai, S.-M., P.-L. Zhou, et al. (2007). "Diffusion entropy analysis on the stride interval fluctuation of human gait." Physica A: Statistical Mechanics and its Applications **375**(2): 687-692.
Campanharo, A. S. L. O., M. I. Sirer, et al. (2011). "Duality between Time Series and Networks." PLoS ONE **6**(8): e23378.
Cardosi, K. (1993). "Time required for transmission of time-critical air traffic control messages in an en route environment." International Journal of Aviation Psychology **7**: 171 - 182.
Cardosi, K. M. (1993). "Time Required for Transmission of Time-Critical Air Traffic Control Messages in an En Route Environment." The International Journal of Aviation Psychology **3**(4): 303-313.
Chatterji, G. and B. Sridhar (2001). Measures for Air Traffic Controller Workload Prediction. 1st AIAA Aircraft, Technology Integration, and Operations Forum. Los Angeles, California.
Chatterji, G. B. and B. Sridhar (2001). Measures for air traffic controller workload prediction. Proceedings of the First AIAA Aircraft Technology, Integration, and Operations Forum, Los Angeles, CA.
Chechik, G., E. Oh, et al. (2008). "Activity motifs reveal principles of timing in transcriptional control of the yeast metabolic network." Nat Biotech **26**(11): 1251-1259.
Clarke, J. P., N. Durand, et al. (2011). Determining the Value of Information for Minimizing Controller Taskload: A Graph-Based Approach. 9th USA/Europe Air Traffic Management Research and Development Seminar. S. Saunders-Hodge and V. Duong. Berlin, Germany.
Clauset, A., C. R. Shalizi, et al. (2009). "Power-law distributions in empirical data." SIAM Review **51**(4): 661 - 703.
Coffey, N., A. J. Harrison, et al. (2011). "Common functional principal components analysis: A new approach to analyzing human movement data." Human Movement Science **In Press, Corrected Proof**.
Colizza, V., A. Barrat, et al. (2007). "Predictability and epidemic pathways in global

outbreaks of infectious diseases: the SARS case study." BMC Medicine **5**(1): 34.

Collet, C., P. Averty, et al. (2009). "Autonomic nervous system and subjective ratings of strain in air-traffic control." Applied Ergonomics **40**(1): 23-32.

Corker, K., B. F. Gore, et al. (2000). 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. The 3rd USA/Europe Air Traffic Management R&D Seminar, Napoli, Italy.

Corker, K. M., B. F. Gore, et al. (2000). Free flight and the context of control: Experiments and modeling to determine the impact of distributed air-ground air traffic management on safety and procedures. 3rd USA/Europe Air Traffic Management R&D Seminar. Napoli, Italy.

Couluris, G. J. and D. K. Schmidt (1973). Air traffic control jurisdictions of responsibility and airspace structure. the 1973 Institute of Electrical and Electronics Engineers (IEEE) Conference on Decision and Control held December. San Diego, CA.

Cox, M. (1994). Task analysis of selected operating positions within UK Air Traffic Control.

Cummings, M. L. and C. Tsonis (2006). "Partitioning Complexity in Air Traffic Management Tasks." International Journal of Aviation Psychology **16**(3): 277-295.

Dasari, D., C. Crowe, et al. (2010). "EEG Pattern Analysis for Physiological Indicators of Mental Fatigue in Simulated Air Traffic Control Tasks." Proceedings of the Human Factors and Ergonomics Society Annual Meeting **54**(3): 205-209.

Davis, C. G., J. W. Danaher, et al. (1963). The influence of selected sector characteristics upon ARTCC controller activities. Arlington, VA.

de Menezes, M. A. and A. L. Barabási (2004). "Fluctuations in Network Dynamics." Physical Review Letters **92**(2): 028701.

Delahaye, D., P. Paimblanc, et al. (2002). A New Air Traffic Complexity Metric Based on Dynamical System Modelization. 21st Digital Avionics Systems Conference.

Delahaye, D. and S. Puechmorel (2010). Air traffic complexity based on dynamical systems. 49th IEEE Conference on Decision and Control (CDC), Atlanta, GA.

Delahaye, D., S. Puechmorel, et al. (2004). "Air traffic complexity map based on non linear dynamical systems." Air Traffic Control Quarterly **12**(4).

Di Stasi, L. L., M. Marchitto, et al. (2010). "Approximation of on-line mental workload index in ATC simulated multitasks." Journal of Air Transport Management **16**(6): 330-333.

Djokic, J., B. Lorenz, et al. (2010). "Air traffic control complexity as workload driver." Transportation Research Part C: Emerging Technologies **18**(6): 930-936.

DONNER, R. V., J. F. Donges, et al. (2010). "Recurrencebased time series analysis by means of complex network methods." International Journal of Bifurcation and Chaos (IJBC) **21**(4): 1019-1046.

Duong, V. (2009). Project Herbert Formal Technical Review. Project Herbert. Bretigny-sur-orge, EUROCONTROL Experimental Center.

Eisler, Z., I. Bartos, et al. (2008). "Fluctuation scaling in complex systems: Taylor's law and beyond." Advances in Physics **57**(1): 89-142.

Eisler, Z. and J. Kertész (2007). "Liquidity and the multiscaling properties of the volume traded on the stock market." EPL (Europhysics Letters) **77**(2): 28001.

Endsley, M. R. and M. D. Rodgers (1994). Situation awareness information requirements for en route air traffic control. Washington, D.C., FAA.

Erdös, P. and A. Rényi (1959). "On random graphs." Publicationes Mathematicae **6**: 8.

Fronczak, A. and P. Fronczak (2010). "Origins of Taylor's power law for fluctuation scaling in complex systems." Physical Review E **81**(6): 066112.

Gautreau, A., A. Barrat, et al. (2009). "Microdynamics in stationary complex networks." Proceedings of the National Academy of Sciences **106**(22): 8847-8852.

Gawron, V., J. Ball, et al. (1989). Intercorrelations among physiological and subjective measures of workload.

Gonzalez, M. C., C. A. Hidalgo, et al. (2008). "Understanding individual human mobility patterns." Nature **453**(7196): 779-782.

Gopikrishnan, P., V. Plerou, et al. (2000). "Statistical properties of share volume traded in financial markets." Physical Review E **62**(4): R4493-R4496.

Grenfell, B. T., K. Wilson, et al. (1998). "Noise and determinism in synchronized sheep dynamics." Nature **394**(6694): 674-677.

Guckenheimer, J. and J. M. Ottino (2009). Foundations for complex systems research in the physical sciences and engineering. Report from an NSF Workshop in September 2008.

Han, X.-P., Q. Hao, et al. (2011). "Origin of the scaling law in human mobility: Hierarchy of traffic systems." Physical Review E **83**(3): 036117.

Haraguchi, Y., Y. Shimada, et al. (2009). Transformation from Complex Networks to Time Series Using Classical Multidimensional Scaling. Artificial Neural Networks – ICANN 2009. C. Alippi, M. Polycarpou, C. Panayiotou and G. Ellinas, Springer Berlin / Heidelberg. **5769:** 325-334.

Harder, U. and M. Paczuski (2006). "Correlated dynamics in human printing behavior." Physica A: Statistical Mechanics and its Applications **361**(1): 329-336.

Hausdorff, J. M., P. L. Purdon, et al. (1996). "Fractal dynamics of human gait: stability of long-range correlations in stride interval fluctuations." Journal of Applied Physiology **80**(5): 1448-1457.

Heathcote, A. (2004). "Fitting Wald and ex-Wald distributions to response time data: An example using functions for the S-PLUS package." Behavior Research Methods, Instruments, & Computers **36**: 678-694.

Hering, H. (2001). Technical analysis of ATC controller to pilot voice communication with regard to automatic speech recognition system. EEC Note. Bretigny, EUROCONTROL Experimental Center.

Hilburn, B. (2004). Cognitive Complexity in Air Traffic Control –A Literature Review. Brétigny-sur-Orge, France, Eurocontrol.

Histon, J. (2002). The Impact of Structure on Cognitive Complexity in Air Traffic Control. Cambridge, ICAT.

Histon, J. and R. J. Hansman (2011). "Air Traffic Controller Operating Modes and Cognitive Complexity Regulation." Proceedings of the Human Factors and Ergonomics Society Annual Meeting **55**(1): 345-349.

Histon, J. M. and R. J. Hansman Jr (2008). Mitigating complexity in air traffic control: the role of structure-based abstractions. Cambridge, ICAT.

Histon, J. M., R. J. Hansman, et al. (2002). Structural Considerations and Cognitive Complexity in Air Traffic Control. 21st Digital Avionics Systems Conference, Los Angeles, CA.

Holme, P. and J. Saramäki (2011). "Temporal Networks." arXiv.

Hunter, J. S., D. E. Blumenfeld, et al. (1974). Modeling Air Traffic Performance Measures. Volume II. Initial Data Analyses and Simulations, Princeton Univ N J Dept of Civil and Geological Engineering**:** 485.

Hunter, J. S., D. E. Blumenfeld, et al. (1998). Modeling Air Traffic Performance Measures. Volume I. Message Element Analyses and Dictionaries, Princeton Univ N J Dept of Civil and Geological Engineering.

Hunter, J. S. and D.-A. Hsu (1977). Applications of the simulation model for air traffic control communications. Atlantic City, New Jersey, Federal Aviation Administration.

Hurst, M. W. and R. M. Rose (1978). "Objective job difficulty, behavioral response, and sector characteristics in air route traffic control centers." Ergonomics **21**(9): 697-708.

ICAO (2005). Doc 9854 Global Air Traffic Management Operational Concept (First Edition). I. C. A. O. (ICAO).

Jepma, M., E.-J. Wagenmakers, et al. (2012). "Temporal expectation and information processing: A model-based analysis." Cognition **122**(3): 426-441.

Kallus, K. W., D. Van Damme, et al. (1997). Model of the cognitive aspects of air traffic control, EUROCONTROL.

Kallus, K. W., D. Van Damme, et al. (1999). Integrated job and task analysis of air traffic controllers: Phase 2. Task analysis of en-route controllers. European Air Traffic Management Programme. Brussels, Belgium, EUROCONTROL.

Kantelhardt, J. W., S. A. Zschiegner, et al. (2002). "Multifractal detrended fluctuation analysis of nonstationary time series." Physica A: Statistical Mechanics and its Applications **316**(1-4): 87-114.

Kirwan, B., R. Scaife, et al. (2001). "Investigating complexity factors in UK air traffic management." Human Factors and Aerospace Safety **1**: 125-144.

Klein, A., M. D. Rogers, et al. (2008). Simplied Dynamic Density: a Metric for Dynamic Airspace Conguration and NEXTGEN Analysis. AIAA/IEEE Digital Avionics Systems Conference. St. Paul, MN.

Kopardekar, P. and S. Magyarits (2002). Dynamic Density: Measuring and Predicting Sector Complexity. AIAA/IEEE Digital Avionics Systems Conference. Irvine, CA.

Kopardekar, P. and S. Magyarits (2003). Measurement and prediction of dynamic density. 5th USA/Europe ATM R&D Seminar. Budapest, Hungary.

Kopardekar, P., J. Rhodes, et al. (2008). Relationship of Maximum Manageable Air Traffic Control Complexity and Sector Capacity. 26th Congress of International Council of the Aeronautical Sciences, Anchorage, Alaska.

Koros, A., P. S. Rocco, et al. (2003). Complexity in Air Traffic Control Towers: A Field Study. Part 1. Complexity Factors. Atlantic City International Airport, NJ 08405, William J. Hughes Technical Center.

Kupfer, M., T. Callantine, et al. (2011). Controller Support Tools for Schedule-Based Terminal-Area Operations. 9th USA/Europe Air Traffic Management Research and Development Seminar. S. Saunders-Hodge and V. Duong. Berlin, Germany.

Lacasa, L., B. Luque, et al. (2008). "From time series to complex networks: The visibility graph." Proceedings of the National Academy of Sciences **105**(13): 4972-4975.

Lacher, J., V. Battise, et al. (2011). Issues for Near-Term Implementation of Trajectory Based Operations 9th USA/Europe Air Traffic Management Research and Development Seminar. S. Saunders-Hodge and V. Duong. Berlin, Germany.

Lamb, P. F., R. M. Bartlett, et al. (2011). "Artificial neural networks for analyzing inter-limb coordination: The golf chip shot." Human Movement Science **In Press, Corrected Proof**.

Lancichinetti, A., F. Radicchi, et al. (2011). "Finding Statistically Significant Communities in Networks." PLoS ONE **6**(4): e18961.

Laudeman, I. V., S. Shelden, et al. (1998). Dynamic Density: An Air Traffic Management Metric, National Aeronautics and Space Administration, Ames Research Center;.

Lee, K., E. Feron, et al. (2007). Air Traffic Complexity: An Input-Output Approach.

Lee, K., E. Feron, et al. (2009). "Describing Airspace Complexity: Airspace Response to Disturbances." Journal of Guidance, Control and Dynamics **132**(1): 210-222.

