

# Adaptative air traffic network: statistical regularities in air traffic management

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**Abstract**—Starting from traffic data on flights trajectories – planned and actual ones – in Europe, we build a navigation point network. We study this network which exhibits different features for different European countries. In particular, some countries use a high number of navpoints, facilitating the planning of the flight plan by air companies at the cost of higher concentrations of traffic in few nodes. Making use of the deviations from the planned trajectories, we find that once again different countries have different control procedures with respect to traffic management. Interestingly, we find that some countries tend to make more deviations when the traffic conditions are low. Moreover, they tend to concentrate the deviations in a few number of nodes, especially during daytime. Finally, the position of these key navigation points are sometimes stable over the days, which shows a consistent use of some navpoint for the same kind of rerouting operations.

**Network science – statistical model – navigation point network – traffic flow management**

## I. INTRODUCTION

The structure of Air Traffic Management (ATM) as it is known today will undergo major changes both in Europe (the SESAR program) and in the USA (the NextGen program). These initiatives aim to radically change the existing transportation system, by intervening on technologies, procedures, role of human actors and organizational aspects.

One of the key innovation drivers of both SESAR and NextGen is the shift from a structured route network to a trajectory-based network, where users (i.e. single flights) will be able to fly their selected trajectory, instead of following a predetermined route grid (made of airways and navigation points) across the sky [1], [2]. Trajectory-based operations will increase the flexible use of the airspace, but they will not result in a totally unstructured airspace. It is reasonable to expect that most characteristics of the current situation (e.g. bottlenecks, main traffic flows and crossing points, boundary points, etc.) will also emerge in the future scenario, resulting in a different structure, probably a highly flexible and changing

one. Another key organization change is the progressive integration of the European airspace into Functional Airspace Blocks (FABs). The Commission Implementing Regulation (EU) No 390/2013 states that performance has to be monitored at the level of FABs, also indicating a set of Key Performance Indicators (KPI) in the Annex 1 [3].

The increase of the complexity degree will cause changes that will be hardly understood by relying on the analysis of single elements and will instead require the understanding of how all the new elements will interact together. The scenario envisioned by SESAR and NextGen entails a system with a bottom-up organisation (the flight structure emerges out of the single trajectories) and increased interconnections (less predefined boundary zones, information being shared by all the actors). Compared to the fixed route scenario, the structure and properties of the future aviation network system will emerge from the interactions among many elements, among which we may quote: users' decisions and actions (i.e. pilots and air traffic controllers), trajectory-based operations, organizational changes, and the temporary deployment of different arrays of resources/tools to manage specific situations, weather and other environmental factors.

The research topic addressed by this contribution concerns the identification of analysis methods to capture the above describe phenomena, i.e. emerging network properties. This contribution focuses on hidden statistical patterns like time fluctuations or local operational practices. The aim of this work is to be able to:

- Monitor differences between the planned use of the network and its actual use, as determined by either controllers or pilots,
- Employ methods that can capture system-level regularities, but that can provide entry points to “drill down” and identify the local causes creating such patterns. The identification in time and space of outliers and unexpected patterns would be the typical example of such an appli-

