IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 12, 2020, accepted August 23, 2020, date of publication September 7, 2020, date of current version September 28, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3022160

Assessing Airport Landing Efficiency Through Large-Scale Flight Data Analysis

MASSIMILIANO ZANIN
Instituto de Física Interdisciplinar y Sistemas Complejos (IFISC), CSIC-UIB, 07122 Palma de Mallorca, Spain
e-mail: massimiliano.zanin@gmail.com

This work was supported in part by the European Research Council (ERC) through the European Union's Horizon 2020 Research and Innovation Programme under Grant 851255, and in part by the Agencia Estatal de Investigación (AEI), Ministerio de Ciencia e Innovación (MCI), Spain, and the Fondo Europeo de Desarrollo Regional (FEDER), European Union (EU), through the Maria de Maeztu Program for units of Excellence in Research and Development, under Grant MDM-2017-0711.

ABSTRACT Trajectories optimisation is a major research topic in air transport and air traffic management, due to its profound impact both on passengers, airlines and the environment in general, and consequently on the perceived value and cost of air transportation. While the challenges associated to the optimisation of the en-route part of a flight are well understood, relative less attention has been devoted to the last part, i.e. the approach and landing. Here we show how open large-scale data sets of aircraft trajectories can be used to characterise the efficiency of flights landing at an airport, measured through the time and distance flown below 10, 000 feet. The yielded picture is highly heterogeneous, with the time spent at low altitude varying from an average of 10 minutes for Zurich, up to 16 minutes for London Heathrow. Flights arriving at the same airport also experience highly different times, e.g. from 12 to 20 minutes for London Heathrow, depending on factors like traffic volumes, time of the year and of the day, and on interactions with other traffic patterns and airports. From a more general perspective, this contribution illustrates how the availability of large data sets can be used to improve our understanding of the real behaviour of the system, and especially its deviation from what planned.

INDEX TERMS Air traffic control, aircraft navigation, big data applications, data mining, air pollution.

I. INTRODUCTION

One of the main concerns in air transport, and specifically in Air Traffic Management (ATM), is the optimisation of trajectories to allow aircraft to reach their destinations in the shortest possible time. A suboptimal trajectory has clear economic consequences, both for passengers (i.e. longer travel times) and airlines (i.e. higher fuel and crew costs); but it also affects the environment, as more fuel burnt implies larger quantities of pollutant emissions - to illustrate, a medium-range aircraft contributes to climate change with around 1.5Kg of CO_2 per minute of flight [1]. While *prima facie* the best trajectory is expected to be a straight (or geodesic) one, real operations are more complex, with multiple factors modifying this trivial solution. For instance, planners try to avoid en-route headwinds, and to take advantage of tailwinds; and they further have to comply with the structure of airspaces and routes, designed to ensure an effective air traffic control, and hence the safety of operations.

The associate editor coordinating the review of this manuscript and approving it for publication was Keli Xiao.

Research efforts to define and measure efficiency in air transport have been focused on three complementary aspects. On one hand, several works have tried to assess how efficient the actual system is from a global perspective, i.e. its capacity of matching flights offer with demand. Examples of this include [2], focusing on the transportation demand of the state of Indiana; [3], focusing on the hub-and-spoke network of the Java Island; and [4], analysing the efficiency of 24 major international airports.

Moving the focus to flights themselves, a second set of works have been focused on understanding the efficiency of different airspaces and on comparing them. Specifically, [5] proposed a set of metrics to define the lateral and vertical deviation from an ideal trajectory, and to evaluate the additional fuel needed because of these deviations. A similar problem was tackled by [6], finding that vertical deviations account for a 3% increase in fuel consumption in the US airspace. Comparable analyses were performed for Japan [7], US [8], Europe [9]–[11] and China [11].

As a third line of research, the focus is finally shifted to individual flights, to understand how decisions can be taken to make them more efficient. This can be approached in two ways. On one hand, one can suppose that the structure of the airspace is given, i.e. it cannot be modified; each aircraft can then try to optimise its trajectory taking into account various elements, like the total distance flown, or more sophisticated costs (i.e. what is known as dynamic cost indexing [12]). While a complete review of these proposals is outside the scope of this work, the interested reader can refer to, among others, [13]–[20]. On the other hand, more radical solutions to improve the efficiency of the airspace can be designed if the underlying structure is allowed to change. This gives rise to the concepts of dynamic airspace sectorisation [21], [22], in which sectors are dynamically reconfigured according to the expected traffic flows; and of free-flight [23], [24], in which flights are not required to follow specific air routes.

The problem of flight efficiency becomes even more complex at the end of the flight, i.e. in the approach phase. This is due to several reasons. First of all, being airports the final destination of all flights, they usually concentrate a large volume of traffic in their surroundings. Some cities further have more than one airport, whose traffic patterns may interact. Additionally, approaches have to be designed taking into account terrain characteristics (e.g. mountains) and other restrictions (as the presence of populated areas). Finally, paths may be altered by changing and adverse weather conditions, forcing the closure of some runways, or the use of specific configurations. Each airport has then to publish a set of approach and landing procedures, called STARs (STandard ARrivals), which substantially deviate from an ideal, straight path. As in the case of trajectories, a substantial amount of research effort has been devoted to the design of more efficient landing procedures, through for instance the concept of continuous descent [25]–[28].

