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A micro view to en-route delays

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Abstract—**The analysis and characterization of delays is one of the most important research topics in ATM, mainly due to their implications in the cost-efficiency and safety of the system. In spite of this, little attention has been devoted to the assessment and study of non-ATFM delays, and specifically of en-route delays. In this contribution, we present a methodology for comparing the planned and real trajectories of a flight, aimed at identifying those events generating both positive and negative delays. This methodology is then applied to an historical data set representing flights crossing the European airspace during several key days of 2011. Among the results obtained, of special relevance are the characterization of the resilience of the European ATM system, measured by the amount of delays generated and absorbed in en-route segments; and the geographical distribution of events, which is characterized by a high heterogeneity. From a more general perspective, this methodology would allow shedding light on the mechanisms involved in the appearance of en-route delays, thus enabling a better systemic performance.**

Keywords-en-route delays; resilience; performance metrics; data science

I. Introduction

The analysis of the causes beyond the appearance and propagation of delays is one of the major topics inside Air Transport Management research. Implications of delays are far-reaching: in terms of costs, both for the airlines and the passengers [1,2], and of safety, especially when delays are not handled through ground programs [3]. Most of the research works have been focused on the study of two phenomena: the generation of delays due to Air Traffic Flow Management regulations, as the ones applied in Europe to cope with capacity and demand imbalances, both because of airports [4] and airspace [5] limited capacity; and the propagation of delays, in which one flight is delayed as a consequence of the late arrival of the preceding flight, an effect also known as "reactionary delay" [6,7].

Significant less attention has been devoted to the study of the mechanisms governing the generation and absorption of delays in the en-route phase. Back in year 2000, EUROCONTROL firstly recognized that non-ATFM delays were not properly understood, and that:

> *"... there is insufficient reliable data to enable the causes, locations and origins of all air transport delays to be clearly identified and analysed."* [8]

"en-route delay statistics and causal information" were then explicitly included in the list of areas that would require improvements in the future [9]. Nevertheless, the last CODA report on delays still does not include such an analysis, with en-route delays being simply represented as an average "Delay Difference Indicator" [10].

This lack of research on en-route delays may be due to the complexity associated with their assessment and analysis. Specifically, their analysis presents both theoretical and computation challenges. First, it is necessary to compare expected and executed trajectories, in order to reliably understand the place where they generate, and their evolution through time. Second, one ought to devise ways for scaling such analysis to handle the thousands of flights daily crossing the European airspace, thus for analyzing huge amount of data.

In this contribution, we make a first step towards the understanding of en-route delays, by presenting a computational framework for their assessment in historical data. Specifically, by comparing planned and executed (radar) trajectories, we show how it is possible to detect all delay-generating events, *i.e.* events that affect the delay of a flight, both in a positive and negative way. This requires merging different disciplines, *e.g.* data science [11] and statistics [12]. Such methodology is then used for tackling specific aspects of the ATM system, like its resilience and its evolution through spatial and temporal dimensions.

This contribution is organized as follows. Section II presents the computational algorithms behind the identification of delay-generating events from planned and real aircraft trajectories. Afterwards, Section III reports on the application of such framework to an historical data set representing European flights in 2011, and presents some initial analyses that the framework enables. Finally, Section IV draws some final conclusions and future lines of research.

II. Extracting delay information from aircraft trajectories

In this Section, we present a general methodology for extracting the delay-generating events that have affected the flight of a given aircraft, provided both planned and real (*e.g.*

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Algorithm: Event Identification Algorithm

```
1:  def PlannedTrajectory(i∈ I,x,y);
2:  def RealTrajectory(j∈ J,x,y);
3:        RealTrajectory(:,1) = RealTrajectory(:,1) –
RealTrajectory(1,1) + PlannedTrajectory(1,1);
          % same time report for first observation
4:        interpolation( k ∈ I ∪ J , PlannedTrajectory);
5:        interpolation( k ∈ I ∪ J , RealTrajectory);
6:        conversion (latitude, longitude) to distance;
7:  def PlannedDistanceToArrival ;
8:  def RealDistanceToArrival ;
9:  def  DifferenceDistance ;
10:def  D = Derivative(DifferenceDistance) ;
11:def  D = MovingAverage(D) ;
12:     #PositiveEvent = function of (Threshold >0, D)
13:     c = count( intersection(Threshold, D) )
14:     if c mod 2 = 1
15:         #PositiveEvent = ( c + 1 ) / 2
16:     else
17:         #PositiveEvent = c  / 2
18:     end
19:    #NegativeEvent = function of (Threshold <0, D)
20:    c = count( intersection(Threshold, D) )
21:    if c mod 2 = 1
22:       #NegativeEvent = ( c + 1 ) / 2
23:    else
24:       #NegativeEvent = c  / 2
25:    end
```

Figure 1. Pseudo-code of the methodology for assessing the presence of delay-generating events. Refer to the main text for further details.

radar track) trajectories are available. By "delay-generating events", we hereby refer to any event that has supposed a change in the course of an aircraft with respect to the planned trajectory. They can be both *positive*, *i.e.* when they introduce an unexpected delay, and *negative*, *e.g.* when an ATC controller assigns a direct route that reduces the travel time[1].