Li, L. and R. J. Hansman (2009). Experimental Studies of Cognitively Based Air Traffic Control Complexity Metrics for Future Operational Concepts.

Liben-Nowell, D. and J. Kleinberg (2008). "Tracing information flow on a global scale using Internet chain-letter data." Proceedings of the National Academy of Sciences **105**(12): 4633-4638.

Loft, S., D. Finnerty, et al. (2011). "Using Spatial Context to Support Prospective Memory in Simulated Air Traffic Control." Human Factors: The Journal of the Human Factors and Ergonomics Society **53**(6): 662-671.

Loft, S., P. Sanderson, et al. (2007). "Modeling and predicting mental workload in en route air traffic control: Critical review and broader implications." Human Factors **49**(3): 376-399.

Madl, T., B. J. Baars, et al. (2011). "The Timing of the Cognitive Cycle." PLoS ONE **6**(4): e14803.

Malmgren, R. D., J. M. Hofman, et al. (2009). Characterizing individual communication patterns. Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining. Paris, France, ACM**:** 607-616.

Malmgren, R. D., D. B. Stouffer, et al. (2009). "On Universality in Human Correspondence Activity." Science **325**(5948): 1696-1700.

Malmgren, R. D., D. B. Stouffer, et al. (2008). "A Poissonian explanation for heavy tails in e-mail communication." Proceedings of the National Academy of Sciences **105**(47): 18153-18158.

Manning, C., C. Fox, et al. (2003). Relationships between measures of air traffic controller voice communications, taskload, and traffic compleixty. The 5th USA/Europe ATM R&D Seminar. Budapest, Hungary.

Manning, C., S. H. Mills, et al. (2002). Using Air Traffic Control Taskload Measures and Communication Events to Predict Subjective Workload. Oklahoma City, Federal Aviation Administration**:** 20.

Manning, C. and E. Pfleiderer (2006). Relationship of Sector Activity and Sector Complexity to Air Traffic Controller Taskload**:** 14.

Martin, C., J. Cegarra, et al. (2011). Analysis of Mental Workload during En-route Air Traffic Control Task Execution Based on Eye-Tracking Technique

Engineering Psychology and Cognitive Ergonomics. D. Harris, Springer Berlin / Heidelberg. **6781:** 592-597.

Marwan, N., J. F. Donges, et al. (2009). "Complex network approach for recurrence analysis of time series." Physics Letters A **373**(46): 4246-4254.

Masalonis, A. J., M. B. Callaham, et al. (2003). Dynamic Density and Complexity Metrics for Realtime Traffic Flow Management. 5 thUSA/Europe ATM R&D Seminar, Budapest, Hungary.

Matzke, D. and E.-J. Wagenmakers (2009). "Psychological interpretation of the ex-Gaussian and shifted Wald parameters: A diffusion model analysis." Psychonomic Bulletin & Review **16**(5): 798-817.

Meignier, S. and T. Merlin (2010). LIUM Spkdiarization: An open source toolkit for diarization. CMU SPUD Workshop. Dallas, Texas, USA.
Mitzenmacher, M. (2004). "A brief history of generative models for power law and lognormal distributions." Internet Mathematics **1**(2): 226 - 251.
Mogford, R., J. A. Guttman, et al. (1995). The complexity construct in air traffic control: A review and synthesis of the literature. NJ, FAA.
Monticone, L. C., R. E. Snow, et al. (2006). Air/Ground Communications Traffic Modeling Capability for the Mid-Level Model (MLM). McLean, Virginia, MITRE Center for Advanced Aviation System Development.
Monticone, L. C., R. E. Snow, et al. (2006). Modeling of air/ground air traffic control communications for fast-time simulation. Proceedings of the 17th IASTED international conference on Modelling and simulation. Montreal, Canada, ACTA Press**:** 407-415.
Morrow, D. and M. Rodvold (1998). Communication issues in air traffic control. Human Factors in Air Traffic Control. M. W. Smolensky and E. S. Stein. San Diego, CA, Academic Press**:** 421-456.
Neal, A., M. Griffin, et al. (1998). Human factors issues in the transition to a CNS/ATM environment: Final report. Brisbane, Australia, University of Queensland.
Newman, M. E. J. (2012). "Communities, modules and large-scale structure in networks." Nat Phys **8**(1): 25-31.
Nolan, M. S. (2010). Fundamentals of Air Traffic Control, Cengage Learning.
Oliveira, J. G. and A.-L. Barabasi (2005). "Human dynamics: Darwin and Einstein correspondence patterns." Nature **437**(7063): 1251-1251.
Onnela, J.-P. and F. Reed-Tsochas (2010). "Spontaneous emergence of social influence in online systems." Proceedings of the National Academy of Sciences.
Pan, R. K. and J. Saramäki (2011). "Path lengths, correlations, and centrality in temporal networks." Physical Review E **84**(1): 016105.
Peng, C. K., S. V. Buldyrev, et al. (1994). "Mosaic organization of DNA nucleotides." Physical Review E **49**(2): 1685-1689.
Popescu, V., H. Augris, et al. (2010). A stochastic model for air traffic control radio channel utilization. 4th International conference on research in air transportation, Budapest, Hungary.
Porterfield, D. H. (1997). "Evaluating Controller Communication Time as a Measure of Workload." The International Journal of Aviation Psychology **7**(2): 12.
Prandini, M., L. Piroddi, et al. (2011). "Toward air traffic complexity assessment in new generation air traffic management systems." IEEE Trans. on Intelligent Transportation Systems **12**(3): 809-818.
Prandini, M., V. Putta, et al. (2010). "A probabilistic measure of air traffic complexity in three-dimensional airspace." International Journal of Adaptive Control and Signal

Processing, special issue on Air Traffic Management: Challenges and opportunities for advanced control **24**(10): 813-829.

Rantanen, E. M., J. S. McCarley, et al. (2004). "Time Delays in Air Traffic Control Communication Loop: Effect on Controller Performance and Workload." International Journal of Aviation Psychology **14**(4): 369-394.

Ratcliff, R. (2001). Diffusion and random walk processes. International encyclopedia of the social and behavioral sciences. Oxford, England, Elsevier. **6:** 3668-3673.

Ratcliff, R. and G. McKoon (2008). "The diffusion decision model: Theory and data for two-choice decision tasks." Neural Computation **20**: 873-922.

Ratcliff, R. and B. B. Murdock (1976). "Retrieval processes in recognition memory." Psychological Review **83**: 190-214.

Ratcliff, R. and B. B. Murdock (1978). "A theory of memory retrieval." Psychological Review **85**: 59-108.

Ratcliff, R. and J. N. Rouder (1998). " Modeling response times for two-choice decisions." Psychological Science **9**: 347-356.

Ratcliff, R. and J. N. Rouder (2000). "A diffusion model account of masking in two-choice letter identification." Journal of Experimental Psychology: Human Perception and Performance **26**: 127-140.

Ratcliff, R. and H. P. A. Van Dongen (2011). "Diffusion model for one-choice reaction-time tasks and the cognitive effects of sleep deprivation." Proceedings of the National Academy of Sciences **108**(27): 11285-11290.

Ratcliff, R., T. Van Zandt, et al. (1999). "Connectionist and diffusion models of reaction time." Psychological Review **106**(261-300).

Robertson, A., M. Grossberg, et al. (1979). Validation of Air Traffic Controller Workload Models. CAMBRIDGE MA, TRANSPORTATION SYSTEMS CENTER 127.

Rocha, L. E. C., F. Liljeros, et al. (2010). "Information dynamics shape the sexual networks of Internet-mediated prostitution." Proceedings of the National Academy of Sciences.

Rodgers, M. D. and G. K. Drechsler (1993). Conversion of the CTA, Inc., En Route Operations Concepts Database into a Formal Sentence Outline Job Task Taxonomy, FAA.

Sæther, B.-E., J. Tufto, et al. (2000). "Population Dynamical Consequences of Climate Change for a Small Temperate Songbird." Science **287**(5454): 854-856.

Sadegh Movahed, M. and E. Hermanis (2008). "Fractal analysis of river flow fluctuations." Physica A: Statistical Mechanics and its Applications **387**(4): 915-932.

Sato, A.-H., M. Nishimura, et al. (2010). "Fluctuation scaling of quotation activities in the foreign exchange market." Physica A: Statistical Mechanics and its

Applications **389**(14): 2793-2804.
Schaefer, D., C. Meckiff, et al. (2001). Air traffic complexity as a key concept for Multi-Sector Planning, Daytona Beach, FL, Institute of Electrical and Electronics Engineers Inc.
Schmidt, D. K. (1976). "ON MODELING ATC WORK LOAD AND SECTOR CAPACITY." Journal of Aircraft **13**(7): 531-537.
Schmidt, D. K. (1978). "A queuing analysis of the air traffic controller's work load." IEEE Transactions on Systems, Man and Cybernetics **8**: 492-498.
Schwarz, W. (2001). "The ex-Wald distribution as a descriptive model of response times." Behavior Research Methods, Instruments, & Computers **33**: 457-469.
Shafiq, M. and A. Liu (2011). A Random Walk Approach to Modeling the Dynamics of the Blogosphere. NETWORKING 2011. J. Domingo-Pascual, P. Manzoni, S. Palazzo, A. Pont and C. Scoglio, Springer Berlin / Heidelberg. **6640:** 294-306.
Song, C., T. Koren, et al. (2010). "Modelling the scaling properties of human mobility." Nat Phys **6**(10): 818-823.
Song, C., Z. Qu, et al. (2010). "Limits of Predictability in Human Mobility." Science **327**(5968): 1018-1021.
Sridhar, B., K. S. Sheth, et al. (1998). Airspace Complexity and its Application in Air Traffic Management. 2 ndUSA/Europe Air Traffic Management R&D Seminar, Orlando.
Stein, E. S. (1985). Air traffic controller workload: An examination of workload probe. Atlantic City, NJ, Federal Aviation Administration Technical Center.
Taylor, L. R. (1961). "Aggregation, variance and mean." Nature **189**(476): 4.
Taylor, L. R. and R. A. J. Taylor (1977). "Aggregation, migration and population mechanics." Nature **265**: 415-421.
Taylor, L. R., R. A. J. Taylor, et al. (1983). "Behavioural dynamics." Nature **303**: 801-804.
Vaquez, A., J. G. Oliveira, et al. (2006). "Modeling bursts and heavy tails in human dynamics." Physical Review E **73**(3): 036127.
Vassilis, K. (2009). "Temporal graphs." Physica A: Statistical Mechanics and its Applications **388**(6): 1007-1023.
Vespignani, A. (2009). "Predicting the Behavior of Techno-Social Systems." Science **325**(5939): 425-428.
Wu, Y., C. Zhou, et al. (2010). "Evidence for a bimodal distribution in human communication." Proceedings of the National Academy of Sciences **107**(44): 18803-18808.
Xu, X., J. Zhang, et al. (2008). "Superfamily phenomena and motifs of networks induced from time series." Proceedings of the National Academy of Sciences **105**(50): 19601-19605.

Zhang, J. and M. Small (2006). "Complex Network from Pseudoperiodic Time Series: Topology versus Dynamics." Physical Review Letters **96**(23): 238701.

Zhao, Q., Y. Tian, et al. (2010). Communication motifs: a tool to characterize social communications. Proceedings of the 19th ACM international conference on Information and knowledge management. Toronto, ON, Canada, ACM**:** 1645-1648.

Zhou, T., H. Kiet, A. T., et al. (2008). "Role of activity in human dynamics." EPL **82**(2): 28002.