One common assumption of efforts focused on improving approach efficiency is that procedures can be changed and optimised, but that, when they are in place, all operations will follow them. In other words, as all flights follow the same rules, they will all suffer from the same inefficiencies, leaving little room for improvement. Several factors may nevertheless affect this. First of all, flights may use different approach procedures, even when coming from similar directions, which may have different efficiencies. Secondly, high volumes of traffic may saturate the runways, forcing aircraft to wait in holding patterns. Finally, and in order to avoid other traffic patterns, aircraft may be forced to fly at lower altitudes, with a consequent increase in fuel consumption. The consequences of these factors are difficult to estimate *a priori*, i.e. at the time of designing the approach procedures or by just looking at a map. A procedure may theoretically be extremely efficient, i.e. leading the aircraft to the runway in an almost straight trajectory; but it may actually be inefficient due to exogenous factors. In a similar way, two aircraft approaching an airport throught the same trajectory may be subject to different circumstances, resulting in substantially different fuel consumptions.

To the best of our knowledge, there has been no systematic evaluation of the real efficiency of airport arrival procedures, mainly because such evaluation is only possible through large-scale real data that have been made available to researchers only in recent years. Some works have resort to simulations, using synthetic data generated by models for different airport configurations [29], [30]. On the other hand, a limited number of works have analysed the efficiency of specific airports, for which data were available, e.g. Stockholm Arlanda Airport [31], Los Angeles airport [32], or Fort Worth [33]. A natural question thus emerges: can the data that are currently freely available, e.g. from ADS-B (Automatic Dependent Surveillance - Broadcast), be used to evaluate the real efficiency of the arrival procedures of an arbitrary airport?

Along this line, this work thus aims at evaluating the arrival and landing efficiency, understood as the distance and time flown at low altitude, of 16 large European airports; at identifying the reasons behind inefficiencies; and at estimating their economic and environmental consequences. A large data set of real trajectories is used, with a special focus on the horizontal and vertical profile of flights below $10,000$ feet. Results depict a large heterogeneity of situations, with a large variability within each airport, and due to different reasons. Beyond these specific results, the present work is an example of how novel technologies (open-source ADS-B trajectory data) and techniques (large-scale data analysis) can be combined to optimise air transport beyond what possible through more classical approaches.

II. DATA GATHERING AND PRE-PROCESSING

The starting point of the analysis here presented is a large data set of ADS-B position reports, covering the time window from May 1^{st}, 2018 to December 31^{st}, 2019, obtained from the OpenSky Network (https://opensky-network.org) [34]. ADS-B (Automatic Dependent Surveillance - Broadcast) is a technology allowing aircraft to continuously send radio messages, stating their position and other information of relevance [35], [36]; these messages are then received by ground stations, and integrated into coherent reports. Messages are collected on average every 6.37 seconds, for a total of 3.4TB of data - i.e. around 5.5GB/day.

For each airport, landing flights have been identified when the last known position was within a radius of 3 nautical miles from the center of the airport, and the last reported altitude below 500 meters. In the case of cities with multiple airports, an additional filter has been applied, to ensure that the landing was in the correct one - e.g., in the case of Madrid Barajas, flights whose longitude was greater than -3.50 were discarded, as they are heading towards Madrid Torrejón. In order to assess the time to land, the first known position of the aircraft between $9,500$ and $10,000$ feet was recorded; if such position was not available, for instance due to bad coverage along the approach path, the flight was discarded. To ensure coherence of the data, flights were also discarded when the time between their crossing the $10,000$ feet

TABLE 1. List of airports considered in this study. *Ranking* refers to the position of each airport in the European ranking of the most busy airports in 2019, according to the number of passengers. The column *# flights* reports the number of flights available in this study, after the filtering described in Sec. II. The columns *# Ops. 2019*, *# Pax. 2019* and *Cargo (t) 2019* respectively refer to the number of movements, passengers and cargo (in tons) for year 2019, as reported in the airport's Wikipedia page. Values marked with a * have been obtained from the airport website, while † indicates values for year 2018. An horizontal dash finally indicates that the airport did not report that value.

ICAO Code	Airport name	Ranking	# flights	# Ops. 2019	# Pax. 2019	Cargo (t) 2019
EDDF	Frankfurt am Main Airport	4	356, 946	513, 912	70, 560, 987	2, 128, 476
EHAM	Amsterdam Airport Schiphol	3	353, 159	496, 826	71, 706, 999	1, 570, 261
LSZH	Zurich Airport	15	287, 657	275, 396	31, 538, 236	334, 650*
EGLL	Heathrow Airport	1	275, 854	475, 861	80, 844, 310	1, 587, 451
LEMD	Adolfo Suárez Madrid-Barajas Airport	5	254, 463	426, 376	61, 734, 037	558, 567
LOWW	Vienna International Airport	14	246, 367	266, 802	31, 662, 189	283, 806
EDDM	Munich Airport	9	234, 276	417, 138	47, 959, 885	338, 517
LIMC	Malpensa Airport	20	169, 728	234, 054	28, 846, 299	558, 481
EBBR	Brussels Airport	24	147, 798	234, 460	26, 360, 003	500, 702
EDDL	Düsseldorf Airport	27	135, 144	218, 820†	24, 283, 967†	75, 030†
LFPG	Charles de Gaulle Airport	2	114, 248	498, 175	76, 150, 007	2, 156, 327
EDDT	Berlin Tegel Airport	28	100, 902	–	24, 227, 570	–
LGAV	Athens International Airport	26	52, 391	225, 628	25, 574, 030	93, 997
LEBL	Barcelona-El Prat Josep Tarradellas Airport	6	42, 166	344, 558	52, 686, 314	177, 271
EGKK	Gatwick Airport	10	4, 788	282, 896	46, 574, 786	–
LIRF	Leonardo da Vinci-Fiumicino Airport	11	1, 798	309.783	43, 532, 573	194, 526

