

Statistical Regularities in ATM: network properties, trajectory deviations and delays

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Foreword - *This paper describes a project that is part of SESAR Workpackage E, which is addressing long-term and innovative research. The Workpackage E ELSA project started in May 2011 so this paper summarizes the results of the first year of the project.*

Abstract—One of the key enabler to the productivity and efficiency shift foreseen by SESAR will be the business-trajectory concept. The path to a deep understanding of how this new concept impacts on the future SESAR Air Traffic Management scenario goes through a better understanding of the actual air traffic network, and this will be done in the present paper by analyzing traffic data within the framework of complex network analysis. In this paper we will consider flights trajectory data from the Data Demand Repository database. In a first investigation, we perform a network study of the air traffic infrastructure starting from the airports and then refining our analysis at the level of navigation points in order to understand what are the main features that may help explaining why some nodes of the network happen to be found in the same community, i.e. cluster. In a second investigation we perform a study at the level of flight trajectories with the aim of identify statistical regularities in the spatio-temporal deviations of flights between their planned and actual 4D trajectories.

I. INTRODUCTION

In the future of Air Traffic Management (ATM) it is expected to observe an increase of traffic demand and new business challenges that will bring the current ATM system to its capacity limits within the 2013-2015. As a consequence, an overall productivity improvement is urgently needed [1]. The structure of ATM system, as it is known today, will therefore change in many aspects. It is commonly accepted that these changes will be hardly understood by relying on the analysis of the single elements constituting the system, i.e. by applying the current state-of-the-art validation approaches. More likely the features of the future ATM system will be the results of a complex interaction among its different key elements [2].

One of the key enabler to the productivity and efficiency shift foreseen by SESAR will be the business-trajectory concept [1]. In the future SESAR scenario airspace users will not fly along structured routes. On the contrary, they will be able to fly a 4D trajectory selected on the basis of their own business and efficiency needs. Within this major change not only the ATM productivity should be drastically enhanced, but consequently also the ATM system safety and resilience standards will have to improve. The path to a deep understanding of how these aspects will impact on the future SESAR ATM scenario goes through a better understanding of the actual air traffic network. This is not only desirable but it is also requested by the Commission in the regulation for performance scheme for air navigation services and network functions [3] where it is indeed said that "For the purpose of target-setting (of the air navigation services), to each key performance area shall correspond one or a limited number of key performance indicators". This will be done in the present paper by analyzing traffic data within the framework of complex network analysis. The aim of the paper is to single out a bundle of significant regularities and patterns. Some of these patterns will be clearly linked to operational aspects (in the sense that the operational experts will be able to explain their causes and show how they are engendered), while others will require further analyses to understand their dynamics and emergence.

In this paper, we will consider flights trajectory data from the Data Demand Repository (DDR) database. In a first investigation, we perform a network study of the air traffic infrastructure starting from the airports, and then by refining our analysis at the level of navigation points. With these two levels of detail we adopt (i) standard network analysis concepts, as degree and betweenness distributions, and (ii) we identify communities, i.e. clusters, within these two networks in order to understand what are the main features that may help explaining why some nodes of the network happen to be found

in the same community. In network theory a “community” of elements is a set of elements interconnected among them to a degree which is higher than the one expected on the basis of random interconnections. In a second investigation, we perform a study at the level of flight trajectories with the aim of identifying statistical regularities in the spatio-temporal deviations of flights between their planned and their actual 4D trajectories.

The paper is organized as follows: in section II we present the data to be considered in our investigations. In section III we present the investigation of the airports and navigation points networks, while in section IV we show the results of our investigations about the spatio-temporal deviations of flights between their planned and actual 4D trajectories. We draw our conclusions in section V.

II. DATA

The database we use is composed of DDR (Demand Data Repository) and NEVAC (Network Estimation Visualization of ACC Capacity) files already described in Ref. [4]. In the present paper, we analyze data referring to the AIRAC (Aeronautical Information, Regulation and Control) cycle beginning on June 2, 2011 and ending on June 29, 2011, corresponding to the AIRAC cycle 348. We extract the information concerning all the flights crossing the ECAC (or Italian, for some analyses) airspace, during this period. The main data consists of the trajectories of flights, along with some additional information about them (IATA code, type of aircraft, among the others), used in order to set some filters.

For each flight, we have access to two different flight plans: the last filed plan (noted M1), and the actual flight plan (noted M3), updated by radar tracks. Both of them are described by a succession of navigation points (nav-points), with some precisely defined latitude and longitude, and time stamp. One can then rebuild any trajectory, with a variable time resolution ranging from 1 to 10 minutes.

From this database we select the flights that we are interested in. We drop a certain number of them because they do not lie in our research scope: military flights in operation are good examples. The following are the filters we adopted to create our set of data:

- only non-military and commercial flights (having a IATA code),
 - only land-plane aircraft, i.e. no helicopter, gyrocopter, etc,
 - flights with a duration longer than 10 minutes,
 - flights having at least two points in the ECAC airspace.
- In some analysis we restricted to the Italian airspace.