APPENDICES

Appendix I. Summary on the study of human dynamics

Activities	Data sources	Analytical results
Email communication	129,135 emails sent by 3,188 users in three months in a university	The response times and inter-activities are described by Power law (PL) distribution, both with exponent 1
		Not a PL distribution, can be explained by cascaded Poisson process
		Lognormal distribution
	1493,441 emails sent between 1,052 mangers in a consulting company between July, 2006 and January, 2007	It found that there are a wide range of distributions. The waiting times ranges from instant reply to over 1000 hours.
Correspondences	30801, 14121, 5858, Letters of Einstein, Darwin, and Florid respectively	The response times are found to be fitted to a PL distribution with exponent 3/2
	3,335 Letters by Zhongshu Qian from 1995 to 2000.	The response times are found to be fitted to a PL distribution with exponent 2.1
	Correspondence of 16 writers, actors, politicians, and scientists for 1500s to 1950s.	The response times is not a PL distribution, and it can be explained by cascaded Poisson process
Short message text	SMS by volunteers with length from 3 months to 6 months	The inter-communication times of the indicial are described by a PL distribution, and the exponents vary from 1.2 to 1.7
	37,577,781 sending records by 6,326,713 users during 2006 New Year.	Inter-communication times are from 30 seconds to 20,000 sends. The exponent of PL distribution is 1.188; Response times are from 60

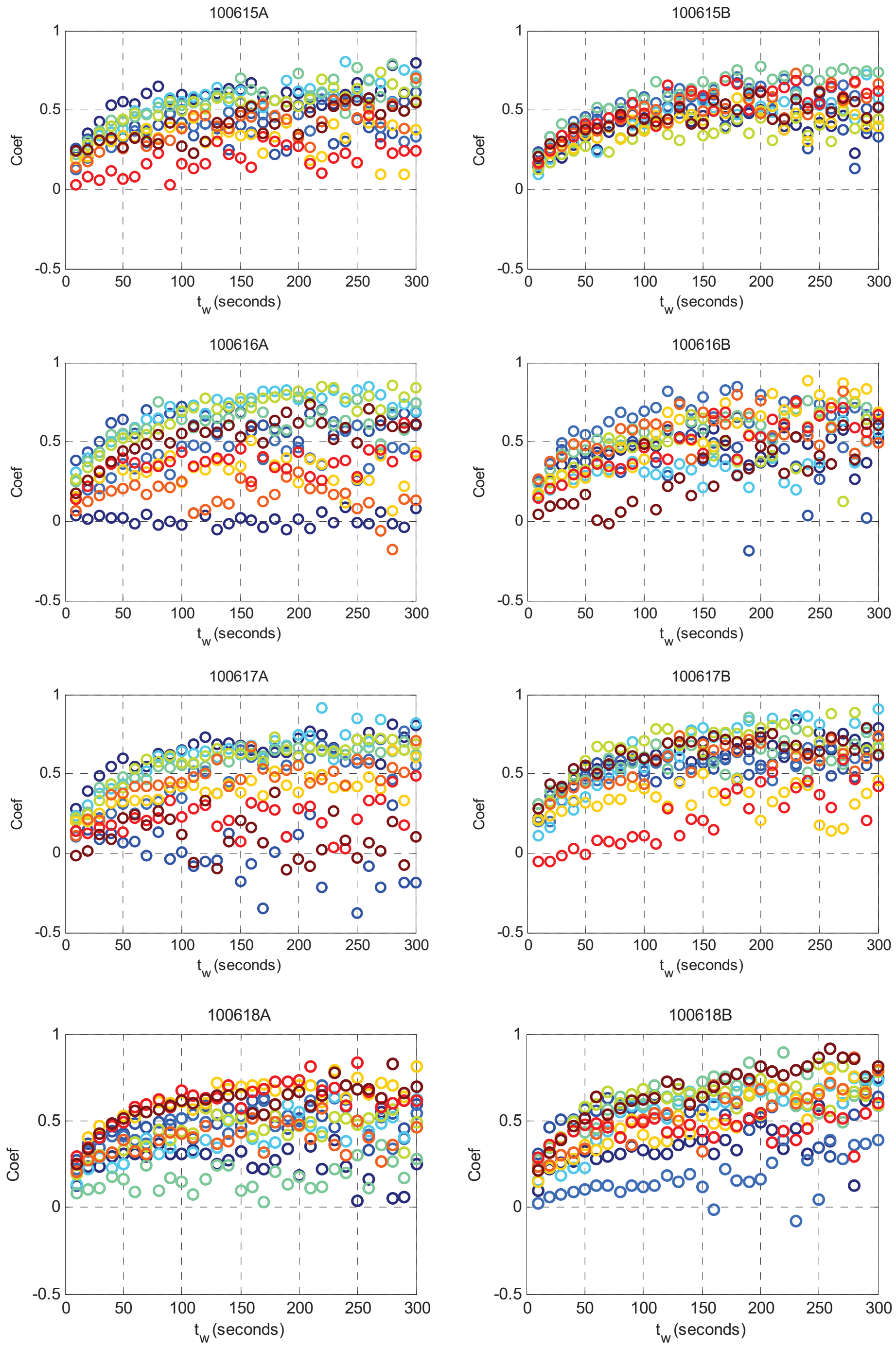
		seconds to 20,000 seconds, and the exponent of PL distribution is 1.148
	1589,869 records of 147,672 users from three companies	Not a PL distribution. It found that a bimodal distribution is fitted to the inter-communication times, with the first part PL, the later part is exponential.
Mobile phone communication	Call records of 6,000,000 users in one month	Inter-times are described by the truncated power law, with exponent 0.9 cutoff at 48 days.
Library loan	48409 loan records of 2,247 faculties of Notre Dame university in three years	Individuals are described by PL distribution with exponent around 1
	772,504 loan records and 647,048 return records of 13,866 faculties of two Chinese universities	Individuals are described by PL distribution with exponent around 1.5 Collective behavior is more complicated.
Financial activities	54,374 transactions initiated by a stockbroker in Sino euro bank from June, 1999 to May, 2003	The intervals are fitted into truncated power law, with exponent 1.3.
	800,000 orders and 540,000 stock transactions at GSK, VOD in March, June, and October in 2002	The intervals exhibit heavy tail feature, but not a PL distribution.
	Online transactions experiments on five candidates for the Major of Taipei lasted 30 days with more than 400 volunteers involved.	Collective behavior is found to be a PL distribution with exponent 1.3
Web surfing	Entertainment website in Hungary from 8 Nov. to 8 Dec. in 2002	The behaviors differ from individual to individuals, but all can be fitted into the PL distribution with exponent around 1.1
		Collective behavior is described by a PL with exponent 1.2; Individuals behaviors can also be described by a PL distribution with exponent 1.14
	Website visiting records at Emory university from 1 April, 2005 to 17 Jan., 2006	Individual behaviors for the same web are fitted into PL distribution with exponent 1.0, while Individuals for different webs are fitted into PL distribution with

		exponent 1.25
	Internet visiting records in Fifteen days in Shanghai Science and Technology	The PL exponents for the individual behaviors vary from 2.1 to 3, while for the collective behavior is 2.82
	17,531,208 records of 7,565,401 users visiting Wiki from 23 Dec., 2004 to 8 Oct. 2008.	Collective behavior can be described by PL distribution with exponent 1.2
Network communication	149,087,003 feedbacks from 748,282 users on EBay from 1998 to 2008	Collective behavior can be described by PL distribution with exponent 1.9
	30 billion communication records of 240 million users on MSN in June, 2006	Collective behavior can be described by PL distribution with exponent 1.53
	Communication records of five volunteers through QQ with periods from 18 months to 1 year	The PL exponents for the individual behaviors vary from 2.0 to 2.5
Internet searching	36,389,566 search requests from 657,426 on American online from 1 March to 31 May in 2006	Collective behavior can be described by PL distribution with exponent 1.9
	498,872 search request from mobile clients from 1 April to 8 April in 2007	Within 24 hours Collective behavior can be described by PL distribution; otherwise the best distribution function is exponential
blog	2.2 million blogs published by 45,000 users from Aug. to Sept. in 2005	Collective behavior can be described by PL distribution with exponent 2.7
	1,627,697 posts by 20,379 users on bbs.nju.eud.cn until 1 Sept. 2009	Collective behavior can be described by PL distribution with exponent 1.98，
		Individual behaviors are fitted into PL form.
	Blogs by four bloggers on sciencenet.cn with recorded number of 588, 191, 536	Individual behaviors are fitted into PL form with cut-off
	Users on blogs and micro blogs	Individual behaviors are fitted into PL form, with exponent from 1.3 to 2.0
	Randomly selected 30% users resisted in 2006 on nine broads of Boards. IE	Collective behavior can be described by PL distribution with exponent 1.7
	Micro blog activities on sina	Collective behavior can be described by PL distribution with

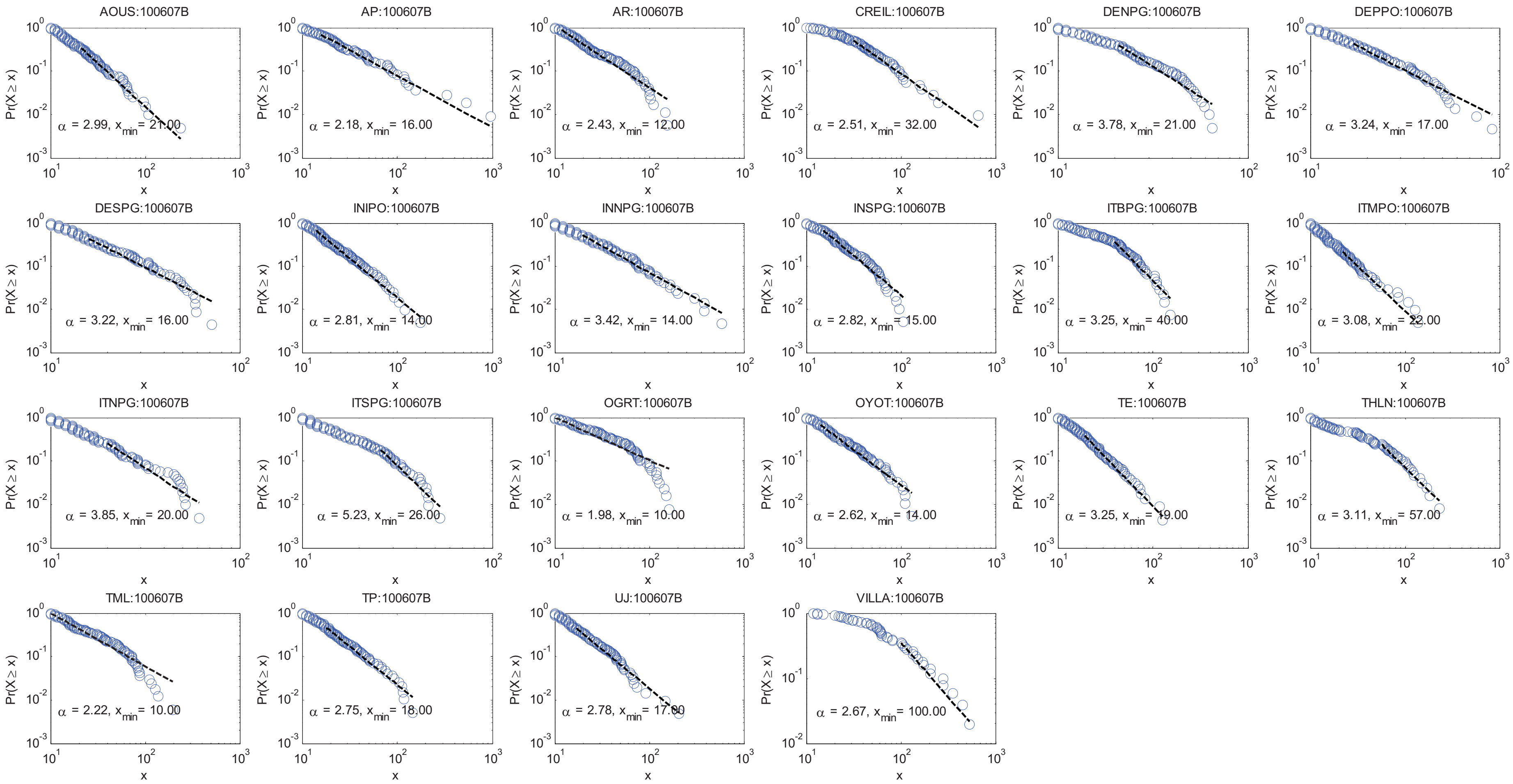
		exponent 1.4
Social network activities	Messages on 17,788,870 users in Cyworld in Korea from June, 2003 to Oct. 2005.	Within 36 minutes, the collective behavior is fitted into PL distribution with exponent 1.696；Between 36 minutes and one day，the PL exponent is 0.910；while longer than one day, the exponent is 2.276
Tasks executing	6,701,406 visiting records by 9,436 tasks by Turkey robot of Amazon, from January, 2009 to April, 2010	The PL exponent is 1.48
	Over 10,000 activities recorded by the computer when user open and close the software	The PL exponent is 1
	Seven historical record on Linux log by six users. Each log contains 12,000 to 93,000 commands.	The PL exponent is between 1.47 and 1.74
		The distribution function should be exponential.
Online services	Film selecting activities on site: www.netflix.com, including 17,770 movies, 447,139 users, nearly 100 millions records	Collective behavior is PL distribution with exponent 2.08; while the individual behavior is heavy tail, but not a PL.
	Log information of an on online music sharing website	The individual behaviors are heavy tailed.
	54,204,641 book marking records of 220,867 users of Delicious website from 1 April, 2004 to 1 Nov, 2007	Collective behavior is fitted into PL distribution with exponent between 1.07 and 2.41
	Buying history of 274,148 on 28,620 goods on 360buy.com from 2 Dec., 2008 to 12 Jan., 2010	The collective behavior is described by PL distribution.
War	54,6789 violent reported	The inter-activities times can be explained by the cascade Poisson process.
	Wars in the history of China	The distribution of inter-war times is exponential.
	8,627 terror attach in Iran and 772 in Afghan	The distribution is PL with exponent between 2.61 and 2.41
Writing	68,022 blogs obtained by Google RSS readers from 11 Feb. 2005 to 2 Oct., 2005	The inter-activities times are fitted into PL distribution with exponent 1.5
	9,641,842 edit records by 81,823 users on Chinese Wiki website from 26 Oct., 2002 to 7 June, 2009	The inter-activities times are fitted into PL distribution