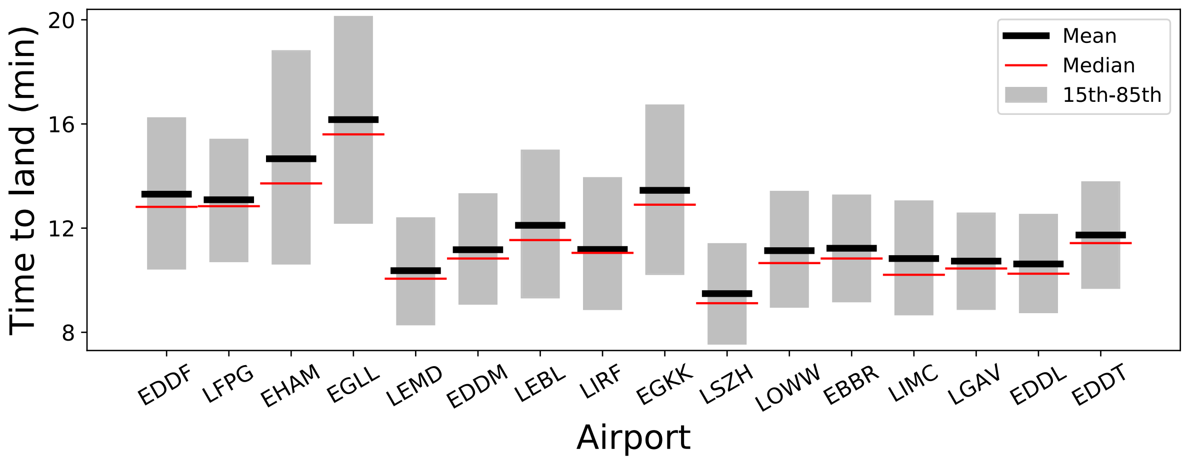

FIGURE 1. Probability distribution of the landing time for the 16 considered airports, calculated as the time between crossing 10, 000 feet and touchdown. Grey bands indicate the 15*th*-85*th* percentiles range; black and red horizontal lines respectively the average and median of the distributions. A great variability can be observed, with times to land going from an average of 10 minutes for Zurich (LSZH) to 16 minutes for London Heathrow (EGLL). Also, flights arriving at a same airport have a high variability, as depicted by the long grey bars.

altitude and landing was below 3 minutes; and when the code of the aircraft was unknown. Finally, the time to land has been calculated as the difference between the time of the last position report and of the 10, 000 level crossing. All computations have been implemented in Python 3.7, with standard data manipulation libraries, and executed on an Apple MacBook Pro (15-inch, 2017 model), with a quad-core Intel Core i7 processor and 16GB of memory.

Data for the top 30 European airports have been extracted and analysed. Nevertheless, and due to the previous filters, inhomogeneous ADS-B coverage across Europe, and the need of having representative trajectories, some of them have been discarded. Details about selected airports and the number of available flights are reported in Tab. 1. It can be appreciated that some of them, i.e. LGAV (Athens International Airport), LEBL (Barcelona-El Prat Josep Tarradellas Airport), EGKK (Gatwick Airport) and LIRF (Leonardo da Vinci-Fiumicino Airport), are still described by a low number of flights; conclusions about them have then to be drawn with due prudence.

III. LANDING EFFICIENCY ASSESSMENT

As a first overview to the results, Fig. 1 reports the distribution of the landing time for all airports. As previously detailed, here landing time refers to the time from crossing an altitude of 10, 000 feet to touchdown. This time is of importance in operations, as flying at low altitude is slower and implies higher fuel consumption; hence, a reduction of this time implies both savings in costs, and a reduction of the environmental impact. Grey bands of Fig. 1 correspond to the 15*th*-85*th* percentiles range, while black and red horizontal lines respectively to the average and median of the distribution. Two relevant observations can already be made. First of all, and opposed with what may be intuitive, airports are characterised by a great variability in the landing time - for instance, it varies between 12 and 20 minutes for aircraft