III. ATM COMPLEX NETWORKS

Complex Networks theory and techniques are nowadays very popular in the scientific community and it is possible to follow their increasing application to many and different research topics. Among many others, during the last decade they have been used to study the structural properties of the

Air Transportation System, too. A number of relevant works [5], [6], [7], [8], [9], [10], [11] have investigated the main network characteristics of the airport network, by analyzing the degree and strength distributions, the betweenness centrality of airports, etc, and have developed theoretical models in order to understand the formation of such networks and the reproduction of their stylized facts. We have reviewed some of the most relevant metrics in the ATM context in Ref. [4]. To our knowledge, a comprehensive community analysis of networks relevant in the ATM context is still lacking (with the only possible exception of [7]), although communities, i.e. groups of highly connected nodes, encode relevant information on the topology of a network and might therefore reveal to be extremely useful for the investigation of the ATM system.

In this section, we study the properties of two different networks: the European airport network and the Italian navigation point network, based on the 4D trajectories of flights respectively crossing the ECAC and the Italian airspace. Particular attention is devoted to the results about the detected network communities and their geographical characterization. In fact, these issues might be relevant for their implications with respect to policies related to airspace division [12].

A. Airport Network

For each day in the AIRAC, let us now consider all flights crossing the ECAC airspace and all active airports, i.e. airports that are the initial or final destination of at least one flight. The number of active airports and flights, as expected, show weekly patterns during the whole AIRAC. In particular, the minimum number of active airports and the number of flights shows minima during the weekends and peaks on the Mondays, Wednesdays and Fridays. In fact, over the weekend the active airports decrease from about 500 to about 450. These closed airports typically are those mainly devoted to cargo and mail services. We would like to understand how these weekly patterns are reflected in the airport network.

In the airport network, nodes are airports, and there is a link between a pair of airports when there is at least a flight connecting them. In this network, we introduce weights for each link by considering the number of flights connecting the two airports. We also assume the network to be symmetric. In fact, in line with previous literature, we find that in any airport the number of departing and arriving flights are almost the same, see also [4]. Our aim is to look for statistical regularities in the system that are maintained over time and to compare them with the existing literature.

Several metrics can be considered in order to characterize a network. We have reviewed some of the most relevant metrics in the ATM context in Ref. [4]. A key metric in understanding the properties of any network is the degree. The degree of each node in a network is given by the number k of links of the node. For our network, the degree of an airport is the number of other airports that can be directly reached from it in a day, i.e. the number of destinations. In line with the existing literature [5], [7], [10], the degree probability density function (pdf) P_k has been found to follow