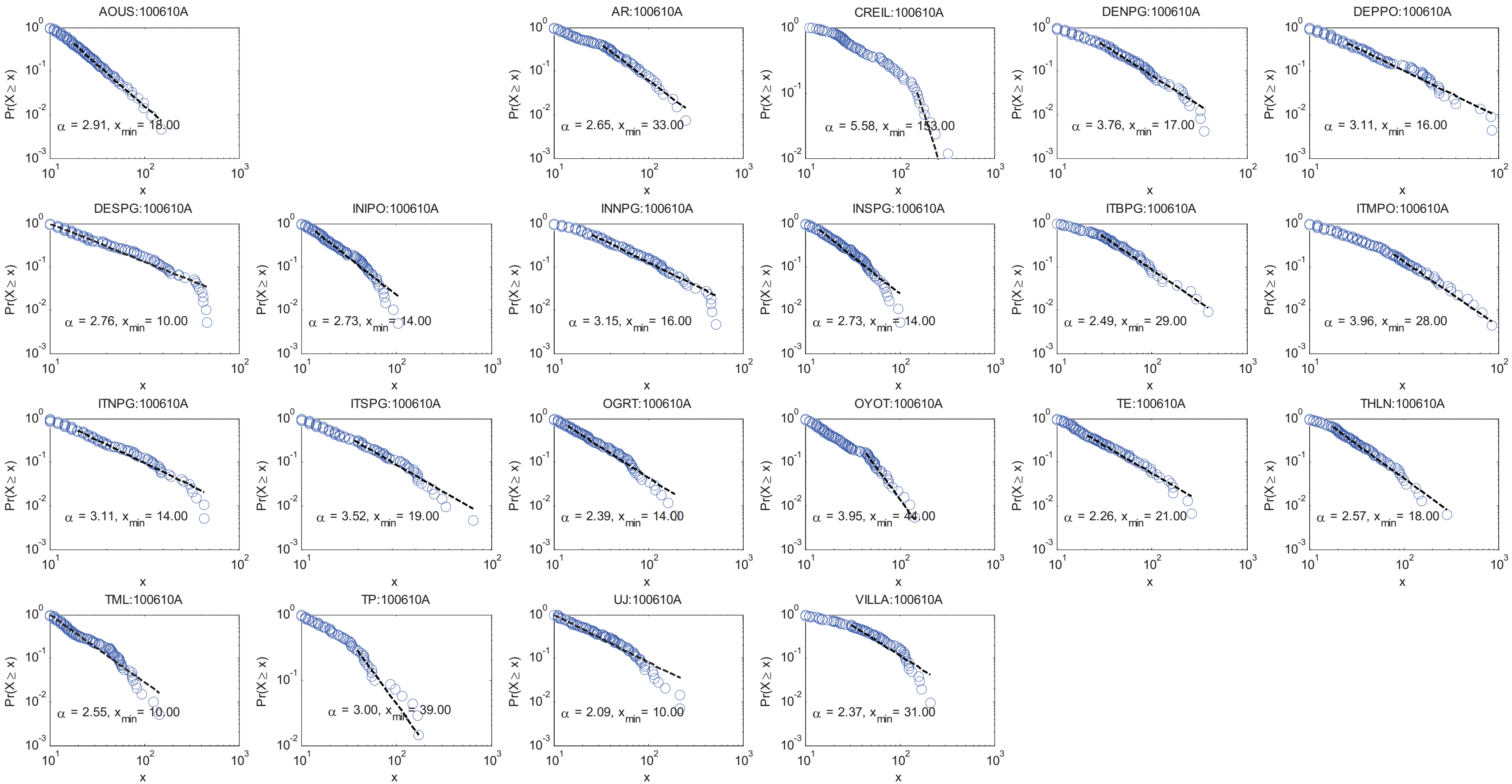
	The times of publication of Su Shi, Stanley, Newman, Barabási	The inter-activities times are fitted into PL distribution.
Physical proximate	54 volunteers in IEEE INFORCOM conferences in May, 2005	The inter-activities times of individuals are fitted into PL distribution with exponent 1.4
		The exponent for the collective behavior is 1.6
	Spatial position records with the length of 9 months of 100 students of MIT who carry blue teeth mobile	The intervals are fitted into PL distribution with exponent 1.51.49
	50 users with RFID at the conference during 13-17 Oct., 2008	Power law
	51,879 records of face to face communication of 163 volunteers in 73 days in a Japanese company	The inter-activities times are fitted into PL distribution with exponent 2.52

Appendix II. Correlations coefficients as a function of time window. ACC sectors in other exercise in D1 dataset.