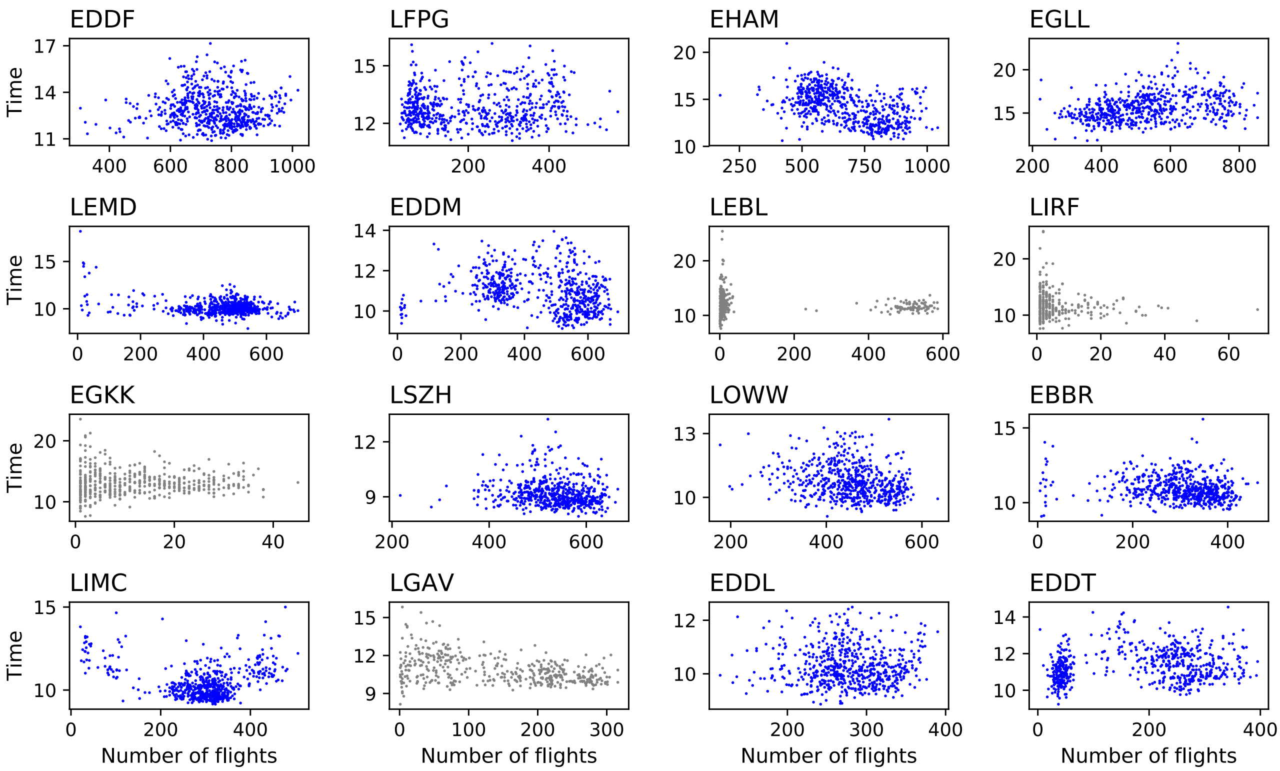

FIGURE 2. Landing time (i.e. time since crossing 10, 000 feet to touchdown) as a function of the traffic. Each point in each scatter plot reports the median of the landing time for one day, as a function of the number of landings detected on the same day. The four airports with the lowest number of reliable flights (LEBL, LIRF, EGKK and LGAV, see Tab. 1) are plotted in grey. Note that no clear relationship can be observed for most airports.

landing at London Heathrow (EGLL). This suggests that landing procedures are not fixed, and that important variations in efficiency can be experienced. Secondly, large airports (e.g. EGLL, EHAM) are generally less efficient than small ones (as, for instance, LSZH or EDDL), pointing towards the complexity of the airspace as the main cause behind inefficiencies. The case of Zurich Airport (LSZH) is especially noteworthy, as it presents a small average landing time and dispersion, even though it is surrounded by mountains and its approach is considered one of the most complex in Europe.

If traffic seems to be globally associated to less efficient approaches, the same may hold true at a more micro-level; in other words, one may expect a larger landing time in those days with a higher volume of traffic. To test this hypothesis, Fig. 2 reports a scatter plot for each airport, depicting the median landing time of each day as a function of the number of operations. Note that, in order to obtain a more reliable estimation, this latter number includes all detected landings, thus not just those fulfilling the filters described in Sec. II. If these was a relationship between landing times and traffic volumes, this would appear as structures in the scatter plot; instead, points are forming clouds, thus suggesting no clear relationship. At the same time, a test indicates that, at least for 7 of the considered airports, such hypothesis can be accepted in a statistically significant way, with increases in the average landing time of around a 10% - see Tab. 2.

TABLE 2. Relationship between the landing time and the daily traffic volume. For each considered airport, the second and third columns report the average landing time of those day whose traffic volume was respectively below and above the median. The fourth column reports the *p*-value of a two-sided t-test for the null hypothesis that both averages are identical. Asterisk mark those airports whose *p*-value is statistically significant at $\alpha = 0.01$ after a Šidák correction for multiple testing [37].

ICAO Code	Time (< median)	Time (> median)	p-value
EDDF	12.84	13.03	0.034
LFPG	12.89	12.80	0.276
EHAM	13.30	15.18	$1.99 \cdot 10^{-47}$ *
EGLL	16.15	15.09	$5.39 \cdot 10^{-18}$ *
LEMD	10.10	10.20	0.118
EDDM	10.67	11.27	$4.79 \cdot 10^{-15}$ *
LEBL	12.07	12.39	0.153
LIRF	11.54	11.98	0.121
EGKK	13.14	13.00	0.461
LSZH	9.04	9.32	$1.11 \cdot 10^{-06}$ *
LOWW	10.56	10.92	$7.25 \cdot 10^{-09}$ *
EBBR	10.77	11.08	$8.23 \cdot 10^{-07}$ *
LIMC	10.40	10.40	0.995
LGAV	10.42	11.30	$5.32 \cdot 10^{-18}$ *
EDDL	10.26	10.32	0.333
EDDT	11.40	11.33	0.336

We further analyse whether the hour of the day and the season have an effect on the average and spread of the landing time. As can be seen in Figs. 3 and 4, depicting the distribution of landing times as a function of respectively the hour of the day and the season, clear trends appear,