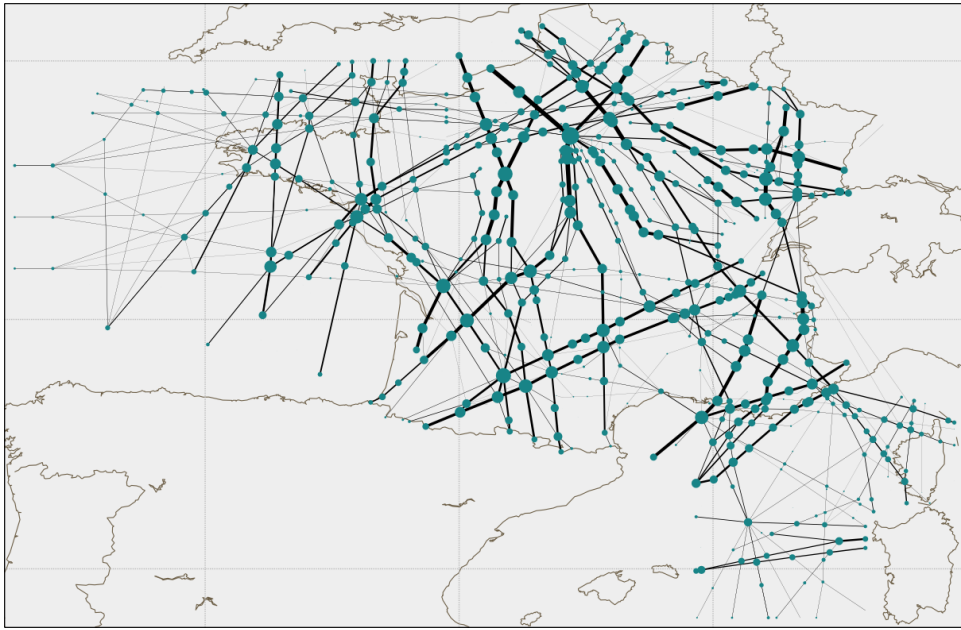


Fig. 1. Navigation point network for French airspace. The nodes are navigation points, with a size proportional to their strength (local traffic). Edges are drawn between nodes linked by at least one flight. The width of the edge is proportional to the number of flights in the time interval. One month of data has been used to generate this network. Trajectories have been cut below flight level 240.

cation.

A further requirement for this study is to develop methods that can be applied to the processing of large amounts of data. The ATM system is a typical multi-layer, multi-scale system, so there is a requirement for analysis methods that can be applied across these layers.

To deal with this challenge, in the last years many papers have applied network science to air traffic issues (for a recent review, see [4]). Many studies have focused on the topological aspect of the airport network [5]–[12], but the same techniques can be used to study subjects more related to air traffic management [13]. In particular, one can consider different elements of the airspace like sectors and navigation points and build some networks which present interesting features [14]. On the contrary of the airport network, these networks are more related to air traffic management and safety. In this communication, we present a study of the navigation point network. Navigation points are fixed two dimensional points in the airspace specified by a latitude and a longitude.

In the following, we will highlight the main features of the navigation point network based on planned traffic data and how the actual trajectories are modified by the controllers in relationship with local traffic.

## II. DATA & METHODS

In order to do this, we used for this communication a set of data composed by all flights crossing the European airspace during 1 month. For each flight, we have access to the “last filed flight plan” and to the radar-updated trajectory. The first one is prepared by the air company a few hours before departure, whereas the second one can be thought as

the “real” trajectory actually flown by the aircraft, up to a finite spatial and temporal resolution. The flight plan is typically a sequence of waypoints, or navigation points – or navpoints – as we call them in the following, together with time stamps and altitudes. This data allows to rebuild all the trajectories in four dimensions.

Moreover, we have access to data concerning the structure of the airspace. We can rebuild in three dimensions the geometrical extent of the different hierarchical levels of the airspace, including the sectors. In this communication, we mainly use the two dimensional boundaries of national airspace.

In the following, we define a “traffic network” of navigation points by:

- a set of nodes: navigation points crossed by a set of flights in a certain area (like the Italian national airspace),
- a set of edges between nodes: two nodes are attached if one flight has flown from one to the other during the time interval. We put a weight on the link corresponding to the number of flights flying this segment during the time window.

This traffic network is as much a product of the traffic as it is of the airspace structure.

Note that in principle we can build two kinds of traffic network: one based on the planned trajectories and the other one based on the updated trajectories. In the following, we consider only the first one and we study the difference between planned and actual trajectories in relationship with the characteristics of the planned network.