Appendix III. The distributions of the inter-communication times of each sector

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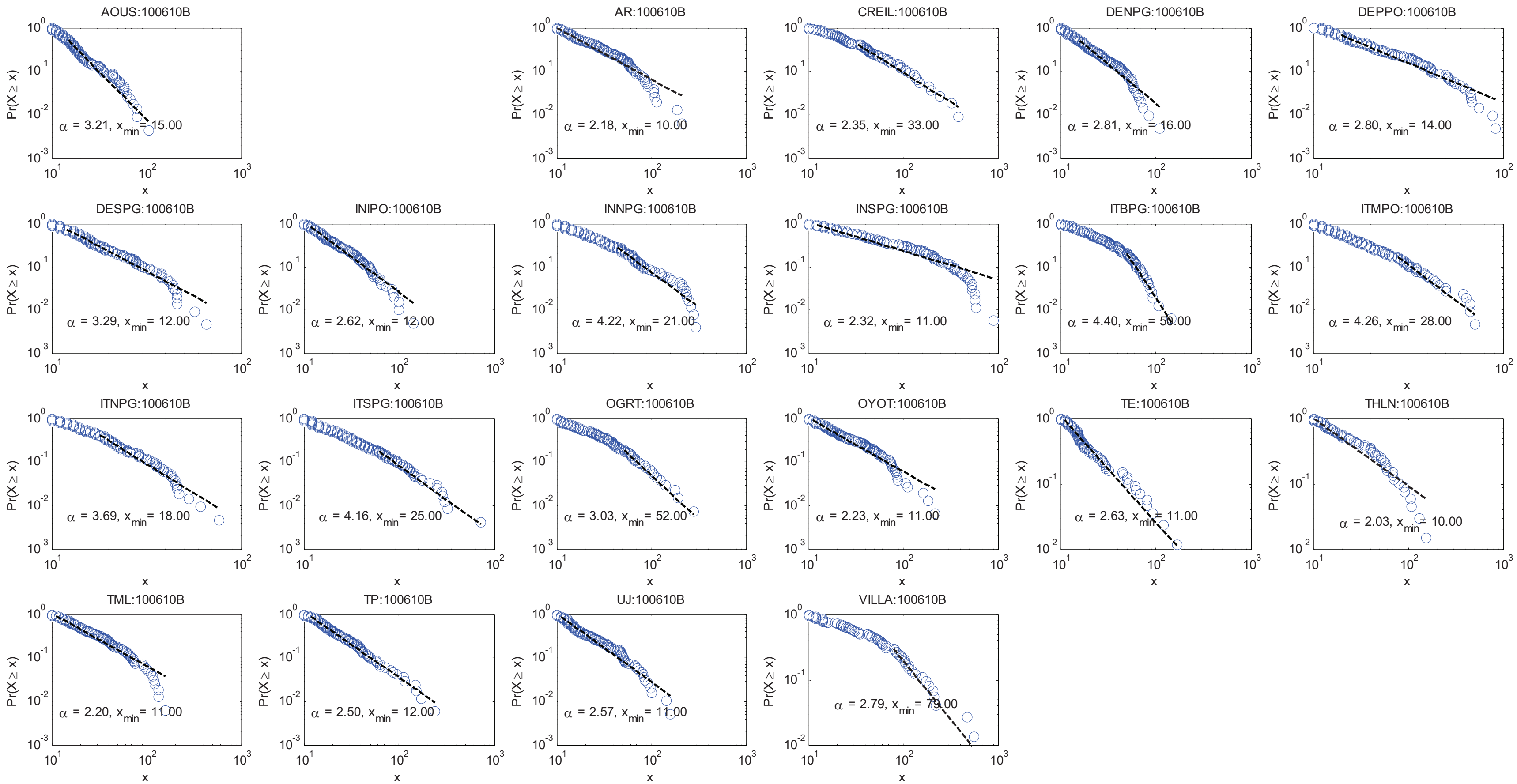
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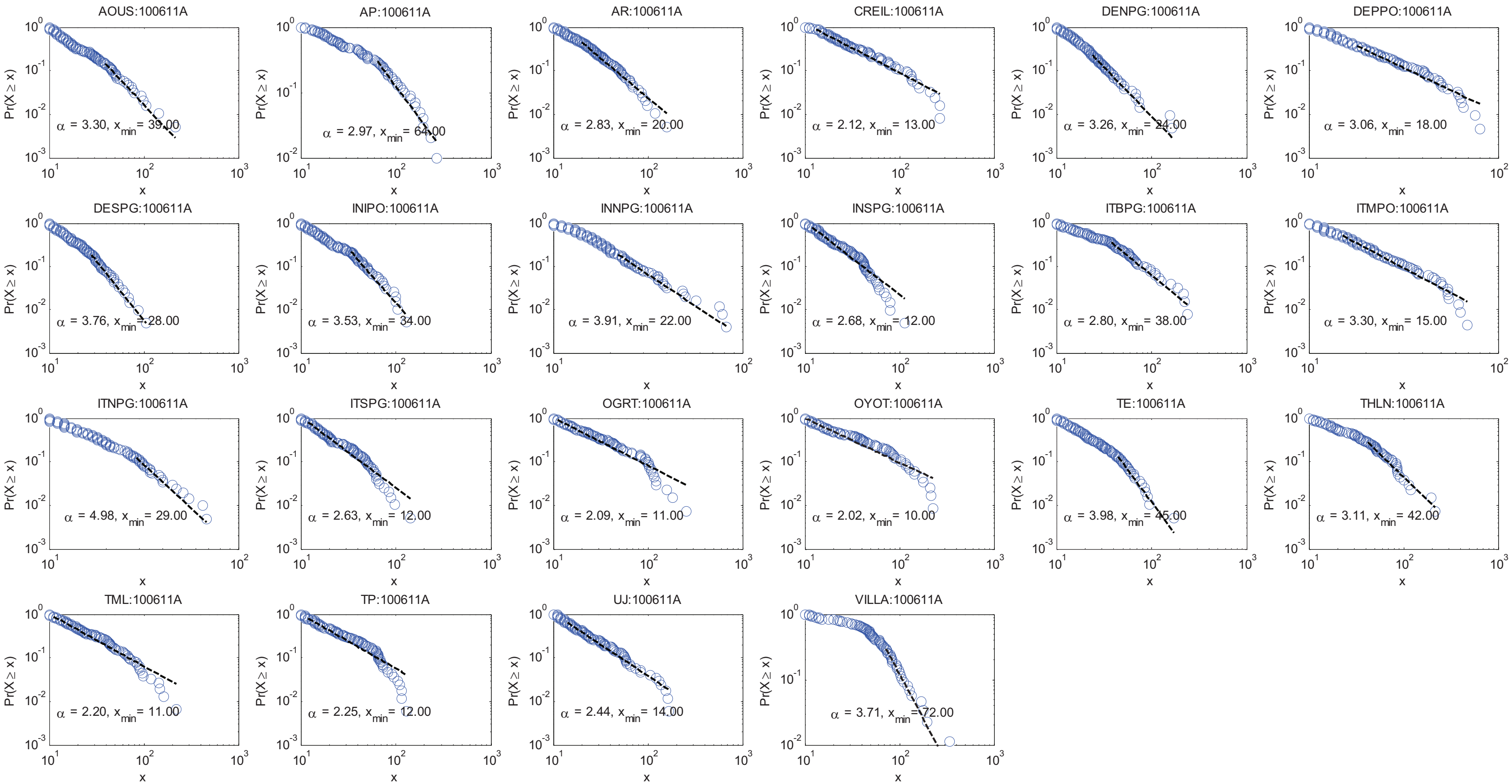
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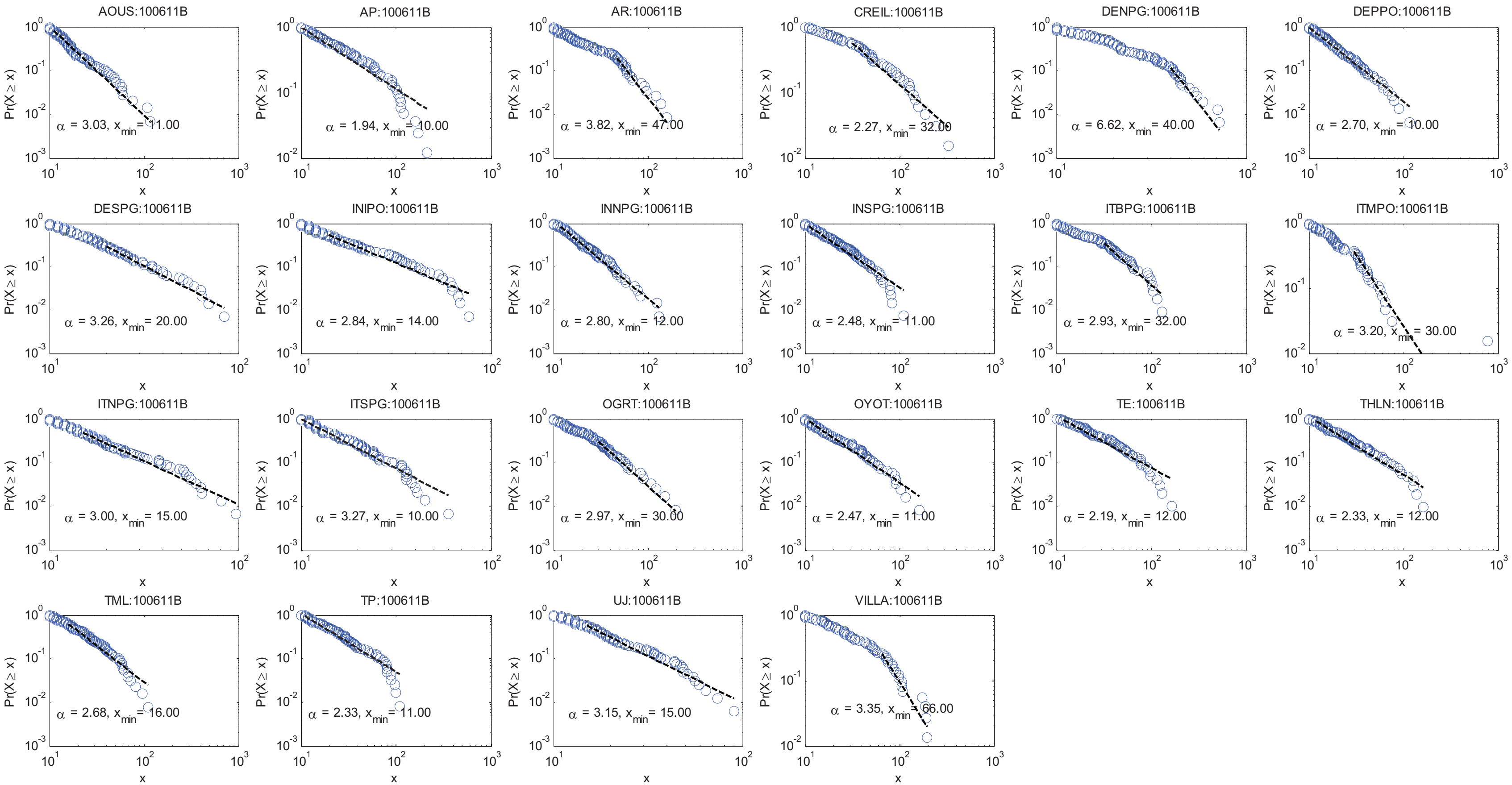
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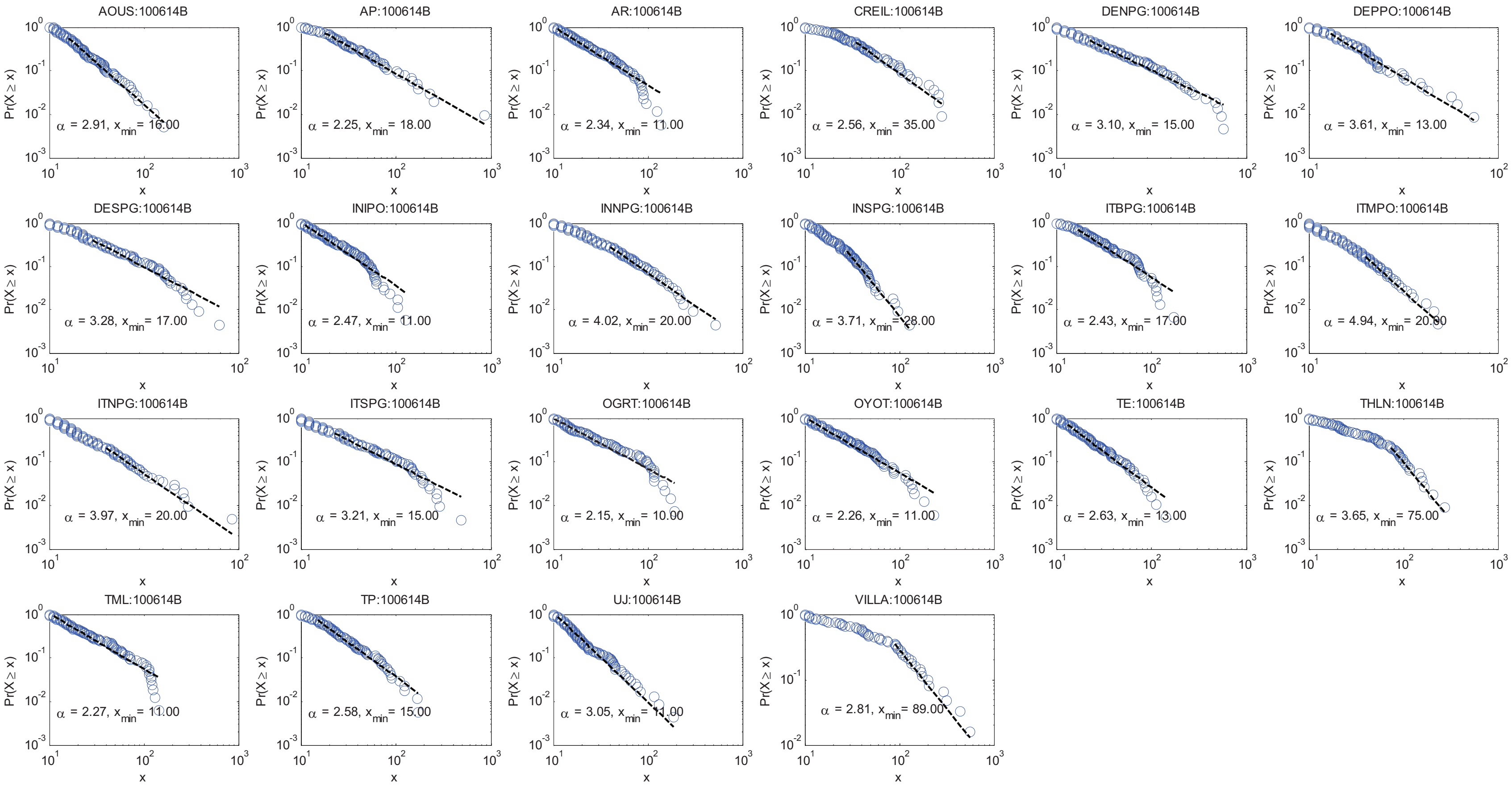
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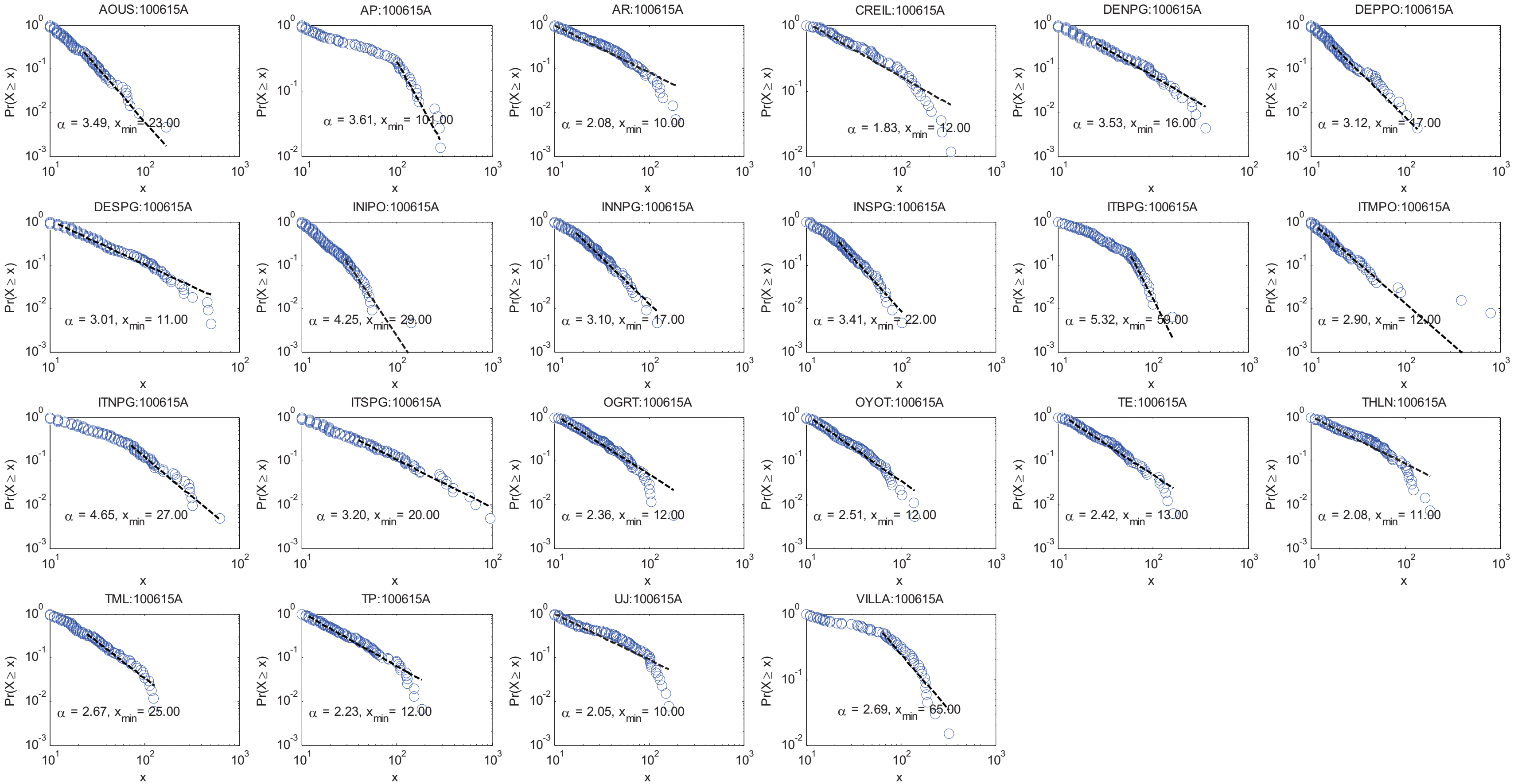
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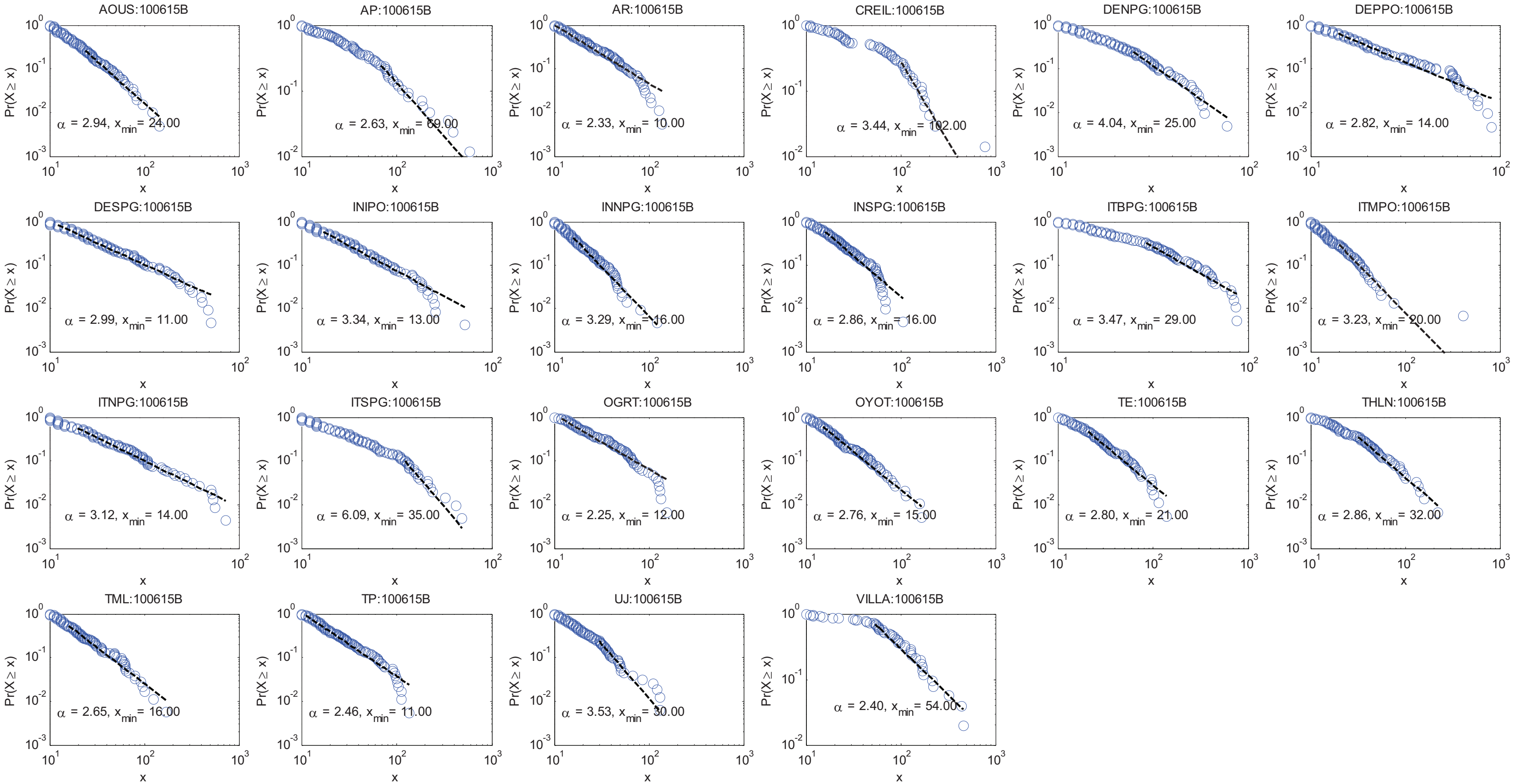