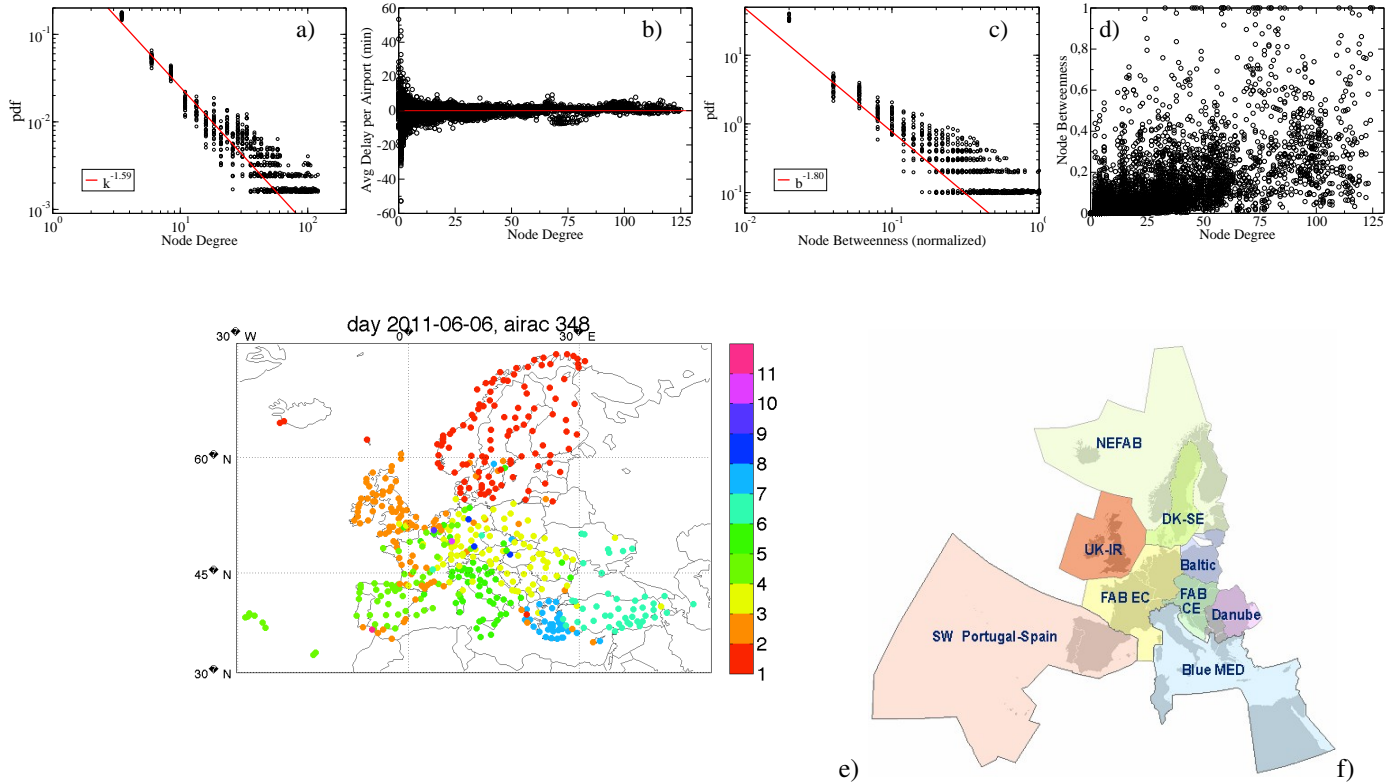


Figure 1. Probability density function of the airport degree (a), scatter-plot of airport degree versus airport en-route delay (ERD) (b), distribution of airport betweenness (c) and scatter-plot of airport betweenness versus airport degree (d). All days in AIRAC 348 are considered. Map of airport network in day 06/06/2011 of AIRAC 348 (e). The circles are the nodes of the airport network, while the links are omitted for readability. The color of the node identify the community each node belongs to. European FABs (f), downloaded from [http://www.skybrary.aero/index.php/File:European FABs.jpg](http://www.skybrary.aero/index.php/File:European_FABs.jpg)

a power law function $P_k \propto k^{-\alpha_d}$ for large degree values, see Fig. 1(a). Thus the probability of finding airports with a very large number of flight connections is much higher than what expected in the case of a Poisson distribution of degrees, usually associated to a random graph [13]. By using the Hill estimator methodology [14] the exponent of the pdf, averaged over all AIRAC days, is $\alpha_d = 1.59 \pm 0.11$. A power law $P_s \propto k^{-\alpha_s}$ for large strength values has been found also for the airport strength pdf: the node strength is simply the sum of the weights associated to the links that originate from (terminate in) it. In our case, the strength of a node gives the total number of flights departing from (arriving to) an airport. In this case the Hill estimator methodology, after averaging over all AIRAC days, gives an exponent $\alpha_s = 1.48 \pm 0.03$.

Then, we have analyzed the relationship between the degree and the en-route delay (ERD) of an airport, the latter one measured as the average difference between the flight duration estimated from the actual flight plan (M3) and that estimated from the planned flight plan (M1), see subsection IV-C, for all flights departing from or arriving to an airport, see Fig. 1 (b). We have found that for large airports, such as Frankfurt and Schiphol, that have degree larger than 200, the average en-route delay is essentially

positive, while for small airports we can have both positive and negative en-route delays. Moreover, small airports can have en-route average delays even larger than large airports. Large en-route delays in large airports can possibly be explained with the fact that in large airports there are long-range flights that are likely to experience such en-route average delays. The situation for small airports is less clear. In fact, it is commonly said that small airport “receive” delay from larger airports, meaning that flights arrive late in small airports because they are delayed in large airports. Note that analogous considerations are valid for the strength distribution.

Another relevant metric characterizing a network is the betweenness centrality [4], which gives a measure of how central is an airport in the network. High values of betweenness indicate that such airport belongs to many paths linking one airport to another. The log-log scale used in Fig. 1 (c), makes evident the power-law behavior of the betweenness distribution, thus suggesting that large airports behave like hubs. In Fig. 1 (d), for each day in AIRAC 348, we report the scatter-plot of the node betweenness versus the node degree, showing that large airports tend to have large betweenness, thus reinforcing the idea that large airports behave like hubs. There exist exceptions, like the Liege cargo airport (EBLG) in

day 06/06/2011, which has unitary betweenness and a degree of 58.

In general, there exists a large portion of medium-size airports with a large betweenness, as also found in [6]. These airports are probably the hubs of medium size airlines. Indeed, the concept of hub should be associated to airlines rather than to airports. It is the airline that organizes its own flight network around one or more airports that are the centre of operations and maintenance, especially for large traditional airlines. On the other hand there might be airports that are relevant for specific services, such as cargo. This explains why small airports end up being central in the network even though they have a not so large number of incoming and outgoing flights.