Such methodology is composed of three parts:

1. Obtain synchronized planned and real trajectories.
2. Calculate the evolution of the distance to destination.
3. Select events in which the derivative of the distance goes above (or below) a given threshold.

A pseudo-code of the methodology is presented in Fig. 1.

As a first step, it is necessary to address the fact that the planned and real trajectories of a flight may not be synchronized, *i.e.* the planned and real position is not reported at the same time, nor with the same frequency. It is thus necessary to *synchronize* them, that is, obtain a set of positions corresponding to the same time steps. Both planned and real

[1] *Positive* and *negative* thus refer to the delay, and not to the benefits/problems generated.

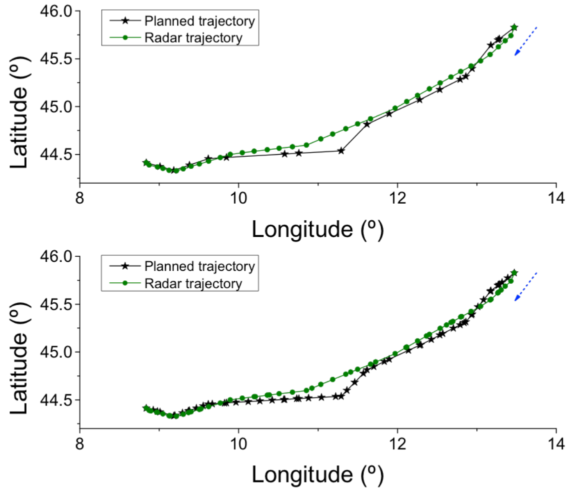

Figure 2. Example of a trajectory synchronization process. The original planned and real trajectories (top panel) have been interpolated, in order to guarantee that a point in one of them always correspond to a point in the other. See main text for further explanations.

2D trajectories[2] are then interpolated, in order to complete the positions that are respectively missing, thus enabling a direct position comparisons (see lines 4 and 5 of the algorithm in Fig. 1). Specifically, each aircraft trajectory, both planned and real, can be written as a vector with m components:

$$f_l^j = [(i_1, x_1^j, y_1^j)^{(l)}, (i_2, x_2^j, y_2^j)^{(l)}, \dots, (i_m, x_m^j, y_m^j)^{(l)}], \quad (1)$$

being (i_k, x_k, y_k) the time stamp and position of aircraft l at observation point k. f_l^j encodes the planned and real position of the aircraft l respectively when $j = 1$ and $j = 2$. Thanks to this first step, the vector length m (*i.e.* the number of observations available) can vary across flights, but is constant across the planned and real trajectories of a single flight. Furthermore, all the $\{i\}_k$ are the same for $j = [1, 2]$. Fig. 2 illustrates the process for a single flight, where the top and bottom panels respectively represent the two original 2D trajectories, and the trajectories after the interpolation. It can be appreciated how both the planned and real interpolated trajectories now include new points, each one of them corresponding to a symmetric point in the other route.

The second step requires converting the position of the aircraft, as obtained in (1), into an absolute measure. It should be noticed that the position of an aircraft and its deviation from the expected trajectory are not absolute measures, in that a deviation may be beneficial or negative in terms of delay, and that no *a priori* rule can be used to discern between both situations. Nevertheless, it is straightforward to realize that a deviation that implies an increase (or a reduction) of the distance to the flight destination is connected to a positive (respectively, negative) delay-generating event. Positions as

[2] Flight's altitude has been neglected, as it is seldom used as a way of recovering delay and, except for the Continuous Descend Approach [13], has little influence in the delay of a flight.