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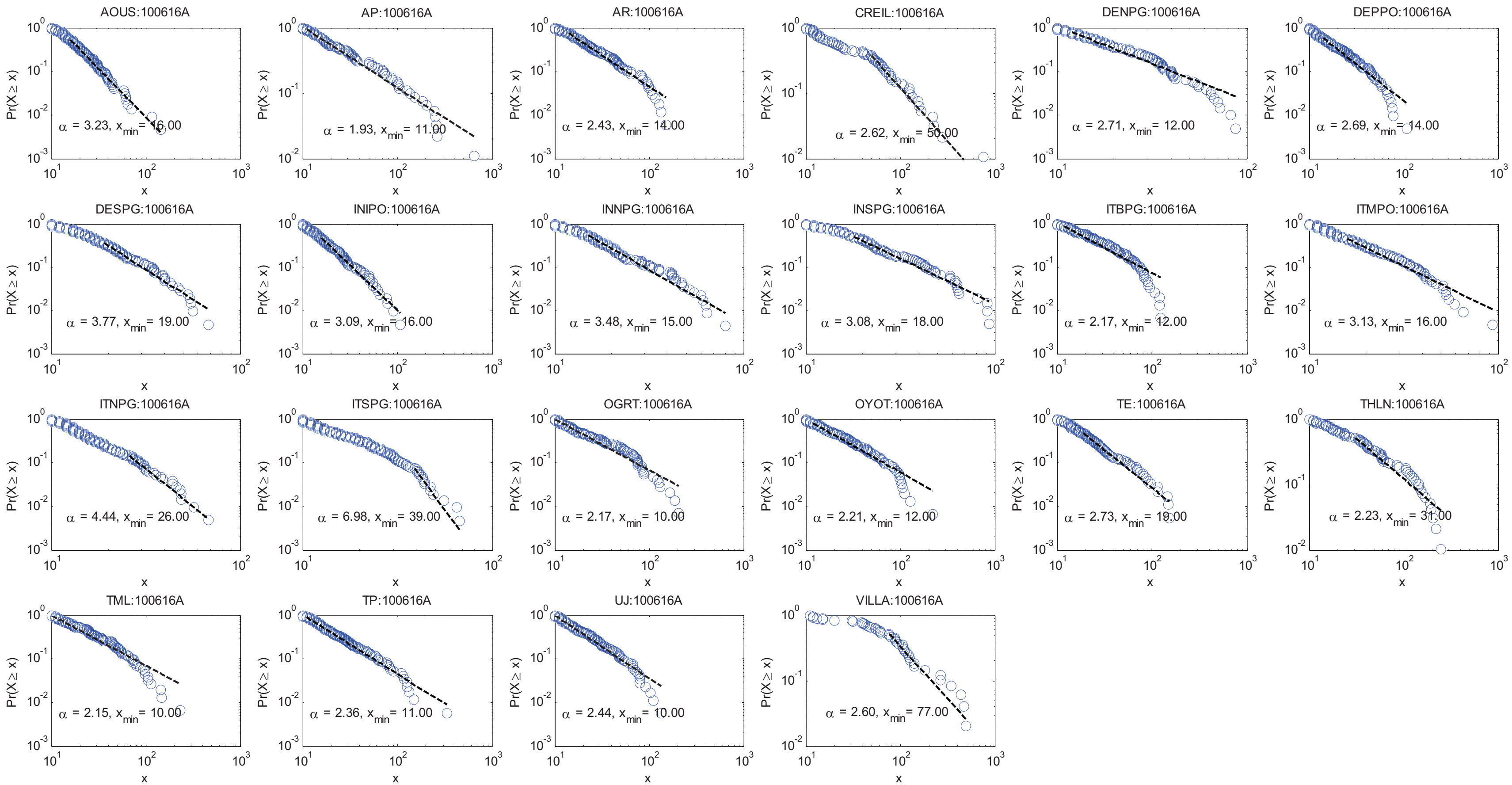
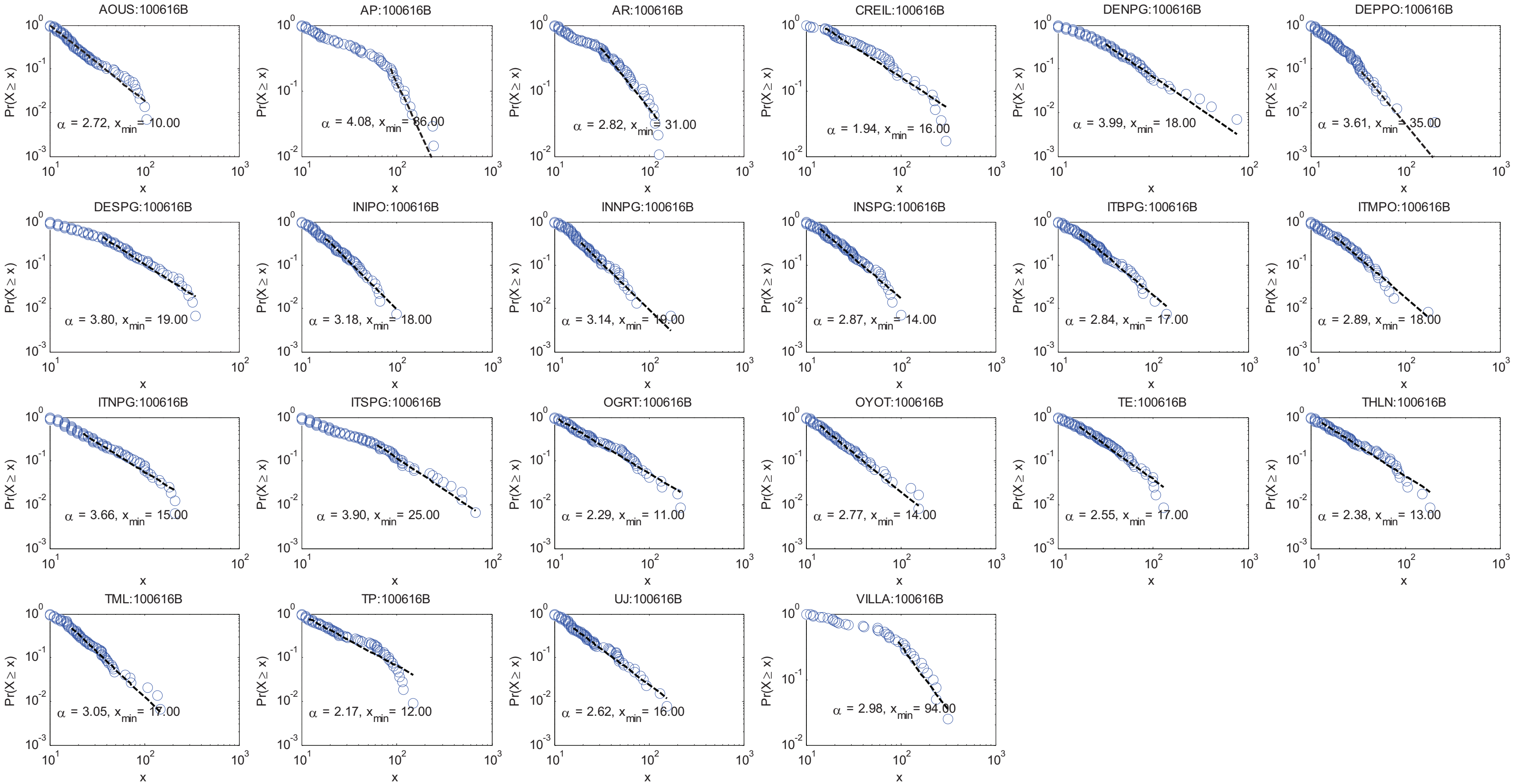
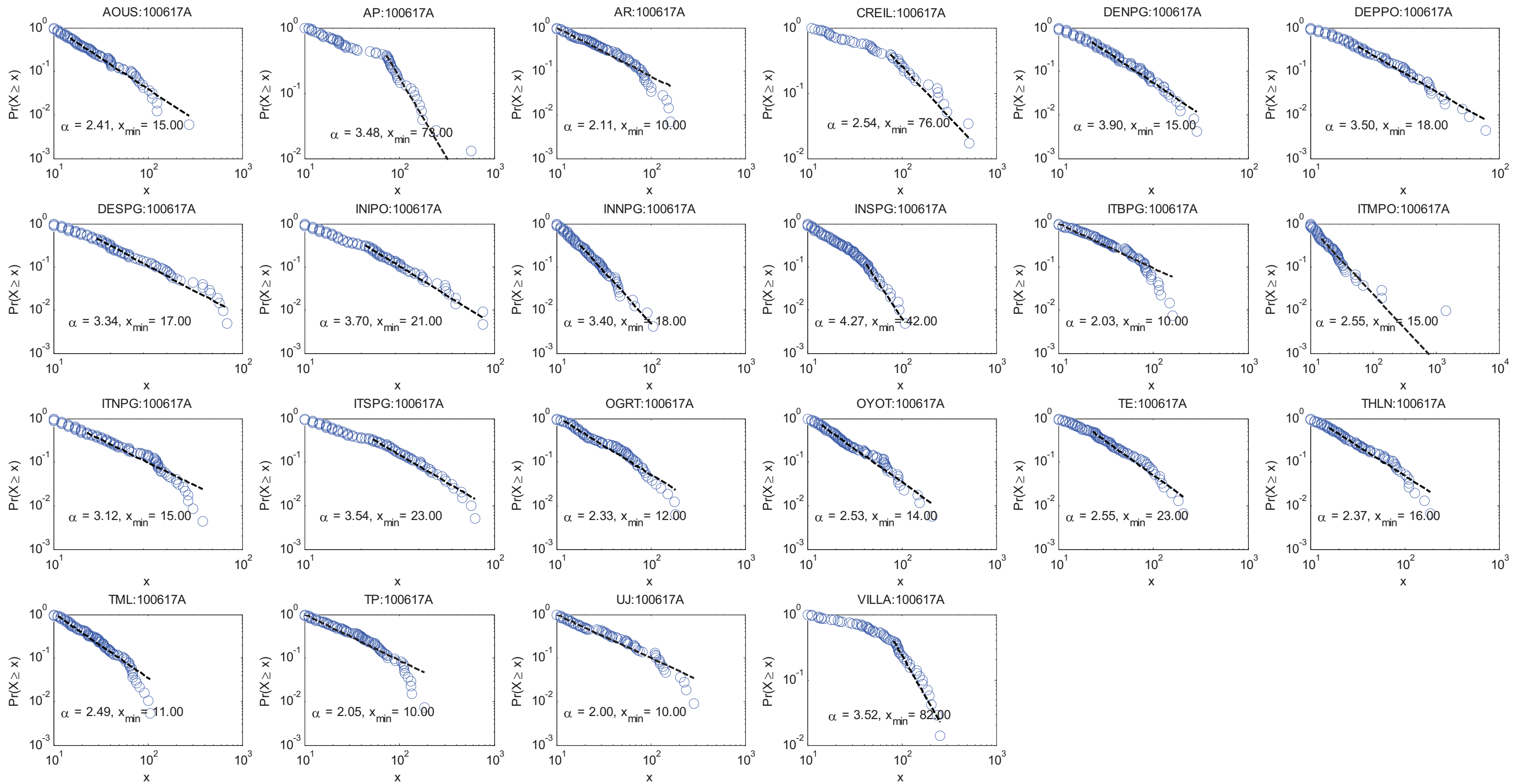
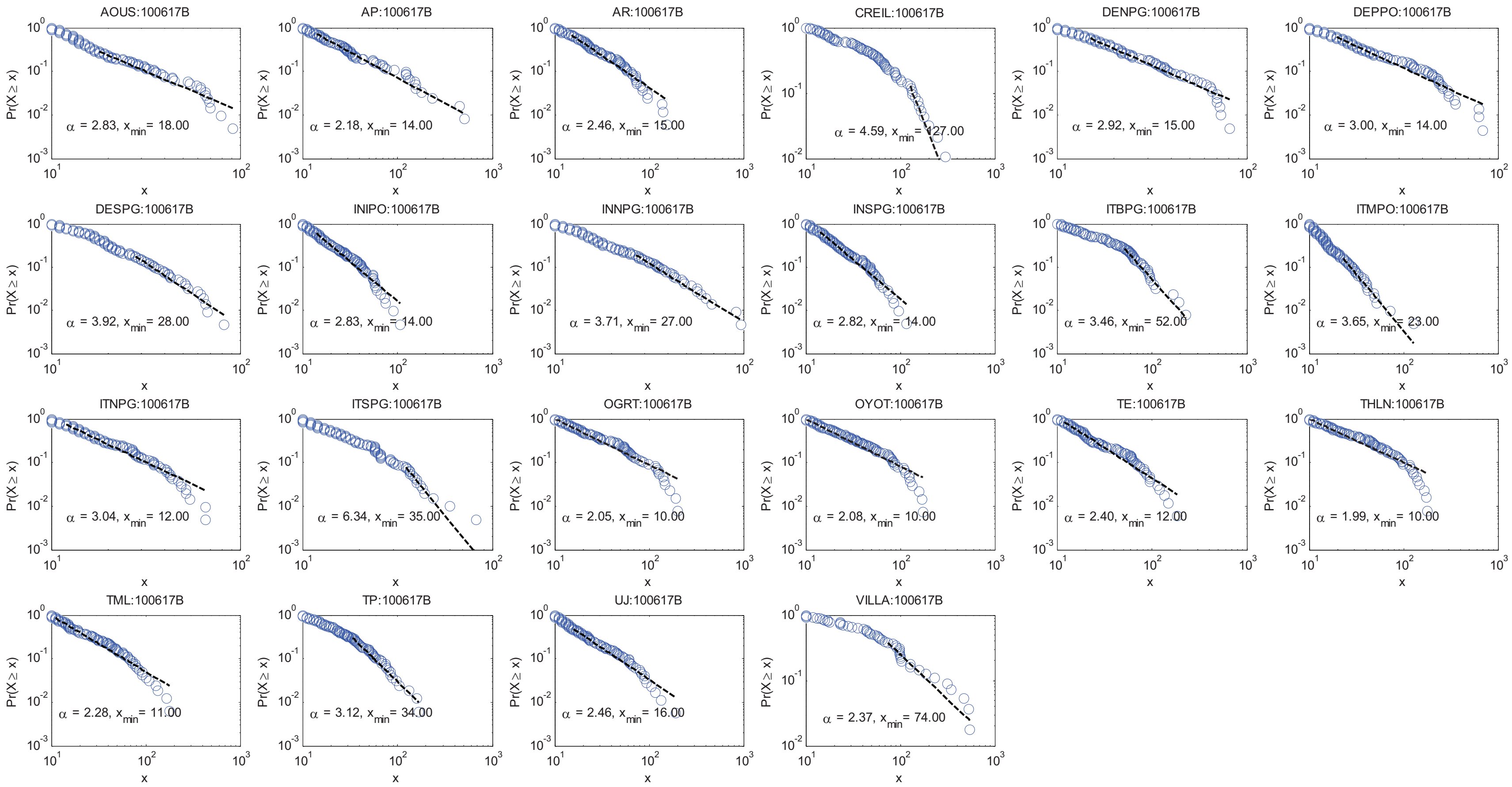
α = 3.47, x_min = 29.00
ITMPO:100615B
α = 3.23, x_min = 20.00
ITNPG:100615B
α = 3.12, x_min = 14.00
ITSPG:100615B
α = 6.09, x_min = 35.00
OGRT:100615B
α = 2.25, x_min = 12.00
OYOT:100615B
α = 2.76, x_min = 15.00
TE:100615B
α = 2.80, x_min = 21.00
THLN:100615B
α = 2.86, x_min = 32.00
TML:100615B
α = 2.65, x_min = 16.00
TP:100615B
α = 2.46, x_min = 11.00
UJ:100615B
α = 3.53, x_min = 30.00
VILLA:100615B
α = 2.40, x_min = 54.00
Pr(X ≥ x)
x