A new aspect of the investigations we present here is the detection of communities within the network and their geographical characterization. In network theory a community of elements is a set of elements interconnected amongst them at a level that is higher than the one expected on the basis of a null hypothesis of random interconnections [15]. The idea is therefore to understand whether in the network it is possible to detect sets (communities) of nodes (airports) that share a common profile with respect to the flights that are departing/arriving in them. In order to identify communities, we considered the Blondel algorithm, see [16]. This algorithm searches for the partition of the network into modules (communities) such that modularity gets its maximal value. Modularity is a network metric computed as the fraction of the links that fall within the given modules minus the expected such fraction if links were distributed at random. Exact modularity optimization is a problematic task from the computational point of view. Therefore, for large networks, algorithms which are searching a subsets of potential partitionings are necessary. This introduces elements of stochasticity in the algorithm search process. We have therefore performed 100 iterations of the algorithm for each day in the AIRAC and we have chosen the one with the highest modularity¹. A visualization of the partitioning of airports in communities is given in Fig. 1 (e). This partitioning presents similarities with the organization of the European sky in FABs (Functional Airspace Blocks) [12]. FABs are airspace blocks based on operational requirements and established regardless of state boundaries, where the provision of air navigation services and related functions are performance-driven and optimized with a view to introduce, in each functional airspace block, enhanced cooperation among air navigation service providers or, where appropriate, an integrated provider. The FABs are illustrated in Fig. 1 (f). The comparison of FABs with the communities of Fig. 1 (e) indicates that some of our communities correspond to FABs (UK and Ireland), while in other cases our communities seem to indicate that the optimal partitioning of the airspace might

¹For each day in the AIRAC we compute the ratio between the standard deviation and the mean value of the modularity over the 100 realizations. The average value of this ratio over all the AIRAC days is 0.0053 ± 0.0016 , thus showing an extremely high stability of the partitions.

be different from the one of FABs. For example, in our case on the selected day 06 June 2011 France and Spain belong to the same community even though they are in different FABs. Our investigations show that the communities may also change over the week, thus resembling the weekly patterns on the number of active airports mentioned above.

The results mentioned above are observed also for other AIRACs, at least qualitatively. A wider presentation of the statistical regularities in the ATM system covering a large number of AIRACs will be given in the forthcoming D1.3 ELSA project deliverable (due by the end of november 2012). To give a flavor of our findings in Fig. 2 we give the number of flights (blue) and airports (green) in all the AIRACs of our database: from AIRAC 333 to AIRAC 348. The figure shows that there exists a seasonality pattern in the number of flights. The effect is almost negligible for the number of active airports. Hence, it is reasonable to expect the same results described above across the whole season.

B. Navigation Point Network

We now move to a finer level of investigation of the air traffic management system infrastructure, by studying the navigation point² network at the Italian airspace level. This type of analysis is quite a novelty in the literature. As far as we know, one of the few similar studies is the one in Ref. [17], where the Chinese airspace has been investigated. It was found that the topology structure of nav-point network is apparently more homogeneous than the one of the Chinese airport network. By examining the scheduled flights, the authors find that the distribution of air traffic flow on the nav-point network is rather heterogeneous with exponential strength distribution.

In our network, the nodes correspond to nav-points, and a link between two nav-points A and B is set whenever there is a flight for which A and B are the begin and end point of a segment (portion between two trajectory points) on the trajectory of the flight, i.e. the aircraft flies directly from A to B. We will refer to such network as the (local) nav-point network. We also consider the network as directional: when there is a flight going from A to B, then we set a directional link between A and B. The adjacency matrix is therefore only approximately symmetric.

As in the airport case, weekly patterns are recognizable in terms of number of active nav-points over a week. Similarly to the airport case, we define active nav-points those that are part of at least one flight trajectory. We observe that the number of nav-points in the planned trajectories is usually smaller than the number of those used in the actual trajectories. The difference between these numbers could be due to the fact that during the planning stage of the flight trajectories some nav-points are not used because they are reserved for military

²The navigation points are also called way points or nav-points, i.e., fix points in the route airways

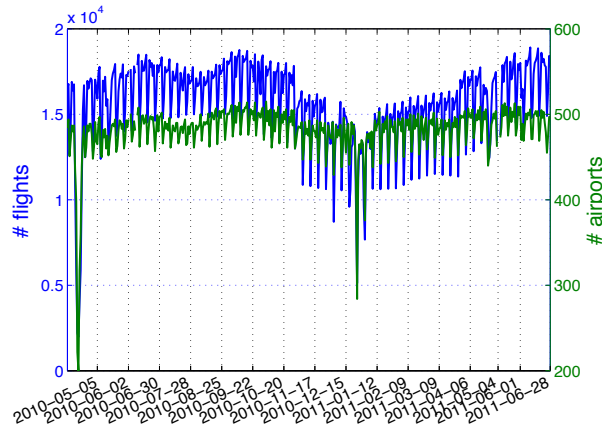


Figure 2. Number of flights (blue) and airports (green) in all the AIRACs of our database [333-348]. Some days in the database are missing in the original files. The dramatic drop in April 2010 is due to the volcano eruption in Iceland, when most of the european airspace was closed.