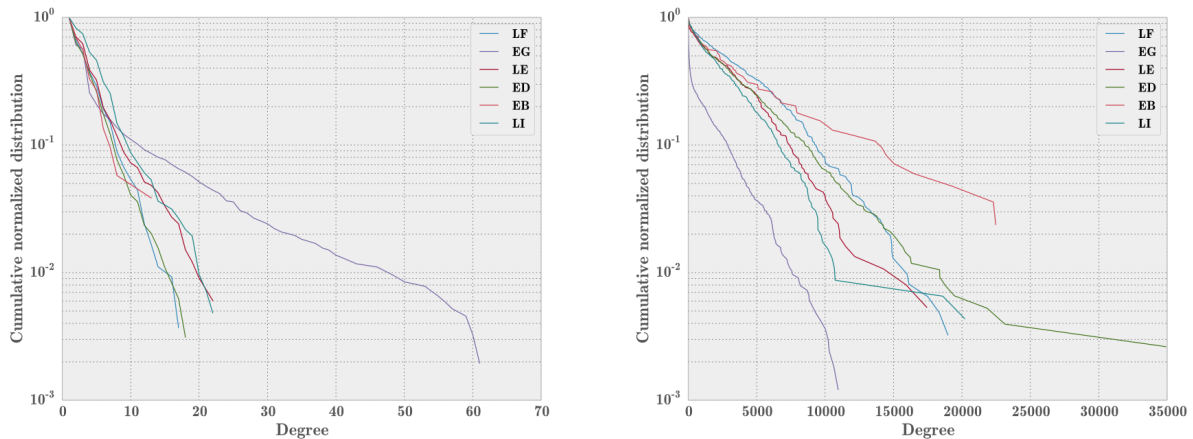


Fig. 2. Left panel: cumulative and normalized distributions of degree for different countries. Right panel: cumulative and normalized distributions of strength for different countries.

### III. NETWORK CHARACTERISTICS

This network is represented on figure 1 for France. It can be studied under with the tools and methodologies of network theory. In particular, we are interested in the “degree”, which is, for a given node, the number of its neighbours, and the strength, which is the sum of the weights of the edges attached to the node, hence the traffic flowing through the node. The degree, on the other hand, can be thought as a measure of the complexity of the node, since a high degree implies many intersecting trajectories at the same point.

For further analysis, we define some non-standard metrics on this network, which are related to the differences between the planned and actual trajectories. Specifically, for each flight, we record the last common navigation point between planned and actual trajectory. At this point, a “fork” happens: the flight should have gone to a given node according to the flight plan, but went to another one for some reason. By counting the number of flights which are deviated from this point with respect the total number of flights flying through it in the time period (the strength), we have an idea of how much the navigation point is a “source” of disturbances for the traffic. We call this metric “fork”. It varies between 0 and 1 and is attached to a particular node, just like the degree and the strength.

All the following results have been obtained with a filter on the data which roughly selects only commercial flights and cuts their trajectories below flight level 240 (24000 feet) – keeping only the en-route phase. In the following, we focus on six countries: France (ICAO code LF), Italy (LI), United Kingdom (EG), Spain (LE), Germany (ED), and Belgium (EB).

In this section we briefly summarize the main features of the traffic network and make a comparison between different countries. Here we build the traffic networks by considering the whole month of data, from the 6th of May 2010 to the 2nd of June 2010. On figure 2, we show the distributions

of degree and strength for each country. All of them are displaying exponential behavior, which signs the existence of a typical degree or strength and a fairly small number of high degree/strength nodes. In other words, it means that network does not have any “hubs” which support most of the traffic while most of the other nodes are supporting very little traffic. In this network, the traffic is quite well spread between nodes – navigation points. This ultimately comes from a requirement from the airspace managers which enforce the fact that a flight cannot plan to use a “shortcut” between two faraway points, but instead has to go through (nearly) all intermediate navigation points.