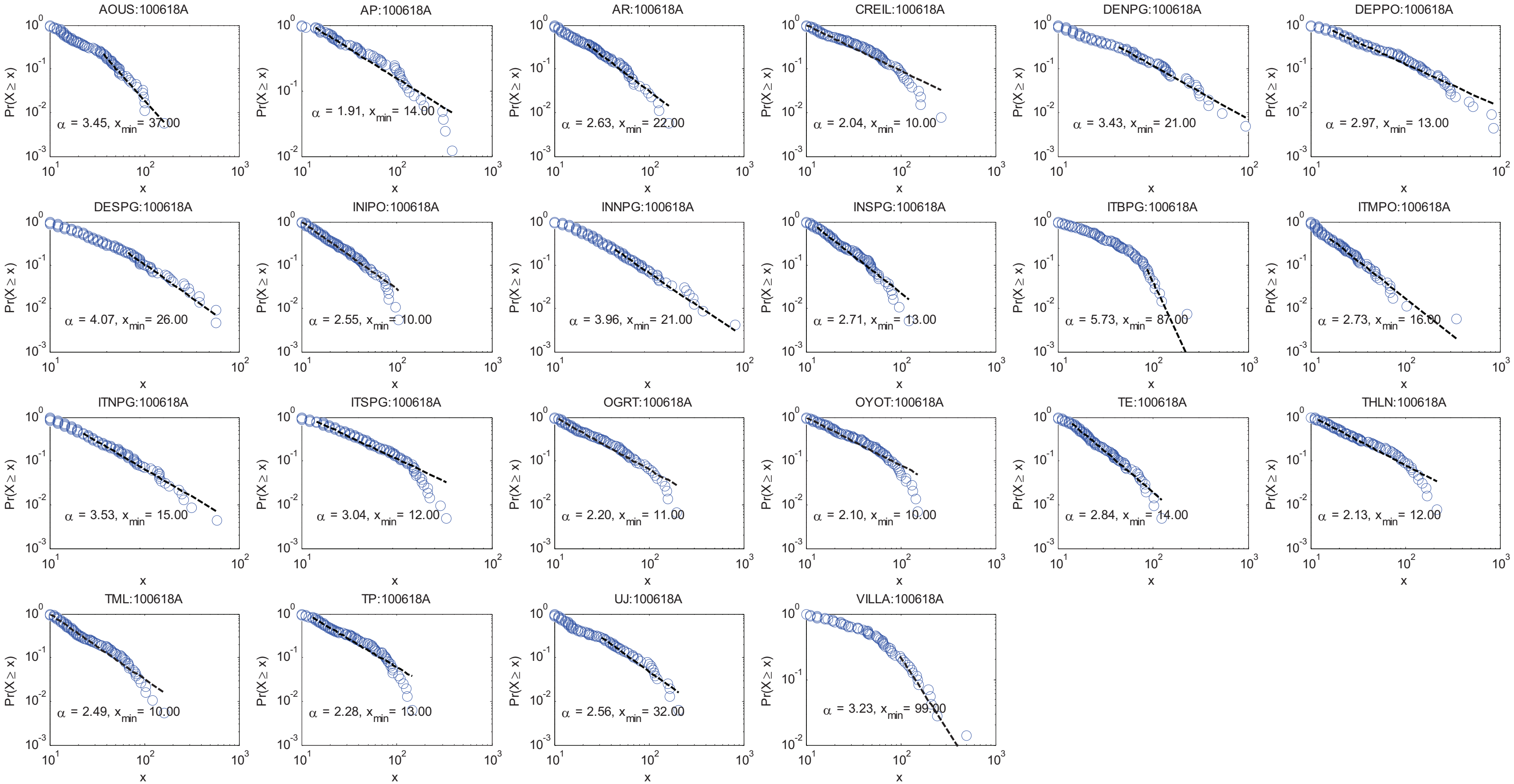

AOUS:100616A
α = 3.23, x_min = 16.00
AP:100616A
α = 1.93, x_min = 11.00
AR:100616A
α = 2.43, x_min = 14.00
CREIL:100616A
α = 2.62, x_min = 50.00
DENPG:100616A
α = 2.71, x_min = 12.00
DEPPO:100616A
α = 2.69, x_min = 14.00
DESPG:100616A
α = 3.77, x_min = 19.00
INIPO:100616A
α = 3.09, x_min = 16.00
INNPG:100616A
α = 3.48, x_min = 15.00
INSPG:100616A
α = 3.08, x_min = 18.00
ITBPG:100616A
α = 2.17, x_min = 12.00
ITMPO:100616A
α = 3.13, x_min = 16.00
ITNPG:100616A
α = 4.44, x_min = 26.00
ITSPG:100616A
α = 6.98, x_min = 39.00
OGRT:100616A
α = 2.17, x_min = 10.00
OYOT:100616A
α = 2.21, x_min = 12.00
TE:100616A
α = 2.73, x_min = 19.00
THLN:100616A
α = 2.23, x_min = 31.00
TML:100616A
α = 2.15, x_min = 10.00
TP:100616A
α = 2.36, x_min = 11.00
UJ:100616A
α = 2.44, x_min = 10.00
VILLA:100616A
α = 2.60, x_min = 77.00
Pr(X ≥ x)
x


AOUS:100616B
α = 2.72, x_min = 10.00
AP:100616B
α = 4.08, x_min = 86.00
AR:100616B
α = 2.82, x_min = 31.00
CREIL:100616B
α = 1.94, x_min = 16.00
DENPG:100616B
α = 3.99, x_min = 18.00
DEPPO:100616B
α = 3.61, x_min = 35.00
DESPG:100616B
α = 3.80, x_min = 19.00
INIPO:100616B
α = 3.18, x_min = 18.00
INNPG:100616B
α = 3.14, x_min = 19.00
INSPG:100616B
α = 2.87, x_min = 14.00
ITBPG:100616B
α = 2.84, x_min = 17.00
ITMPO:100616B
α = 2.89, x_min = 18.00
ITNPG:100616B
α = 3.66, x_min = 15.00
ITSPG:100616B
α = 3.90, x_min = 25.00
OGRT:100616B
α = 2.29, x_min = 11.00
OYOT:100616B
α = 2.77, x_min = 14.00
TE:100616B
α = 2.55, x_min = 17.00
THLN:100616B
α = 2.38, x_min = 13.00
TML:100616B
α = 3.05, x_min = 17.00
TP:100616B
α = 2.17, x_min = 12.00
UJ:100616B
α = 2.62, x_min = 16.00
VILLA:100616B
α = 2.98, x_min = 94.00
Pr(X ≥ x)
x