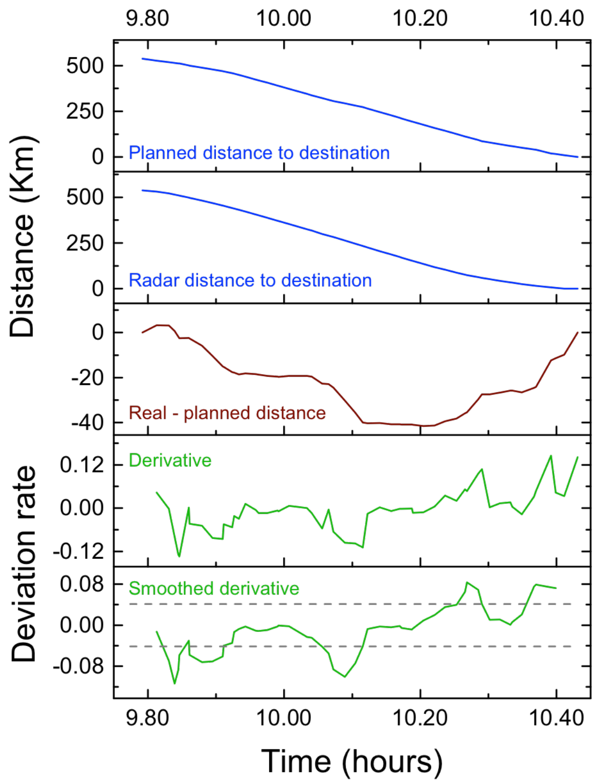

Figure 3. Example of the delay-generating events detection algorithm. From top to bottom: evolution of the distance to the destination airport, for the planned and real trajectory; evolution of the difference between real and planned distances; derivative of the difference function; smothered derivative, and application of a threshold (dashed gray lines). Refer to the main text for further details on the procedure.

defined in (1) are thus converted to distances to the arrival airport, by means of a Haversine formula [14] (see line 6 of Fig. 1), thus yielding a new distance vector:

$$d_l^j = [(i_1, d_1^j)^{(l)}, (i_2, d_2^j)^{(l)}, \dots, (i_m, d_m^j)^{(l)}]. \qquad (2)$$

Distances to destination for the flight depicted in Fig. 2 are reported in Fig. 3 (two top panels).

Finally, by looking at the evolution of the difference between planned and real distances to arrival (Fig. 3, middle panel), we can identify the time windows in which the aircraft is lagging behind (or is ahead of time with respect to) the scheduled trajectory. For the rest of the paper, we suppose that we the planned distance to arrival is subtracted from the real distance. A positive value thus implies a bigger distance to arrival than planned, hence a loss of time and a positive delay[3]. On the other hand, a decreasing difference indicates a gain of time (*i.e.* delay recovery). Note that doing the opposite, *i.e.* subtract the real distance from the planned one, just reverses the conclusions.

As previously introduced, the appearance of positive (or negative) delays is indicated by a growth (respectively, a decrease) in the distances' difference, which can easily be detected as peaks if one considers the derivative of the difference function (fourth panel in Fig. 3). Given the noisy behavior of the derivative, which may lead to the detection of false peaks, it is convenient to smooth it by calculating a short-window moving average (see Fig. 3, bottom panel).

Given a threshold τ, whose choice will be discussed in the next Section, one can look at the intersections of the smoothed derivative function with the horizontal line of height equal to the chosen threshold. The last panel of Fig. 3 represents such process. Two thresholds are considered, a positive and a negative one, in order to account for both positive and negative delay-generating events.

We note that when the derivative of the distance function is bigger than the chosen threshold, it means that a delay of a magnitude superior or equal to the threshold is generated (or recovered, in the case of negative τs). Hence the number of delay-generating events is a function of the number of intersections between the constant function representing the threshold, and the smoothed distance function derivative (see lines 11 – 25 in Fig. 1). In concrete, each continuous time window in which the smoothed derivative is above a positive threshold counts as a positive event (*i.e.* an event that generates a positive delay). Conversely, each continuous time window in which it is below a negative threshold counts as a negative event (*i.e.* an event that generates a negative delay or, in other worlds, a recovery of delay). In the example presented in the last caption of Fig. 3, we can count two positive events and three negative ones.

III. Application to the European transport network

In this Section, the proposed methodology has been applied to a data set describing real flights crossing the European airspace during year 2011. Results will be used to discuss three applications of the methodology: a descriptive analysis (Subsection B), assessment of the resilience of the system (Subsection C), and analysis of the geographical distribution of delays (Subsection D).

A. Data set description

Flights information has been extracted from the Flight Trajectory (ALL-FT+) data set as provided by the EUROCONTROL PRISME group. It includes information about planned and executed trajectories for all flights crossing the European airspace, with an average resolution of 2 minutes. The data set covers the period from 1st March to the

[3] Under the hypothesis that aircrafts' velocity is constant throughout their flight, which is usually fulfilled in the en-route phase. Even if this simplification can be restrictive, it is worth noticing that this is equivalent to studying the increment (or decrement) in the distance travelled by aircraft, and thus to assess the efficiency of the system.

31st December 2011, including a total of 10.3 million flights [15,16].