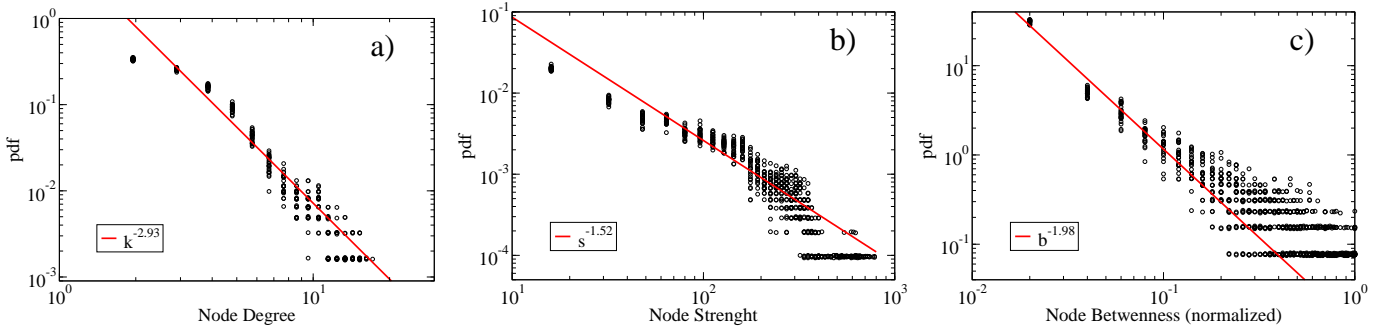


Figure 3. Probability density function of the nav-points degree (a), strength (b) and betweenness (c) according to the actual flight plans (M3 files).

usage (CDR - Conditional Routes). Under specific conditions these nav-points can be subsequently made available for civil usage, and therefore considered when using the realized flight trajectories.

As for the airport network, the degree and the strength pdf of the navigation points used by the planned trajectories shows a power-law decay, see Fig. 3, (a) and (b), as well as the betweenness centrality pdf, see Fig. 3, (c). By using the Hill estimator methodology one obtains that the exponent of the degree pdf, averaged over all AIRAC days is $\alpha_d = 2.93 \pm 0.06$ and the exponent of the strength pdf, averaged over all AIRAC days is $\alpha_s = 1.52 \pm 0.02$. Also in the case of the (local) navigation points network, we have performed a community search analysis by using the Blondel algorithm. A visualization of the organization of navigation points in communities is given in Fig. 4 for the actual nav-points local network on Monday 06/06/2011. A regional clusterization of nodes is clearly visible. We believe that this analysis might be relevant for the design of the optimal partitioning of the airspace in sectors. A comparison of sectors and communities within

the context of the navigation points network would be as relevant as a comparison between communities and FABs in the case of the airport network. This would anyway benefit from considering the nav-points network for different periods of the day, in order to investigate whether or not there exists an intraday dynamics of communities and how this compares with the fact that sectors are opened and closed in order to comply capacity needs.

IV. DEVIATIONS AND DELAYS

The second type of analysis we performed on the DDR dataset aims at identifying statistical regularities in the spatio-temporal deviations of flights between their planned (according to M1 files) and their actual (according to M3) 4D trajectories.

The aim of this analysis is manifold. First, it aims at finding statistical regularities describing the deviation of flights in order to understand their origin and their possible impact on the system. Second, it aims to introduce several possible metrics for delays, each able to capture some aspect of deviations. For lack of space, in this paper we will present results based on simple metrics in order to give an idea of our approach. We will not consider more complex metrics

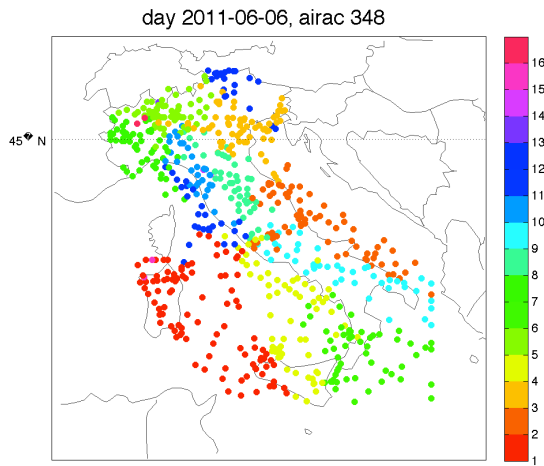


Figure 4. Map of nav-point local network in day 06/06/2011 of AIRAC 348 (d). The circles are the nodes of the nav-points, while the links are omitted for readability. The colors of the nodes identify the communities each node belongs to.

and the analysis of the relation between them. The third motivation behind our analysis is more operational and aims at creating maps of “hotspots” of airspace, i.e. points where deviations are more likely to occur. We believe these maps might be useful to identify criticalities in the system and to improve it.

Due to the different nature of deviations, we treat separately horizontal deviations, vertical deviations and delays. We present in the following the results of our analysis of the Italian airspace during the 27 days of AIRAC 348.

A. Horizontal deviations

We first consider horizontal deviations. Fig. 5 (a) gives a quantitative idea of how much the flights are deviated. More precisely, if l_{M1} is the length of the trajectory in the filed plan and l_{M3} the length of the actual trajectory, then Fig. 5 (a) shows the histogram of $(l_{M3} - l_{M1})/l_{M1}$. This figure displays a big peak around 0, which shows that many flights are only marginally deviated. However, a significant number of flights have a significant change in length, which proves that they do not follow their planned trajectory. Moreover, this graph is pretty symmetric, so the deviations lengthen the trajectories as much and as frequently as they shorten it. Obviously these two parts of the graph have very different causes.