Even if the distributions are fairly similar for all countries, there are some interesting differences. The relevant ones are summarized in table I. Interestingly, some countries seem to have a preference for a high number of navpoints (France for instance), reducing the mean degree and hence the local complexity at each node<sup>1</sup>. This could be due to a decision taken to allow more navigation points as well as some geographical peculiarities.

The second striking feature is the strength of the nodes. Looking at the table I, it seems that UK is spreading its traffic on a much higher number of nodes than other countries like France, hence having a much lower local traffic at individual nodes (almost one fifth of the traffic in Belgium). This may be due to the airspace design strategy, but can also be influenced by geographical constraints. For instance, Belgium has a limited geographical space available which leads to a few number of nodes and hence a high traffic per node.

These differences of structure in the networks have a very important impact on the air companies. Even without mentioning the difficulty to find a valid route for a flight, on which we do not have any information, the efficiency of the trajectories depends on the network. The “efficiency” of the trajectory is defined here by the length of the best trajectory

<sup>1</sup>But obviously not the overall complexity.

Country (ICAO code)	Nodes	Deg.	Max Deg.	Str.	Max Str.	Efficiency
Italy (LI)	468	5.2	24	2586	22757	0.94
France (LF)	663	3.8	22	3590	25828	0.954
UK (EG)	1754	5.2	62	732	12087	0.955
Spain (LE)	394	4.3	29	2780	21235	0.947
Germany (ED)	771	3.8	21	3242	36075	0.938
Belgium (EB)	85	3.0	17	4320	25900	0.98

TABLE I

TOTAL NUMBER OF NODES, AVERAGE DEGREE, MAXIMUM DEGREE, AVERAGE STRENGTH, AND MAXIMUM STRENGTH FOR NETWORKS OF DIFFERENT COUNTRIES. HERE WE BUILT THE NETWORK BY USING A WHOLE MONTH OF DATA FOR EACH (MORE PRECISELY AN AIRAC CYCLE, I.E. 28 DAYS).

[16] – the straight line, or the grand circle more precisely – over the actual length of the flight. For instance, without considering the altitude, an efficiency of 95% means that the consumption of fuel could be lowered by roughly 5% if the straight line was to be taken. Hence, the efficiency of the trajectories, directly linked to the structure of the network, is of tremendous importance for air companies. As one can see, the efficiency in different countries can vary significantly, from 93.8% to 98%.

All these results have been obtained with the planned traffic network. Thus, they are intrinsic to the strategic phase of air management, where the air navigation service providers (ANSPs) deploy different strategies to handle the traffic based on past data and air companies use the network as it is structured. In the following section, we are interested in the way in which the controllers are actually changing the trajectories in response to changing conditions of air traffic. For this, we will compare for each flight the planned trajectory and the actual one.

#### IV. DEVIATIONS

##### A. Aggregated values

In this section, we use the metrics we already presented in section II. In particular, in the horizontal plane we record for each flight the last common navpoint between the planned and actual trajectories. This gives a measure of how much a given navigation point is a “source” of disturbances. In table II, we report some values for different airspaces.

The first value is the absolute relative difference between the length of the actual trajectory and the real one. The absolute values are significant for all of them (more than 9%) – denoting an overall change of efficiency which can be important to air companies – and some differences appear between countries. More specifically, trajectories in Spain and Germany seem to undergo some pretty heavy deviations, above 15% in relative terms, whereas controllers in France modifies much less the length of the trajectories. Note also that the non-absolute values are usually positive (non displayed here), which means that the real trajectory is longer than the planned one, except for Italy. This reveals also different practices in the air traffic management, as Italian controllers seem to give much more “directs” than the others. As a consequence, the average delay is very negative for Italy, whereas other countries have a better punctuality – meaning they tend to adhere to the flight plan – like UK, which has less than a tenth

of second of delay per kilometre. Germany is undergoing the heaviest negative delay, close to one second per kilometre and is also experiencing a very poor predictability – meaning that delay can vary a lot between flights – superior to 4 seconds per kilometre. On the other hand, as expected from the relative difference in length, France has a good predictability compared to other countries. Note also the case of Spain, which despite having a big difference in length of trajectories, has a quite good predictability. This could be due to systematic errors in the planning phase, for instance because the CFMU (Central Flow Management Unit) is not estimating the velocity properly in this area.