All flights have been pre-processed, and those presenting abnormal behaviors in their radar trajectories have been filtered out. Reasons for discarding a flight included, among others, the absence of complete radar trajectories, separation between radar points greater than 20 minutes, or the presence of segments with higher-than-sound speeds.

Furthermore, a conventional measure of en-route delay has been calculated for each flight, as the difference between the real and the planned landing time. As such, this delay only represent en-route and arrival inefficiencies, and does not include the effect of regulations issued before take-off.

B. Descriptive analyses

The methodology presented in Section II will here be applied to the previously described data set, with the aim of providing some descriptive statistics, and thus starting shedding light on the mechanisms underlying en-route delay generation. Since the average delay at landing is the metric of choice for evaluating the performance of the system, a comparison will also be made between them.

The algorithm, as depicted in Fig. 1, calculates the number of delay-generating events as a function of the threshold τ. In other words, it counts the number of occurrences in which the delay generated is superior or equal to the threshold. Conversely, in the case of a negative threshold, it counts the number of occurrences in which the delay generated is lower or equal to τ (*i.e.* the recovered delay is greater than $|\tau|$). Dividing these two values by the total number of flights yields two pseudo complementary cumulative distribution functions (ccdf), or tail distributions, representing the probability distribution of the delay magnitude generated by a single event per flight. As positive and negative events are computed separately, one must be careful reconstructing the overall distribution:

$$\bar{F}(\tau) = P(D \geq \tau) = \int_{\tau}^{+\infty} f_D(t)dt, \quad \tau > 0, \quad (3)$$

and,

$$F(\tau) = P(D \leq \tau) = \int_{-\infty}^{\tau} f_D(t)dt, \quad \tau < 0. (4)$$

A discretization of this distribution, by choosing thresholds τ uniformly spaced in [-*m*, *m*][4], yields:

[4] *m* has empirically been chosen in order to include every possible event. It has been calculated as the maximum height of the derivative of the distance function between real and planned trajectories from a subset of 1000 flights. Its value here is 0.852.

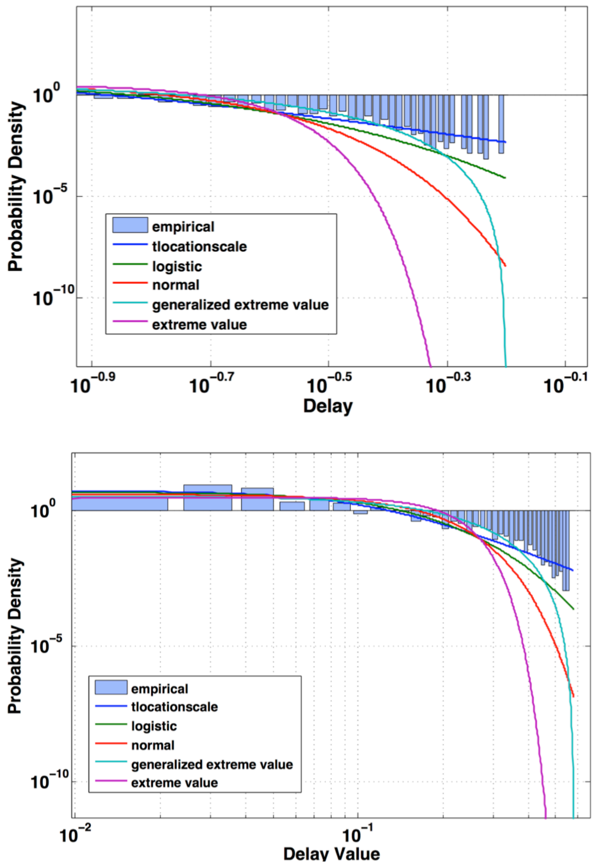

Figure 4. Example of different fits of the delay magnitude distribution function. Top and bottom panels respectively correspond to the flights of the 4th of April 2011 and of the 6th of August 2011.

$$P(D = \tau) = \bar{F}(\tau) - \sum_{\tau_i > \tau} p(\tau_i), \quad \tau > 0 \quad (5)$$

and,

$$P(D = \tau) = F(\tau) - \sum_{\tau_i < \tau} p(\tau_i), \quad \tau < 0 \quad (6)$$

As previously mentioned, the threshold values correspond to the delay values generated by an event. Hence, for every delay value in [-*m*, *m*], the probability of this delay to happen per flight is obtain as follow:

$$p(\tau_i) = \frac{\#event(\tau_i) - \#event(\tau_{i+1})}{\#Flights}, \quad (7)$$

with $i \in \{\tau_i > 0, \tau_j > \tau_i \; \forall \; j > i\}$ and $\#event(d_{m+1}) = 0$; and:

$$p(\tau_i) = \frac{\#event(\tau_i) - \#event(\tau_{i-1})}{\#Flights}, \quad (8)$$

being $i \in \{\tau_i < 0, \tau_j < \tau_i \; \forall \; j < i\}$ and $\#event(d_{m-1}) = 0$.