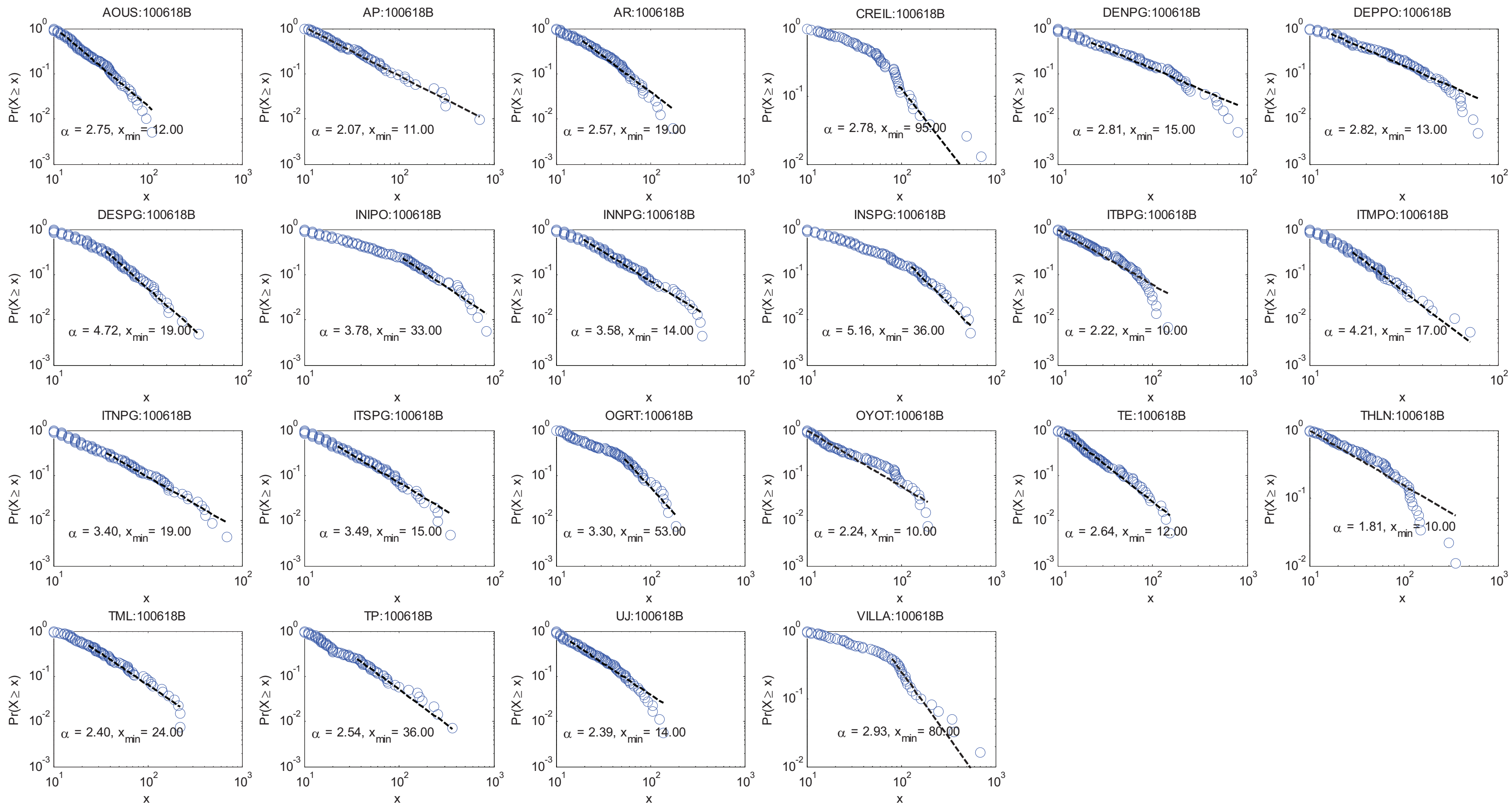

AOUS:100617A
α = 2.41, x_min = 15.00
AP:100617A
α = 3.48, x_min = 79.00
AR:100617A
α = 2.11, x_min = 10.00
CREIL:100617A
α = 2.54, x_min = 76.00
DENPG:100617A
α = 3.90, x_min = 15.00
DEPPO:100617A
α = 3.50, x_min = 18.00
DESPG:100617A
α = 3.34, x_min = 17.00
INIPO:100617A
α = 3.70, x_min = 21.00
INNPG:100617A
α = 3.40, x_min = 18.00
INSPG:100617A
α = 4.27, x_min = 42.00
ITBPG:100617A
α = 2.03, x_min = 10.00
ITMPO:100617A
α = 2.55, x_min = 15.00
ITNPG:100617A
α = 3.12, x_min = 15.00
ITSPG:100617A
α = 3.54, x_min = 23.00
OGRT:100617A
α = 2.33, x_min = 12.00
OYOT:100617A
α = 2.53, x_min = 14.00
TE:100617A
α = 2.55, x_min = 23.00
THLN:100617A
α = 2.37, x_min = 16.00
TML:100617A
α = 2.49, x_min = 11.00
TP:100617A
α = 2.05, x_min = 10.00
UJ:100617A
α = 2.00, x_min = 10.00
VILLA:100617A
α = 3.52, x_min = 82.00
Pr(X ≥ x)
x

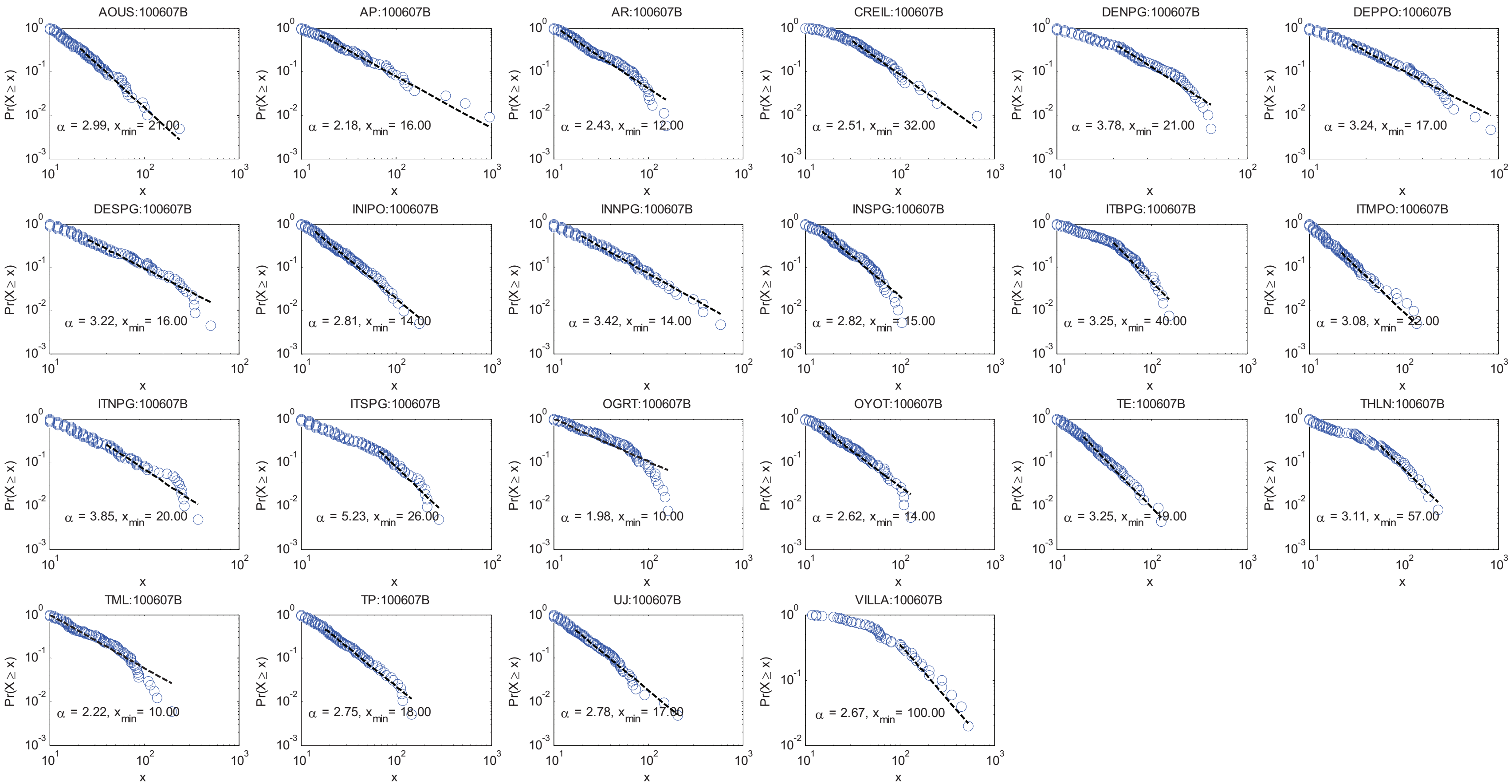


AOUS:100617B
α = 2.83, x_min = 18.00
AP:100617B
α = 2.18, x_min = 14.00
AR:100617B
α = 2.46, x_min = 15.00
CREIL:100617B
α = 4.59, x_min = 127.00
DENPG:100617B
α = 2.92, x_min = 15.00
DEPPO:100617B
α = 3.00, x_min = 14.00
DESPG:100617B
α = 3.92, x_min = 28.00
INIPO:100617B
α = 2.83, x_min = 14.00
INNPG:100617B
α = 3.71, x_min = 27.00
INSPG:100617B
α = 2.82, x_min = 14.00
ITBPG:100617B
α = 3.46, x_min = 52.00
ITMPO:100617B
α = 3.65, x_min = 23.00
ITNPG:100617B
α = 3.04, x_min = 12.00
ITSPG:100617B
α = 6.34, x_min = 35.00
OGRT:100617B
α = 2.05, x_min = 10.00
OYOT:100617B
α = 2.08, x_min = 10.00
TE:100617B
α = 2.40, x_min = 12.00
THLN:100617B
α = 1.99, x_min = 10.00
TML:100617B
α = 2.28, x_min = 11.00
TP:100617B
α = 3.12, x_min = 34.00
UJ:100617B
α = 2.46, x_min = 16.00
VILLA:100617B
α = 2.37, x_min = 74.00
Pr(X ≥ x)
x



AOUS:100618A
α = 3.45, x_min = 37.00
AP:100618A
α = 1.91, x_min = 14.00
AR:100618A
α = 2.63, x_min = 22.00
CREIL:100618A
α = 2.04, x_min = 10.00
DENPG:100618A
α = 3.43, x_min = 21.00
DEPPO:100618A
α = 2.97, x_min = 13.00
DESPG:100618A
α = 4.07, x_min = 26.00
INIPO:100618A
α = 2.55, x_min = 10.00
INNPG:100618A
α = 3.96, x_min = 21.00
INSPG:100618A
α = 2.71, x_min = 13.00
ITBPG:100618A
α = 5.73, x_min = 87.00
ITMPO:100618A
α = 2.73, x_min = 16.00
ITNPG:100618A
α = 3.53, x_min = 15.00
ITSPG:100618A
α = 3.04, x_min = 12.00
OGRT:100618A
α = 2.20, x_min = 11.00
OYOT:100618A
α = 2.10, x_min = 10.00
TE:100618A
α = 2.84, x_min = 14.00
THLN:100618A
α = 2.13, x_min = 12.00
TML:100618A
α = 2.49, x_min = 10.00
TP:100618A
α = 2.28, x_min = 13.00
UJ:100618A
α = 2.56, x_min = 32.00
VILLA:100618A
α = 3.23, x_min = 99.00
Pr(X ≥ x)
x


AOUS:100618B
α = 2.75, x_{min} = 12.00
AP:100618B
α = 2.07, x_{min} = 11.00
AR:100618B
α = 2.57, x_{min} = 19.00
CREIL:100618B
α = 2.78, x_{min} = 95.00
DENPG:100618B
α = 2.81, x_{min} = 15.00
DEPPO:100618B
α = 2.82, x_{min} = 13.00
DESPG:100618B
α = 4.72, x_{min} = 19.00
INIPO:100618B
α = 3.78, x_{min} = 33.00
INNPG:100618B
α = 3.58, x_{min} = 14.00
INSPG:100618B
α = 5.16, x_{min} = 36.00
ITBPG:100618B
α = 2.22, x_{min} = 10.00
ITMPO:100618B
α = 4.21, x_{min} = 17.00
ITNPG:100618B
α = 3.40, x_{min} = 19.00
ITSPG:100618B
α = 3.49, x_{min} = 15.00
OGRT:100618B
α = 3.30, x_{min} = 53.00
OYOT:100618B
α = 2.24, x_{min} = 10.00
TE:100618B
α = 2.64, x_{min} = 12.00
THLN:100618B
α = 1.81, x_{min} = 10.00
TML:100618B
α = 2.40, x_{min} = 24.00
TP:100618B
α = 2.54, x_{min} = 36.00
UJ:100618B
α = 2.39, x_{min} = 14.00
VILLA:100618B
α = 2.93, x_{min} = 80.00
Pr(X ≥ x)
x


AOUS:100607B
α = 2.99, x_min = 21.00
AP:100607B
α = 2.18, x_min = 16.00
AR:100607B
α = 2.43, x_min = 12.00
CREIL:100607B
α = 2.51, x_min = 32.00
DENPG:100607B
α = 3.78, x_min = 21.00
DEPPO:100607B
α = 3.24, x_min = 17.00
DESPG:100607B
α = 3.22, x_min = 16.00
INIPO:100607B
α = 2.81, x_min = 14.00
INNPG:100607B
α = 3.42, x_min = 14.00
INSPG:100607B
α = 2.82, x_min = 15.00
ITBPG:100607B
α = 3.25, x_min = 40.00
ITMPO:100607B
α = 3.08, x_min = 22.00
ITNPG:100607B
α = 3.85, x_min = 20.00
ITSPG:100607B
α = 5.23, x_min = 26.00
OGRT:100607B
α = 1.98, x_min = 10.00
OYOT:100607B
α = 2.62, x_min = 14.00
TE:100607B
α = 3.25, x_min = 19.00
THLN:100607B
α = 3.11, x_min = 57.00
TML:100607B
α = 2.22, x_min = 10.00
TP:100607B
α = 2.75, x_min = 18.00
UJ:100607B
α = 2.78, x_min = 17.00
VILLA:100607B
α = 2.67, x_min = 100.00
Pr(X ≥ x)
x