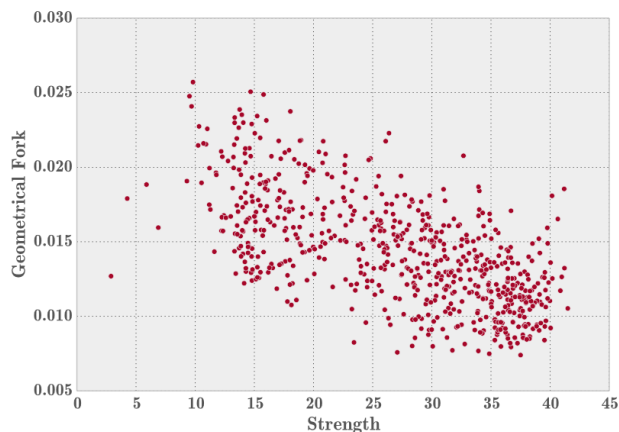


Fig. 3. Scatter plots of fork against strength (local traffic) for every navpoints of France hour by hour.

##### B. Daily pattern

We are now interested in how these measures vary during the day with different traffic conditions, or, in other words, how controllers react to traffic.

For this, we record hour by hour the “fork” value for each navpoint as well as the other metrics (degree, strength). We present on figure 3 a scatter plot between fork and strength – representing the local traffic at the node. We clearly see that there is a correlation between fork and the traffic, mainly due to the intra-day pattern. Surprisingly, this correlation is negative, which means that higher traffic conditions imply fewer deviations from the planned trajectory. This might be counter-intuitive because higher conditions are usually associated to

Country (ICAO code)	$ l_r - l_p /l_p$	fork	En-route delay	$\Delta$ En-route delay
Italy (LI)	0.13	0.012	-0.69	2.50
France (LF)	0.09	0.014	-0.21	1.58
UK (EG)	0.15	0.018	-0.04	2.03
Spain (LE)	0.18	0.010	-0.23	1.86
Germany (ED)	0.16	0.013	-0.73	4.22
Belgium (EB)	0.13	0.014	-0.59	3.40

TABLE II

THIS TABLE PRESENTS DIFFERENT METRICS RELATED TO HOW CONTROLLERS MANAGE FLIGHTS. FROM LEFT TO RIGHT: RELATIVE ABSOLUTE DIFFERENCE OF LENGTH OF TRAJECTORIES BETWEEN PLANNED AND REAL TRAJECTORIES, AVERAGE FRACTION OF FLIGHTS DEVIATED AT NAVPOINTS, AVERAGE EN-ROUTE DELAY IN SECONDS PER KILOMETRE OF FLIGHT, STANDARD DEVIATION OF DELAY IN SECONDS PER KILOMETRE OF FLIGHT.

higher risks of collisions, which turns into further controllers' actions. It seems that the contrary is happening, and the most obvious reason would be that controllers actually stabilize the horizontal trajectories during high traffic, while they give more directs when the low traffic creates less constraints on their actions.

It is also fruitful to compare different countries. Indeed, as reported in table III, different countries display different values of the correlation coefficients. This shows that they have different responses to changing traffic conditions – or that the initial structure of the network leads to different way of controlling. Hence, the analysis of the deviations reveal the different operational practices which exists in Europe concerning traffic management. Enriching these data with follow-up studies – concerning for instance safety – could give interesting insights on the underlying mechanisms at play.