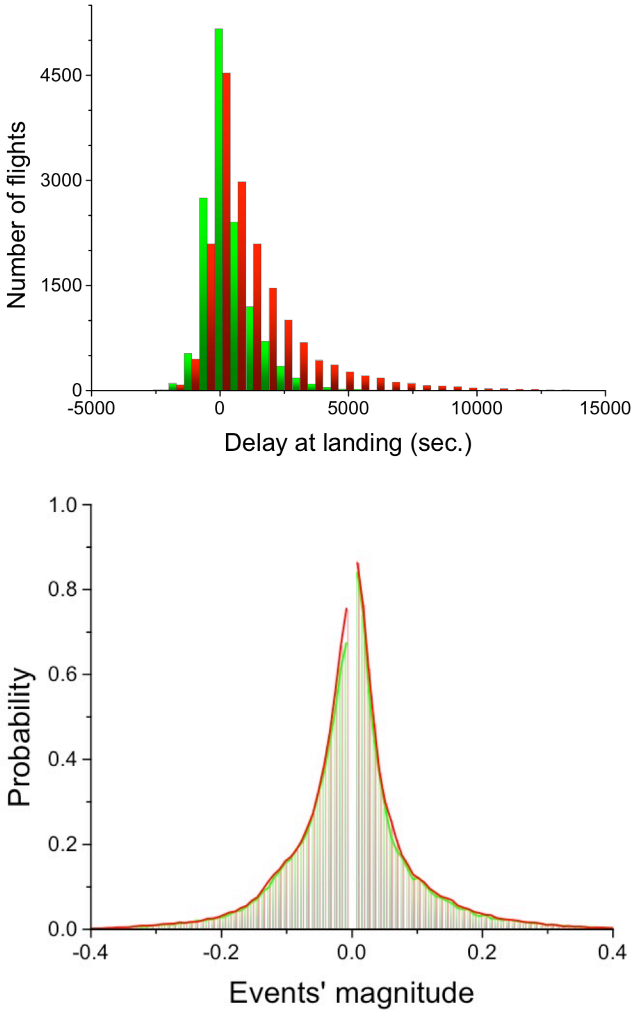

Figure 5. Probability distribution functions of the global delay at landing (top panel) and of the events' magnitude (bottom panel), for two different days of 2011.

Once the delay magnitude distribution has been reconstructed, the first descriptive analysis involves characterizing the nature, *i.e.* the shape of it. Five probability functions have been considered. First, the normal distribution, due to its generality. Additionally, as heavy tails can be noticed in the reconstructed distribution, and these are usually associated with extreme (unexpected) conditions and processes, Extreme Value (EV) or Generalized Extreme Value (GEV) distributions have been included. Finally, one ought to consider the possibility of encountering extreme values that are the result of other causes, *e.g.* emergent phenomena: logistic and t-location-scale functions are therefore potentially valid model.

The goodness-of-fit of the model is assessed using the Bayesian Information Criteria (BIC), also known as the Schwarz criterion [17]. While there is no objective criterion to define when two models are significantly different, a common rule states that a difference in BIC of more than 10 is large

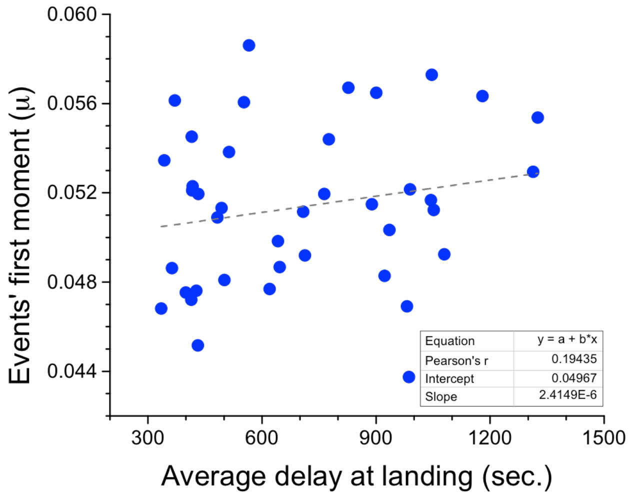

Figure 6. Scatter plot of the expected events' magnitude, as defined in (9), as a function of the average delay at landing. The dashed gray line represents the best linear fit of the data set.

enough for most purposes.

Using this methodology, the delays corresponding to a set of 55 days, as extracted from the data set described in Section IIIA, has been analyzed. Throughout the set, the t-location-scale distribution is the parametric function that yields the best fit. This is confirmed by Fig. 4, which depicts the fit for two different days: it can be appreciated that the tails are best modeled by a t-location-scale distribution (blue solid line).