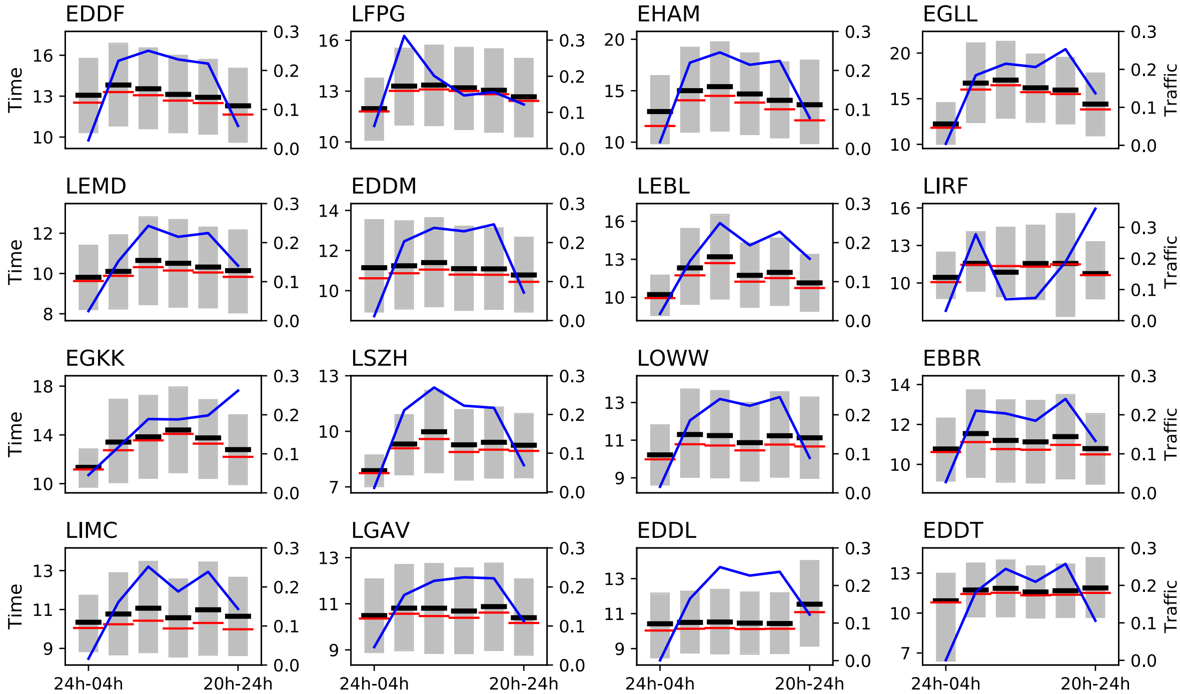

FIGURE 3. Probability distribution of the landing time across flights for the 16 considered airports, as a function of the time of the day. The six columns respectively correspond to the time windows 24h-04h, 04h-08h, 08h-12h, 12h-16h, 16h-20h, and 20h-24h. Grey bands indicate the 15*th*-85*th* percentiles range; black and red horizontal lines respectively the average and median. Finally, the blue line (right axes) reports the fraction of traffic observed in each bin.

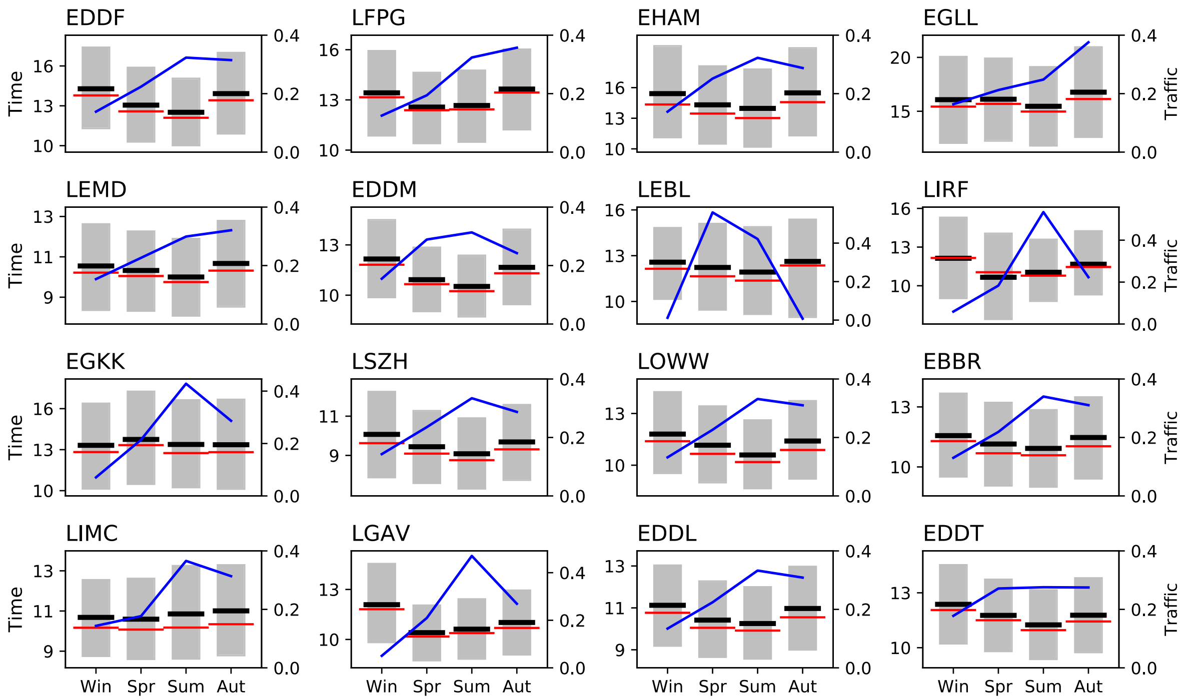

FIGURE 4. Probability distribution of the landing time across flights for the 16 considered airports, as a function of the season of the year. Bands and line are defined as in Fig. 3. Win: winter; Spr: spring; Sum: summer; Aut: autumn.

at least in some airports. For instance, Amsterdam Airport Schiphol (EHAM) and Barcelona-El Prat (LEBL) present a clear positive correlation between mean landing time and traffic, with peaks in the 8h-12h time band. On the other hand, the situation is less clear in the case of seasons, with some airports (e.g. Schipol or Zurich Airport LSZH) even presenting a negative correlation; this is probably due to the too low resolution of an analysis based on four consecutive months. In order to better spot the presence of an overall correlation, Fig. 5 reports two scatter plots, with the