Planned and actual trajectory can also be compared by considering the navigation points of the trajectory. Let n_{M1} and n_{M3} represent the numbers of nav-points crossed by a flight. Fig. 5 (b) shows the histogram of $n_{M3} - n_{M1}$ (in blue). This histogram is strikingly different from the one in Fig. 5 (a) because it is very asymmetric. In fact, flights can skip many nav-points during their trajectory, but rarely add

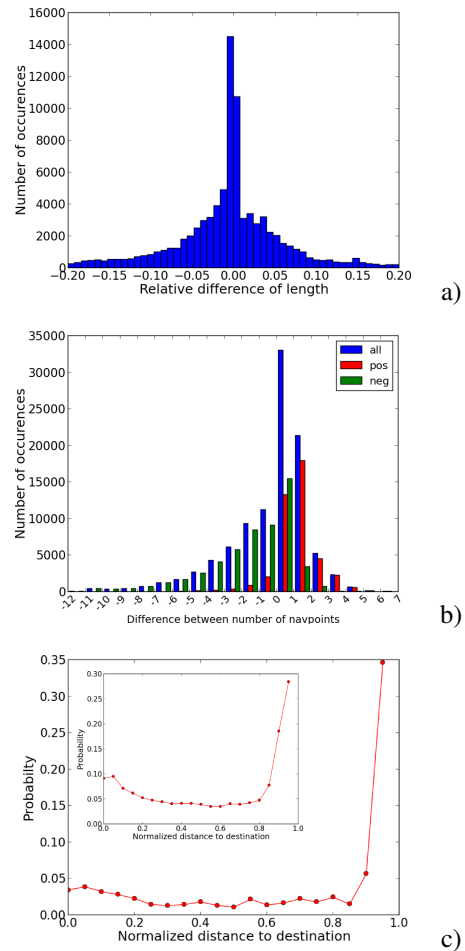


Figure 5. a) Histogram of the relative difference of length between the planned and the actual trajectories. b) Histograms of the difference in the number of nav-points in the planned and the actual trajectories. The blue bars are computed by considering all the flights, whereas red bars are computed only with flights having a longer (shorter) trajectory in the actual trajectory than in the planned one. c) Probability that the beginning of the first deviation of a flight occurs at some point of the trajectory. In abscissa, the distance to the start of the trajectory is renormalized between 0 and 1 by the total length. The probability does not start from 0 because trajectories are cut at the borders of the airspace. Inset: probability that the flight crosses a temporary point.

more than 3 nav-points. These portions of trajectories where the flight skips at least one nav-point are called “directs” and are usually given by air controllers when no safety issue is expected ahead. Note also that there is a large number of flights which are having only one nav-point more than expected: we will see why in the following. Finally, the colors (explained in the caption) indicates that skipping nav-points is typically associated with a shortening of the trajectory, even if some exceptions are present.

Fig. 5 (c) gives a more local information on where the deviations typically occur. It shows the probability that the first deviation occurs at a given point of the trajectory. As one can see, more than one third of the flights are deviated at the very end of the trajectory. The inset shows that in fact this

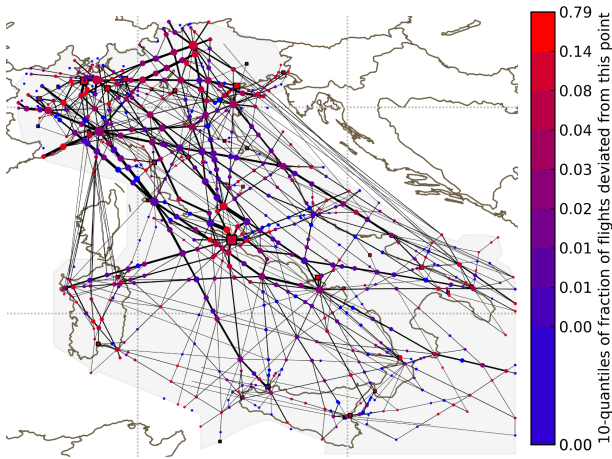


Figure 6. Image of the nav-point network. Each circle is a navigation point, the squares being the airports. Nav-points are linked if at least one flight passes from one to the other consecutively. The links are weighted by the number of flights passing from one to the other, represented by thickness on the image. The size of the node is proportional to its strength. Finally, the color codes the probability that a flight deviates from this node. There is one color for each decile of this quantity, so there is the same number of nodes of each color on the image. The network is computed with the planned trajectories (M1).

deviation occurs with one temporary point at the end of the trajectory. Thus, these deviations seem to be small refinements of the trajectories close to landing.

One might ask where are flights typically deviated? To answer this question, we create maps of the trajectory nav-point network (see Sec. III-B) attributing to each nav-point a score quantifying how frequently or how much a flight is deviated at this point. We can create maps for different deviation metrics. An example of this approach is shown in Fig. 6 where trajectory nav-points are colored according to the probability that a given flight is deviated from its planned trajectory when crossing this point.