A relevant question that may arise is whether the presented event magnitude distribution provides more information than a simple analysis of the average landing delay; or, in other words, whether there is a strong correlation between a micro-scale, as here presented, and a macro-scale vision, as currently used in delay analyses [10].

Fig. 5 addresses this issue by presenting the global delay histogram (top panel) and the delay per event histogram (bottom panel) for two different days randomly chosen. The differences in the global delay histograms are evident, while the same does not hold in the latter case. This is also confirmed by the low correlation (Pearson's $r = 0.19$) between the average delay at landing and average delay per event (Fig. 6). By generalizing these results, one can conclude that the en-route part presents a behavior that is uncorrelated with the behavior of the whole system. A decrease in the apparent global delay (*i.e.* at landing) does not thus imply an improvement in all the phases of the flight. This confirms the importance of having a better understanding of the dynamics of the system, throughout all the flight phases.

C. *Delays and en-route resilience*

Resilience is a concept that has extensively been studied in different scientific fields, among which the most important are material science and ecology. Specifically, in ecology, resilience represents the fundamental property of a natural ecosystem to recover after the incurrence of disturbances, may it be abnormal weather or the introduction of a new species [18]. Only in 2006 this idea was introduced in engineering and management: the so-called “resilience engineering” focuses on the human and organisational aspects enabling a good design of safety-critical, socio-technical systems, by helping people coping with complexity when exposed to pressure [19].

This last idea has been adopted by EUROCONTROL in 2009, fostering the investigation of resilience and aimed at deriving means to mitigate negative impacts on the ATM system’s performance [20]. It is well known that a large number of disturbances deteriorate daily the performance of the system: from adverse weather, to equipment failures. Yet, in order to start designing means for mitigate negative impacts, it is firstly necessary to define a method for numerically assessing the resilience of the system, such that different scenarios can then be compared [21].

Here we propose the use of the presented micro-scale delay analysis for assessing the resilience of the system in its en-route part, *i.e.* not accounting for delays generated or managed on the ground. Specifically, the basic idea is to see if the system is able to compensate with negative events to the appearance of positive (or delay generating) events. In other words, the ATM system can be defined as resilient if, for each event creating a positive delay, the system reacts creating an event recovering that perturbation.

Towards this aim, it is necessary to define the first moment of the distribution considering respectively its right and left sides:

$$\mu^+ = \sum_{\tau>0} \tau * p(\tau), \tag{9}$$

and

$$\mu^- = \sum_{\tau<0} \tau * p(\tau), \tag{10}$$

If, for a given period of time, μ^+ and μ^- are of the same order of magnitude, the system can be considered as resilient; on the other side, if $\mu^+ > \mu^-$, the system is not able to compensate for all positive events, *i.e.* it is not able to fully recover en-route delays, and thus is not resilient.

Fig. 7 presents the result of plotting μ^-as a function of μ^+, in which each point represents the behavior of the system in a different day: first Monday (black squares) and Saturday (blue circles) of every month, thus representing days respectively with high and low traffic levels; and a selection of days presenting the highest (red triangles) and lowest (green triangles) average delay at landing.

It can be appreciated that all points lie above the main diagonal (gray dotted line): one can then conclude that the ATM system is perfect resilient in its en-route phase, independently on the characteristics of the day considered.

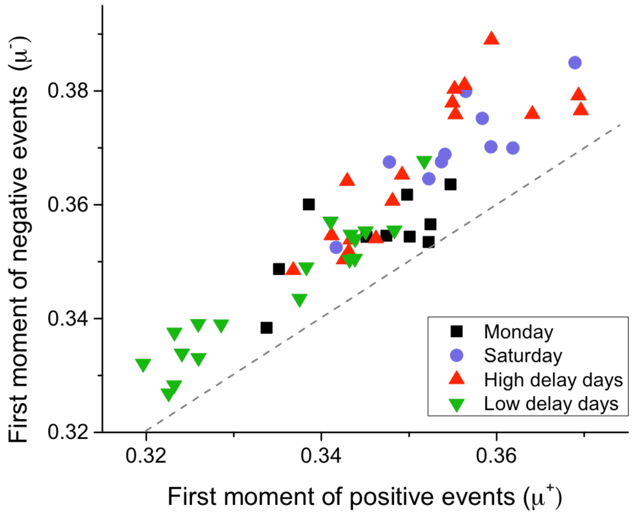

Figure 7. Resilience of the en-route part of the ATM system. Points represent the value of the first moment of positive and negative events - see (9) and (10) in main text. The dashed gray line divides the plane into resilient (top) and non-resilient (bottom) regions.