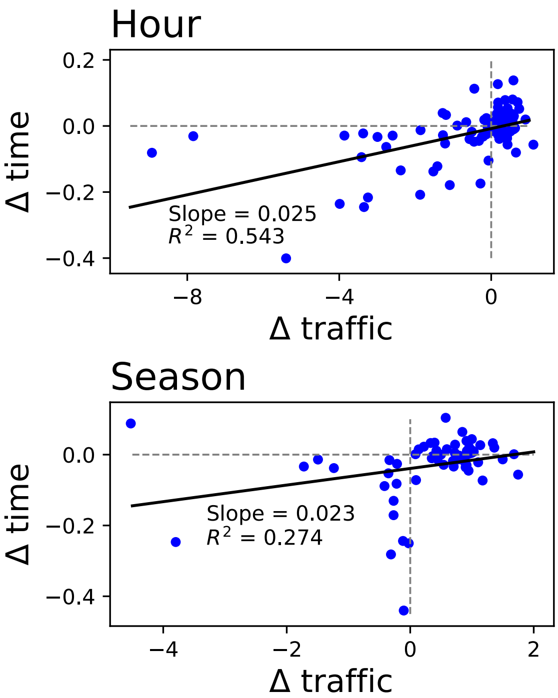

FIGURE 5. **Scatter plots of the deviation from the median landing time as a function of the deviation from the median traffic volume, aggregated by hour of the day (top panel) and season (bottom panel). Each point represents one airport at a given hour (top) or season (bottom). See main text for details about the calculation of the deviations.**

deviation of landing time as a function of the deviation of traffic, for the hour- (top panel) and season-based (bottom panel) aggregation. Here, the deviation of the landing time is defined as $\Delta time = \log_2 M_h/M_{global}$, where M_h is the median of the landing time in the considered hour band, and M_{global} the median of all landing times for the studied airport. In other words, a value of $\Delta time = +1$ indicates that the landing time for a given hour band is the double of what normally expected; conversely, a value of -1 indicates a 50% reduction. Similarly, $\Delta traffic = \log_2 T_f/(1/6)$, where T_f is the fraction of traffic observed, and $1/6$ accounts for an expected uniform distribution of traffic across the six bands. For the bottom panel of Fig. 5, the same definitions apply, except that values are calculated for seasons instead of hour bands. A weak positive correlation is observed in both cases, stronger in the case of the hour bands (R^2 of 0.543 *vs.* 0.274), thus confirming the importance of traffic towards the landing efficiency.

IV. DETECTING THE ORIGIN OF INEFFICIENCIES

If a higher volume of traffic seems to be driving the system towards more inefficient landing trajectories, the next logical step is to understand how these trajectories are modified. Towards this aim, Fig. 6 reports, for the top-4 airports, the 100 most and less efficient trajectories - i.e. the ones with the smallest (blue, top panels) and largest (red, bottom panels) landing times. This is complemented by Fig. 7, reporting, for the same $100 + 100$ trajectories, the distribution of the distance between the first available location below 10, 000 feet and the touchdown point. In both cases, these flights correspond to the first week of June 2019.

Two different situations can be observed. Firstly, one may consider the cases of Amsterdam Airport Schiphol (EHAM) or of Heathrow Airport (EGLL). Fig. 7 indicates that the best and worst flights are crossing the 10, 000 feet altitude at around the same distance - note that the medians (red horizontal lines) are qualitatively the same.[1] This is also confirmed by Fig. 6, as the initial points of all trajectories seem to be the same. The main difference then resides in the distance traveled below 10, 000 feet. Specifically, in the case of Heathrow, most flights are forced into holding patterns; while, for Schipol, many flights arriving from the north have to approach the runway from the south. A second scenario can be clearly observed for Charles de Gaulle Airport (LFPG): trajectories are similar, but aircraft get below 10, 000 feet farther away from the airport - see the large difference in medians in Fig. 7. This seems to be due to different approach patterns, requiring different altitudes. To illustrate, let us consider the case of an aircraft landing at runway 26L - i.e. the bottom runway, and landing from the east (right to left). Two main options are available. Firstly, the approach *BANOX 6Y*, in which aircraft get below 10, 000 feet at approx. 48.9 latitude and 2.5 longitude, thus very close to the airport. Secondly, the approach *OKIPA 6Y*, in which aircraft have to get below that altitude at the *OKIPA* IAF, at approx. 48.6 latitude and 3.8 longitude. In the first case, the aircraft has to fly 18.9 NM till intercepting the ILS,[2] compared to 36.3 NM in the second case, i.e. almost the double. The higher efficiency of the first approach is probably due to the presence of the airport of Le Bourget (LFPB) in the south, forcing aircraft to fly higher. This analysis supports the idea that inefficiencies come from two different sources. On one hand, higher volumes of traffic may force the use of holding patterns; on the other hand, some traffic flows are associated to less efficient approach procedures. Thus, while the first is conjunctural, the second is systemic and could be solved - e.g. by letting aircraft fly higher until closer to the airport.

A different way of visualising this same information is provided in Fig. 8. The top panels depict the evolution of the altitude of flights as a function of time for the four largest airports - where $t = 0$ is the moment at which the aircraft crossed the 10.000 feet altitude. In an ideal scenario, all aircraft would follow a continuous descent approach, i.e. the more efficient in terms of fuel usage, which would show as a constant-slope diagonal line. On the contrary, Fig. 8 presents several horizontal lines, corresponding to segments where several flights were kept at the same low altitude - in some cases, even during 10 minutes. On the other hand, the bottom panels of Fig. 8 report the cumulative probability distribution of the extra landing time for the same airports,

[1] A Mood's median test yields a p-value of respectively $4.07 \cdot 10^{-4}$ and 0.066 for EHAM and EGLL, thus very close to statistical significance.

[2] Instrumental Landing System, i.e. the final part of the landing procedure, and common to all flights.