As one can see, nav-points have very different probabilities of deviations, which shows that different nav-points have different roles in the nav-point network. This allows to identify hotspots in the nav-point network. For instance, nav-points close to big airports seem to have a higher probability of deviation. Moreover, while the majority of the points have a probability of generating a deviation below 14%, a small number of points have very high probabilities, up to 79%.

In conclusion, horizontal deviations are pretty frequent and allows a change in length of 4% on average. These deviations are pretty symmetric between positive and negative values, when one considers the length, while they are quite asymmetric, when one compares the number of nav-points crossed. Many deviations are actually directs or small refinements for landing. A small number of nav-points carry the most part of the deviations. As a consequence, points around airports are more likely to provoke deviations compared to the other nav-points.

B. Deviations in altitude

The vertical dimension of space is very different from the others for aircraft, because of the gravity and because of its much smaller scale. Hence, one can expect that changes in altitude appear very differently from changes in the horizontal plane. In Fig. 7 (a) we present the histograms of the average altitude of the segments (portion between two trajectory points) of all the flights extracted from the last filed flight plan (main panel) and from the actual flight (inset).

We observe that the two histograms are globally similar. This shape is dictated by geographical constraints (distance between airports) as well as by the Italian airspace's configuration. However, on a finer scale, the two distributions show significant differences. The M3 plot exhibits a much smoother curve than the M1, as well as an increase in the number of segments at low altitude. Since the companies build their initial flight plan on factors like fuel, mostly in an automated way, then the results are often similar for the same pairs of airports – or routes. Hence, the M1 distribution exhibits sharp peaks and holes. On the contrary, air controllers tend to relax the load on flight levels by changing the planned altitude. Hence, the altitudes are spreading, because flights are fleeing the most crowded flight levels. Since this spreading is small in magnitude, the global shape remains the same.

On the other side, the shape of the left part of the histogram undergoes a change which is not due to this relaxation, but is again related to Fig. 5 (c). Indeed, we saw that many flights were deviated at the end of their trajectory to refine the landing trajectory, typically by adding one point to their trajectory. Hence, in M3 trajectories many segments are created at low altitude and they can be observed in Fig. 7 (a). This conclusion is confirmed by the analysis of the *load* of a flight level, i.e. the total length of segments flown at a given flight level. Fig. 7 (b), shows the histogram of the load of actual trajectories and it can be seen that the peak observed in the inset of Fig. 7 (a), disappears. In fact, the load is monotonously increasing with the altitude, confirming our explanation above.

C. Temporal deviations: delays

Delay is the last dimension to consider for 4D trajectories, but is quite different from the others. In fact, whereas vertical or horizontal deviations cannot occur before the beginning of the flight, delay can. As a consequence, we define three types of delays for each flight:

- Departure Delay (DD): difference between the departure time in M3 and the departure time in M1.
- Arrival Delay (AD): difference between the arrival time in M3 and the arrival time in M1.
- En-Route Delay (ERD): difference between AD and DD.

These three types of delays are very different from each other, with different magnitudes. DD and AD are typically of 20 minutes, whereas ERD is usually under 5 minutes. They are also different because they have different causes. Whereas DD can be due to airport problems or network management, ERD can only be due to re-routing or variations of speed.

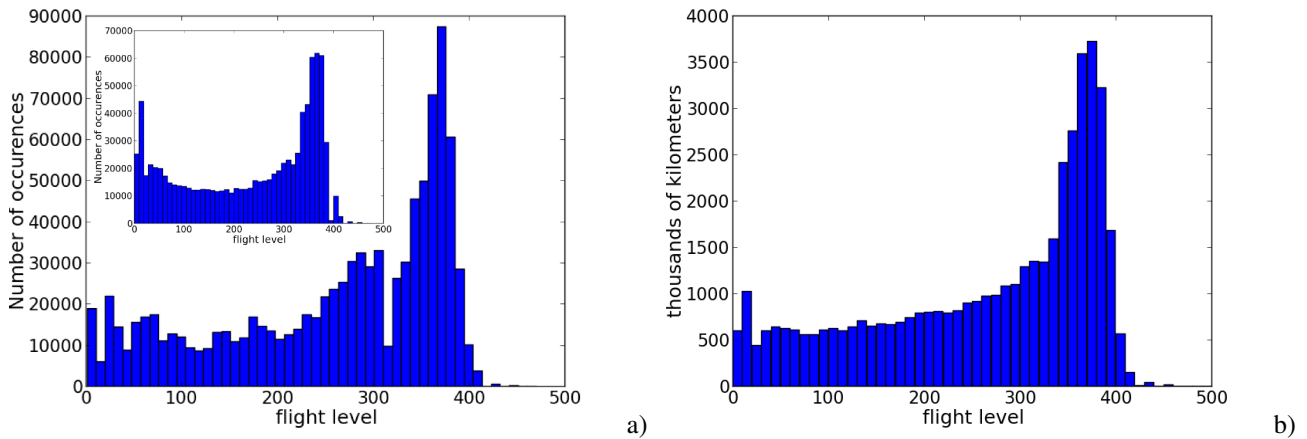


Figure 7. a) Histograms of the mean altitude of segments during the flights, in M1 (main panel) and M3 (inset) data. b) Measure of the load of each layer of altitude. The load is measured by computing the total length of segments flown at each altitude during the whole AIRAC cycle.