D. Geographical distribution of delays

As a final application of the proposed methodology, here we present how it can be applied to perform a spatial analysis of the appearance and recovery of en-route delays. Specifically, we aim at identifying the European airspace sectors most problematic in terms of positive delay-generating events, and at comparing their respective resilience.

To achieve this, the European airspace has been divided into regions of 10º longitude by 10º latitude. Different μ^+ and μ^- have been calculated for each one of them, by only considering those positive and negative delay-generating events occurring inside each region.

Given two regions, if their μ^+s are not of the same order of magnitude, one of those regions is then more prone to generate delays than the other[5]. In a similar way, comparing the ratio between μ^+ and μ^- across different regions allows to compare their respective resilience. Specifically, and as previously presented in Fig. 7, if $\mu^-/\mu^+ > 1$ for a given region, then that region can be considered resilient; conversely, $\mu^-/\mu^+ < 1$ suggests that the system is not able to absorb delays within those boundaries.

Fig. 8 (left panel) presents the geographical evolution of μ^+ throughout the European airspace, with blue and red colors respectively indicating low and high values of μ^+. In the left panel of Fig. 8 a similar plot if presented for the resilience

[5] Such comparison is possible due to the fact that both μ^+ and μ^- are calculated over the probability distribution of events, and are thus independent on the number of flights.

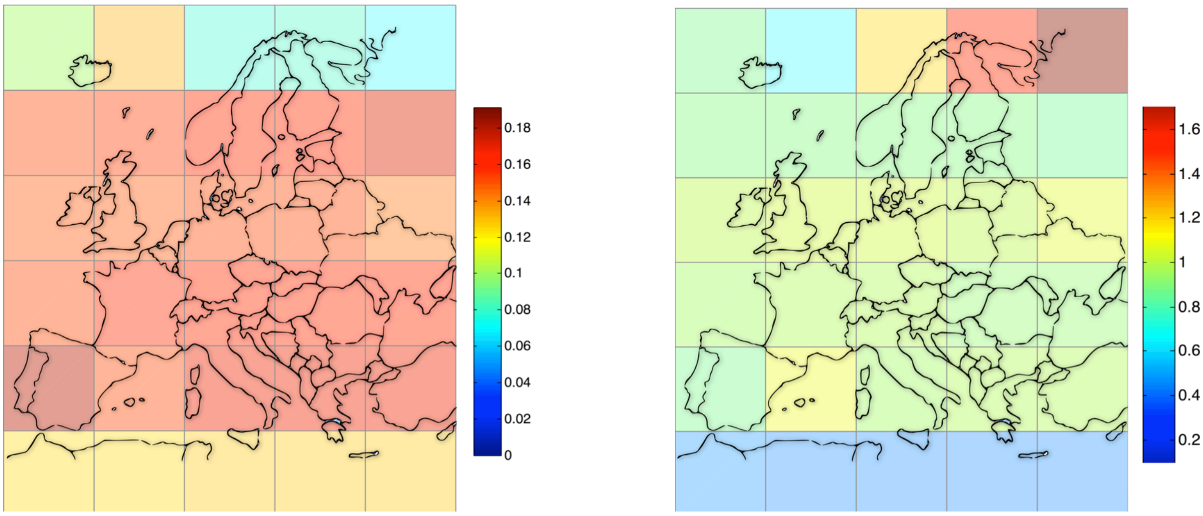

Figure 8. Spatial analysis of en-route delays. Left and Right panels respectively represent the spatial distribution of μ^+ and of the resilience metric μ^-/μ^+.

metric (μ^-/μ^+). These results have been obtained using the same days as the ones in Fig. 7.

It can be appreciated that the worst region, in terms of positive delay-generating events, lies above continental Portugal and Spain. At the same time, this same region is associated to a low resilience metric: more delays than average are generated, and the system is not able to cope with them. The reader may also notice that sea regions are characterized by a low resilience; this can be explained by the absence of alternative (or straight) routes to recover delays, as aircraft are usually already flying the most direct course.

From this analysis, a general conclusion can be drawn. While the ATM system is globally resilient in its en-route phase, important differences can be found when the spatial dimension is included, both in terms of quantity of delays generated, and of recovery capacity. Furthermore, from a methodological point of view, it is worth noticing that the micro-delays study yields a measure of the en-route resilience of the system, but it does not provide clues on the causes behind such values. Shedding light on the reasons behind the lack of resilience of some air spaces would require cross-referencing these results with other data sources, *e.g.* procedures implemented in reach sector and weather conditions, which are beyond the scope of this contribution.