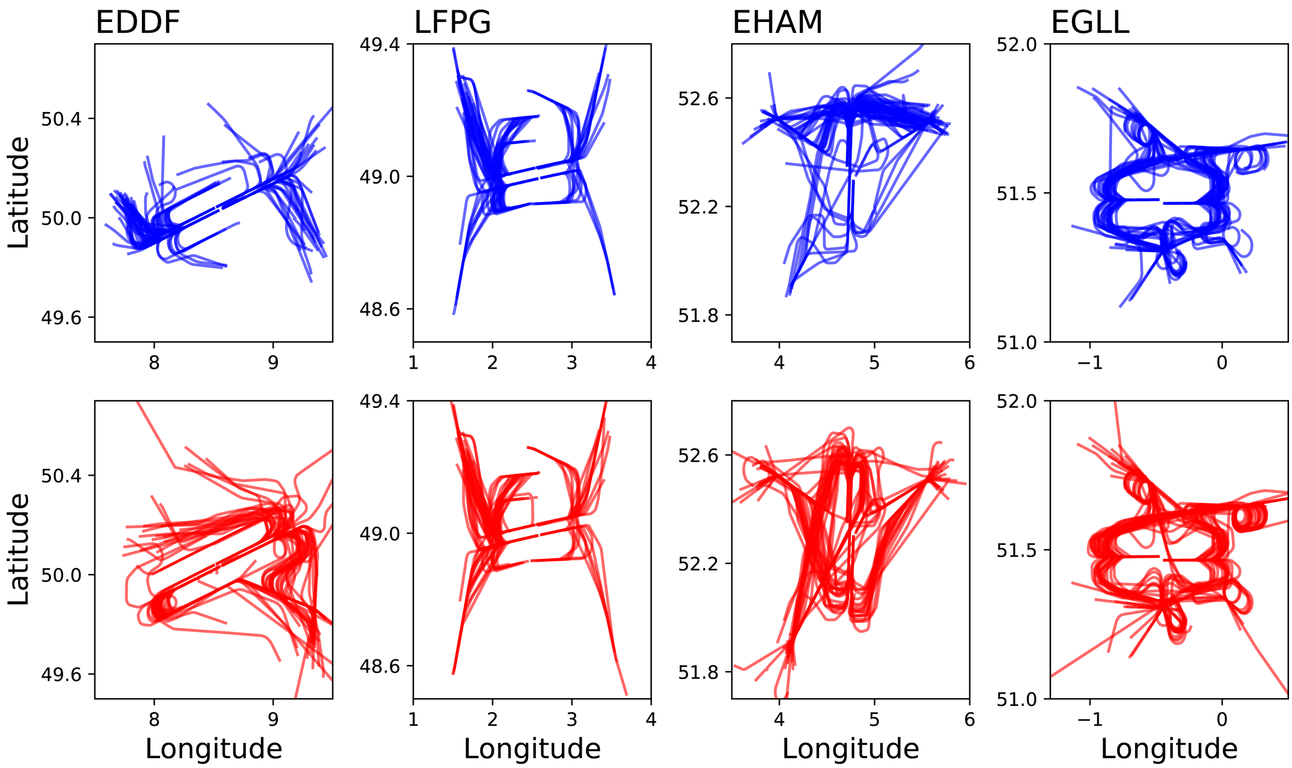

FIGURE 6. Trajectories of the 100 flights with smallest (top panels, blue) and largest (bottom panels, red) landing time, for the four biggest airports here considered.

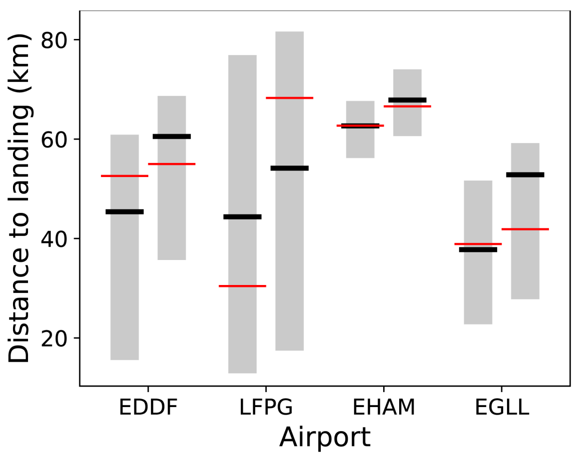

FIGURE 7. Distribution of the distance between the first available location below 10, 000 feet and the touchdown point. The two bands of each airport correspond to the most (left bar) and least efficient (right bar) trajectories, as depicted in Fig. 6. Grey bands indicate the 15*th*-85*th* percentiles range; black and red horizontal lines respectively the average and median.

i.e. the additional time that each flight is flying below 10, 000 feet when compared with the fastest one. To illustrate, the cumulative probability for EDDF at 600 seconds is 0.097; this indicates that 9.7% of flights had to fly an additional 10 minutes or more below 10, 000 feet before landing, when compared to the most direct flight. Therefore, the smaller the area under these curves, the more efficient (and consistent) are the landing procedures. The value of this distribution at a given threshold, as depicted by horizontal dashed lines in the bottom panels of Fig. 8, can readily be used as an efficiency measure; for the data here available, LFPG and EGLL are respectively the most and least efficient airports.