Country	Pearson corr. coeff.
LI	-0.01
LF	-0.64
EG	-0.68
LE	-0.36
ED	-0.56
EB	0.036

TABLE III

PEARSON CORRELATION COEFFICIENTS BETWEEN TRAFFIC AND "FORK" FOR DIFFERENT COUNTRIES.

### C. Over-expressed nodes

The previous results lead us to think that the controllers react in a non-trivial way to traffic, although it is not clear from aggregated values like the previous ones if some portions of the airspace play a major role in determining these patterns. In order to investigate this point, we use a statistical model to reveal which are the nodes which support the heaviest deviations with respect to their local planned traffic.

For this, we consider a null hypothesis whose statistical predictions can be expressed in terms of the hypergeometric distribution. We call  $N = \sum_{i=0}^{N_f} N_i^{nvp}$  where  $N_f$  is the number of the active flights in the considered time-window,  $N_i^{nvp}$  is the number of navpoints crossed by the  $i$ -th aircraft in the considered time interval and  $N_r$  the total number of rerouting operations (fork).

Hence, knowing that  $n_f$  flights crossed a given navpoint, the probability to have  $n_r$  rerouting operations (fork) by chance at this navpoint is given by the hypergeometric distribution:

$$P(n_r, n_f, N_r, N) = H(n_r | n_f, N_r, N) = \frac{\binom{N_r}{n_r} \binom{N - N_r}{n_f - n_r}}{\binom{N}{n_f}}.$$

In other words, all flights have an equal probability to be deviated at any navigation point. Hence, by setting a p-value, we are able to test the null hypothesis of randomness according to which the number of flights deviated at any node is following the hypergeometric distribution. The nodes which reject the null hypothesis are special nodes that we call "overexpressed": we do not expect to have such a high number of flights deviated at this point only by chance. As p-value, we choose 1%, which is considered as conservative, and that we need to correct since we are doing multiple tests. Indeed, performing multiple statistical tests might yield high numbers of false positives. In order to correct this, we choose the Bonferroni correction, which is the most conservative one (see [15] for other possible corrections), i.e. we use  $1\%/N_{nvps}$  for the p-value, where  $N_{nvps}$  is the total number of navigation points in the area at this time – thus, the number of tests.

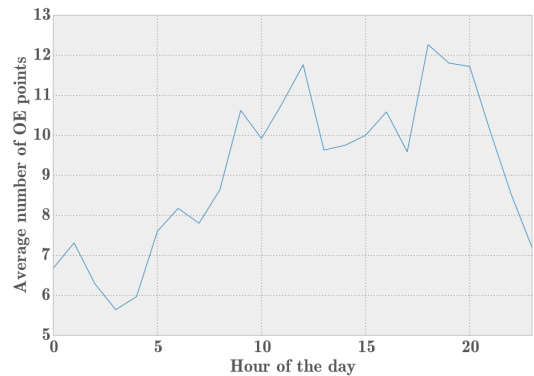


Fig. 4. Number of overexpressed nodes in the Italian airspace during the different hours of the day.

Since we perform the analysis hour by hour, the number and places of overexpressed nodes are changing over time. Figure 4 shows the number of overexpressed nodes during the day. The first remark is that *there are* some overexpressed nodes,



i.e. some nodes whose deviations cannot be understood by chance (the null model). These navpoints can be special for two non-independent reasons:

- either because the traffic is naturally very concentrated in some areas,
- or because the controllers themselves direct the traffic on these navpoints for some specific operational reason.

The exact reason cannot be revealed with the data we have, since we lack the exact actions of the controllers which lead to this situation. However, identifying these special points could be the starting point to carry out in-depth studies, by performing a task analysis or by interviewing experts.

Another insight on the behaviour of air controllers is presented in figure 5. We show on this figure the distribution of fork at different hours of the day. Strikingly, the patterns are very similar for hours during the day and for hours during the night. More precisely, we find that during the night, controllers are using less nodes, with an overall value of deviations, including the maximum, but no “special nodes”. On the contrary, during the day, controllers use more navpoints and spread the deviations on more nodes, but they keep a few nodes which bears high deviations with respect to their traffic.