IV. Discussion and Future Outlook

Back in year 2000, EUROCONTROL recognized the importance of understanding and assessing delays beyond the one produced by ATFM regulations, like for instance those appearing in the en-route phase of a flight. 15 years later, there is yet no consolidated methodology for their characterization and analysis. In this contribution, we take a first step towards this aim, and propose a set of algorithms enabling the detection of events that contribute to the appearance of positive and negative delays in the flight of an aircraft. It is based on the comparison of planned and real trajectories, through the detection of deviations of the latter with respect to the former in terms of the remaining distance to the destination airport.

General properties of these delay-generating events have been presented, like their independence from the global delay of the flight. We further presented two applications of this methodology, namely the assessment of the resilience of the system, and an analysis of the geographical distribution of these events. This, in turns, allowed us to extract some interesting information about the system, as for instance the existence of regions of the airspace in which delays can hardly be recovered.

Beyond what has here been presented, this methodology for studying en-route delays on a micro-scale opens new doors towards the understanding and measurement of where and how delays are generated and absorbed. Future works will thus be aimed at studying the temporal sequences of delays, that is, the relationships between positive and negative events, as for instance the number of negative events needed to counteract a single positive one; and their causal relations, *i.e.* if negative events generate randomly, or if they are intentionally triggered by positive ones. Additionally, causal spatio-temporal patterns in the distribution of delay-generating events could be linked to specific procedures enforced in each air spaces, yielding clues about the most efficient ways for managing air traffic. Finally, this methodology will be applied to the analysis of systems in which most of the delays are handled in the air, like the US airspace, with the benefit of reducing the influence of the European ground delay program.

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REFERENCES

[1] A. J. Cook, G. Tanner, R. Jovanovic andA. Lawes, “The cost of delay to air transport in Europe: quantification and management,” 2009.

[2] A. J. Cook and G. Tanner, “European airline delay cost reference values,” 2011.

[3] D. I. R. K. Duytschaever, “The Development and Implementation of the EUROCONTROL Central Air Traffic Flow Management Unit (CFMU),” Journal of Navigation, vol. 46, pp. 343-352, 1993.

[4] M. Hansen, “Micro-level analysis of airport delay externalities using deterministic queuing models: a case study,” Journal of Air Transport Management, vol. 8, pp. 73-87, 2002.

[5] G. D. Glockner, “Effects of air traffic congestion delays under several flow-management policies,” Transportation Research Record: Journal of the Transportation Research Board, vol. 1517, pp. 29-36, 1996.

[6] S. AhmadBeygi, A. Cohn, Y. Guan and P. Belobaba, “Analysis of the potential for delay propagation in passenger airline networks,” Journal of air transport management, vol. 14, pp. 221-236, 2008.

[7] M. Jetzki, “The propagation of air transport delays in Europe,” Master's thesis, RWTH Aachen University, 2009.

[8] Performance Review Commission, “Third Performance Review Report (PRR 3),” EUROCONTROL, 2000.

[9] Performance Review Commission, “Fourth Performance Review Report (PRR 4),” EUROCONTROL, 2001.

[10] CODA, “Delays to Air Transport in Europe – Annual 2013”, 2014.

[11] W. S. Cleveland, “Data science: an action plan for expanding the technical areas of the field of statistics,” International statistical review, vol. 69, pp. 21-26, 2001.

[12] N. Cressie, “Statistics for Spatial Data: Wiley Series in Probability and Statistics,” 1993.

[13] I. Wilson and F. Hafner, “Benefit assessment of using continuous descent approaches at Atlanta,” Digital Avionics Systems Conference, 2005. DASC 2005, 2005.

[14] R. W. Sinnott, “Virtues of the Haversine”, Sky and Telescope, vol. 68, pp. 159, 1984.

[15] M. Zanin, “Synchronization Likelihood in aircraft trajectories,” Proceedings of the Tenth USA/Europe Air Traffic Management Research and Development Seminar, Chicago, USA, 2013.

[16] M. Zanin, “Network analysis reveals patterns behind air safety events,” Physica A, vol. 401, pp. 201-206, 2014.

[17] G. E.Schwarz, “Estimating the dimension of a model,” Annals of Statistics, vol. 6, pp. 461-464, 1978.

[18] L. H. Gunderson, “Ecological Resilience - in Theory and Application,” Annu. Rev. Ecol. Syst., vel. 31, pp. 425-39, 2000.

[19] E. Hollnagel, D. D. Woods and N. Leveson (Eds.), Resilience engineering: Concepts and precepts, Aldershot, UK: Ashgate, 2006.

[20] EUROCONTROL, “A white paper on Resilience Engineering for ATM,” 2009.

[21] O. Gluchshenko, “Definitions of Disturbance, Resilience and Robustness in ATM Context,” DLR Report IB 112-2012/28, 2012.

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