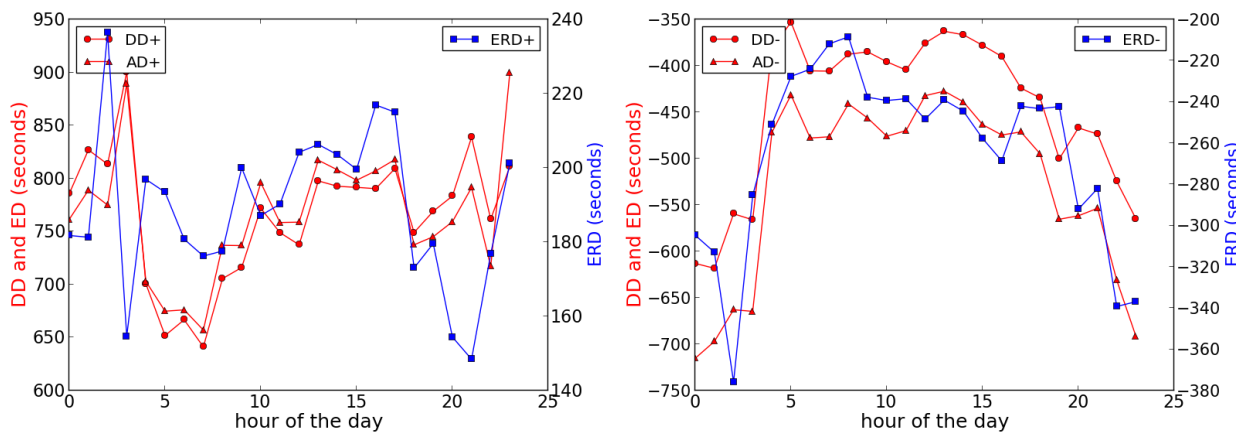


Figure 8. Evolution of Departure Delay (DD), En-Route Delay (ERD) and Arrival Delay (AD) during the day. The hour in abscissa is the departure hour for DD and ERD and the arrival time for AD. The left plot is computed only with positive values of delays, whereas the right one is computed only with negative values (colors online).

In Fig. 8 we present the variation of these delays during the day, and we consider separately positive values (left panel) and negative values (right panel) of delays for each flight. Despite being quite different in nature, the three quantities display a roughly similar pattern in each graph, which suggests common causes.

On the other hand, the variations during the day are very different for the positive and the negative parts of the delays, *i.e.* for early flights and delayed flights. In fact the negative part shows a strong daily seasonality, whereas the positive part does not display strong variations during the day. This can be compared to the daily seasonality of traffic intensity during the day. Indeed, we see that flights tend to be early at the very beginning and at the end of the day. This can be due to the fact that controllers are more likely to give directs to pilots, which shorten the trajectory, during the hours where the traffic is low and easy to manage. On the other hand, delayed flights seem to be quite insensitive to the traffic, since the plots

are almost flat, although it seems also that the delays are slightly increasing during the day. One may want to attribute this phenomenon to the reaction delay – flights may be delayed because their aircraft was used by a previous flight and this one was delayed. However, we can not be sure about this. Indeed, we have only access to M1, which is the last filed flight plan, and not the “M0”, which would be the real initial flight plan. Hence, reaction delay (M3 - M0) can be absorbed by the new flight plan M1. How many companies are doing this is still unclear to us.

V. CONCLUSIONS AND FUTURE WORK

We have described a few statistical tools able to capture relevant information about the Air Traffic System. In the first part of the paper we have shown how community detection on airports and nav-points networks can be relevant for the design of the optimal partitioning of the airspace in FABs. In the second part of the paper we have shown how basic statistical

analysis of appropriate proxies may reveal important features of the system.

The analysis is still ongoing and it is too early to discuss any finding and improvement actions related to the ATM system. Our expectation is to obtain the following insights from the analyses discussed in this paper.

- As for the community detection analysis, the different communities will be identified and compared to identify seasonal variations and communities associated to the different types of flights, for example by analyzing the communities generated by flights belonging to the same market segment. The end goal of this analysis is to identify which group of airports (and group of nav-points) are functionally connected, potentially resulting in dynamic FABs, or in ad hoc connections between one airport and a specific FAB.
- The analyses on deviations presented in the second part of the paper will be used to carry out a case study by comparing a set of key nav-points in the Italian airspace. The aim of this case study is to start from an operational taxonomy of key nav-points and describe it by means of a set of statistical measurements. The end goal is to reverse-engineer the process, so to be able to use these measures to identify key nav-points across Europe, and characterize them in different taxonomy types. This could drive airspace design intervention by identifying critical bottlenecks, or crossings, by data mining, and not only relying on experts input.

A research gap still exists between the results obtained in the academic community and the ATM world. The next phase of our research is to bridge this gap, at least partially, by iteratively discussing our results with ATM domain experts.

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