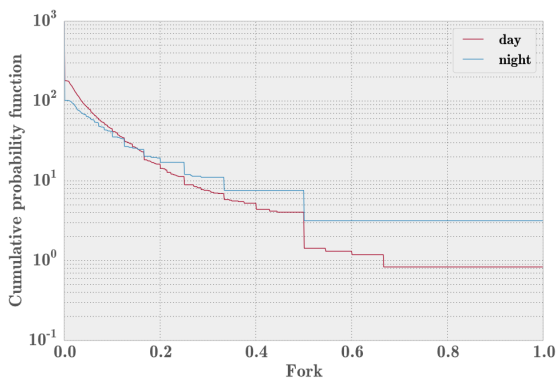


Fig. 5. Semilog plot of cumulative distributions of fork in the French airspace gathering the values during during the day (7am–11pm) and during the night. A Kolmogorov-Smirnov test indicates that the probability that both samples (night and day) are drawn from the same distribution is around  $10^{-12}$ .

At this point, it is still not clear if the controllers use always the same special points which concentrate the deviations. To investigate this, we use the plot of figure 6. On this figure, each vertical line represents a distinct navigation point, and the y-axis represents the time of the day. The color codes the frequency in which the given node is overexpressed at this given hour for all days of the dataset. When a red dot appears, it means that this navpoint is always overexpressed at this hour. If a straight red vertical line appears, it means that this navigation point consistently exhibited a high rate of deviations for several hours throughout the days. As one can see, there are half a dozen of lines. Some of these lines are interrupted during the night, while there are a couple of lines which are only present during the night. This means that controllers do not choose the same “special nodes” through

the day. Hence, this diagram is a snapshot of the (over-)usage of some navigation points.

Some of these overexpressed navpoints are shown on figure 7. Hence, this procedure is able to produce maps which can be analysed by experts in order to detect potential issues in the design of the airspace.

## V. CONCLUSION

By using only traffic, we revealed some important features about:

- how the airspace is designed and used in the strategic phase,
- how the trajectories are modified by controllers.

Concerning the first point, we saw that different countries have different characteristics concerning the navigation point network. This choice impacts the local traffic and complexity at each navigation point, which will impact in return the controllers’ workload. On the other hand, these choices have also an impact on the efficiency of the trajectories, i.e. how straight they are, which in turn impacts the air companies.

We saw that, maybe because of the previous differences, the controllers in different countries have different behaviours. They tend to modify the trajectories in different ways, thus impacting the punctuality and the predictability of flights as well as the fuel consumption. More importantly, they react differently to traffic. Some countries tend to decrease the number of deviations when the traffic is high, whereas others are less sensitive to traffic.

We showed that the controllers tend to modify the spatial distributions of deviations during nights and days. In particular, at night, they tend to use fewer nodes with a higher number of deviations. On the other hand, during day, they use more navigation points but choose among them some nodes which will support most of the deviations. These “overexpressed” nodes – in terms of deviations – can be spatially and temporally tracked. In particular, some of them seem to be used during long periods of times, denoting special conditions of traffic or special rerouting operations. These special points can be spotted spatially and subject to more in-depth analysis.

The analyses presented in this work may bring benefits to the ATM community by supporting a data-driven approach to monitoring and managing the airspace. Network of Operations and ANSPs may use them to detect hidden problems, or regularities over different time periods (from one single day to months, or a whole year).

In particular, the analysis of correlation between safety occurrences and network metrics [17] has been recognized by ATM safety experts (ENAV and MUAC Safety teams, EUROCONTROL DNM Safety Unit) as already mature. It can be proposed as a tool for Safety Monitoring [18], [19] that could already be introduced into operations, to identify and investigate the most dangerous areas in the airspace.

## ACKNOWLEDGEMENTS

The authors thank M. Ducci for fruitful discussions.

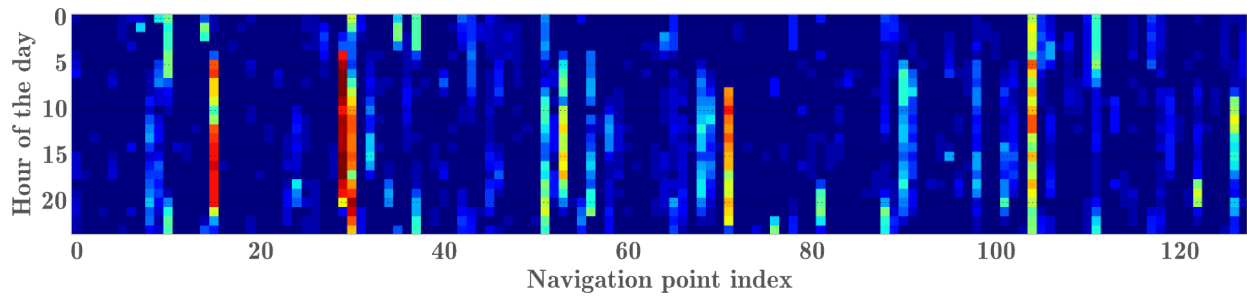


Fig. 6. Stability diagram of overexpressed navpoints for the French airspace. Each vertical line represents a different navigation point, the y-axis represents the time of the day and the color is the frequency of the overexpression of the node during the time interval conditioned on the hour. 1 (red) means that the point is *always* overexpressed at this hour during the 28 days of the time interval, 0 (blue) means that it is never overexpressed.

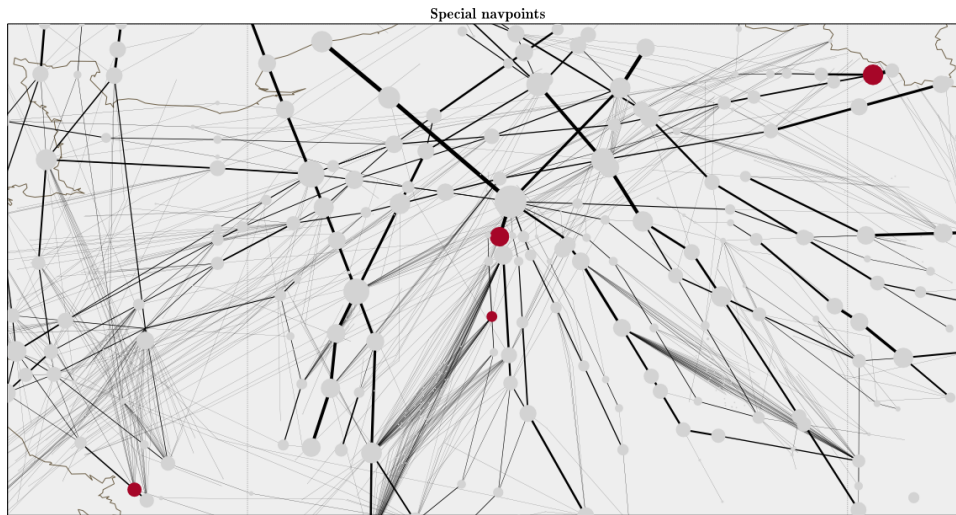


Fig. 7. Zoom on the French airspace displaying the most stable navpoints (in red) as discovered by the plot of figure 6. We display the network based on the actual trajectories, only for one day of data (6th of May). Note that some of the stable points are clearly the source of many very small edges, which are part of some deviations from the planned trajectories.

This work was co-financed by EUROCONTROL on behalf of the SESAR Joint Undertaking in the context of SESAR Work Package E project ELSA “Empirically grounded agent based model for the future ATM scenario”.

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## BIOGRAPHIES

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