The next logical question is how much the difference between two approaches, as the ones previously analysed for Charles de Gaulle Airport, implies in economic and environmental terms. For that, we here use the Open Aircraft Performance Model (OpenAP) model in Python [38] to model the fuel consumption of a standard aircraft, i.e. an Airbus A320 with CFM56-5B4 engines [39]. We compare two scenarios: the *OKIPA 6Y* approach, with 36.3 NM flown at 7, 000 feet; and the *BANOX 6Y* approach, with 18.9 NM flown at 7, 000, plus 17.4 NM at 13, 000 feet (to keep the total distance constant). Average velocities of 230 (above 10, 000 feet) and 200 knots (below 10, 000 feet) are used, in accordance with published speed restrictions. The first case yields a consumption of 144.16 Kg of fuel, while the second 136.56 Kg. The difference, i.e. approx. 7.6 Kg, yields an increased emission of 23.94 Kg of CO2, using the equivalence of 3.15 grams of CO2 per gram of fuel [1]. While this number seems small, it is equivalent to the CO2 emission of 15 minutes of an average flight, or one tenth of the emissions of a 2.5 hours flight. Avoiding these emissions, e.g. by allowing the aircraft to keep a higher altitude, or by allowing a continuous descent approach, would thus have a significant positive environmental impact. Note that, while

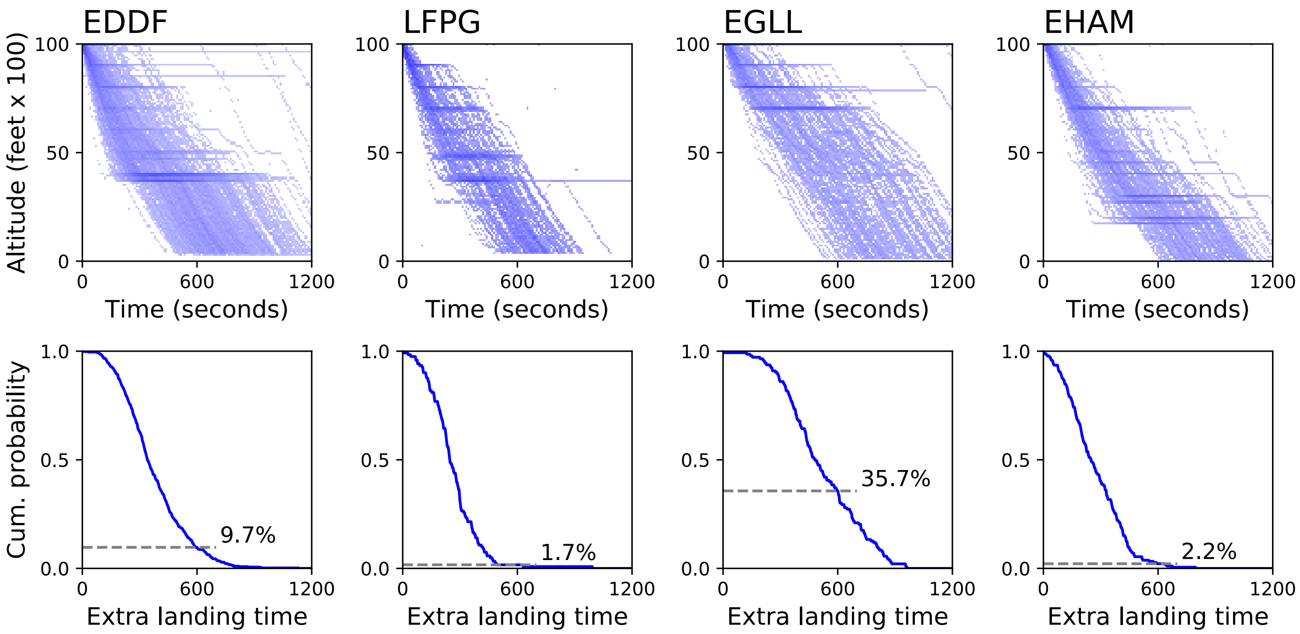

FIGURE 8. Vertical trajectories and efficiency of flights landing at the four largest airports here considered. Top panels represent the vertical profile of flights landing at each airport, i.e. their altitude as a function of the time passed since crossing 10, 000 feet. The bottom panels depict the cumulative probability distribution of the extra landing time, i.e. the additional time from crossing 10, 000 feet to landing compared to the fastest flight. The horizontal dashed lines indicate the fraction of flights taking 10 extra minutes (600 seconds) or more to land.

these two scenarios have been chosen for being easily identifiable both in Figs. 6 and 8, similar analyses can be performed on any pair of approach procedures, and especially on those with near entry waypoints.

V. DISCUSSION AND CONCLUSION

The last minutes of a flight have a non-negligible impact in the overall efficiency of the same, both in terms of the total travel time (and hence its cost) and of pollutant emissions. Still, this last phase has mostly been neglected by research efforts trying to optimise air transport. This may be due, firstly, to the relative low impact of the approach, when compared for instance to the departure in terms of fuel burnt; and secondly, to the difficulty inherent securing precise trajectory data.

This contribution illustrates how a large-scale data set of ADS-B messages can be used to characterise the last minutes of flights arriving at one airport, and consequently the efficiency and consistency of its arrival procedures. Specifically we have focused on the trajectories of aircraft arriving at 16 large European airports, starting from the moment they crossed the 10, 000 feet altitude; and studied the relationships between the time to land and factors like traffic volume, time of the day and approach direction. This time between crossing 10, 000 feet and landing is of major relevance, as aircraft burn comparatively more fuel at low altitudes and low speeds. This time can then be used as a proxy of the efficiency of the landing procedure, as smaller times imply not just higher efficiency in terms of costs, but also in terms of a more reduced environmental impact.

Results indicate that airport efficiency is highly heterogeneous, both between airports (e.g. between EGLL and LEMD, see Fig. 1, and between EGLL and LFGP, see Fig. 8), and within the same airport. Aircraft experience less efficiency with high volumes of traffic, as it may be expected, especially when analysed intra-daily (Fig. 3); but most airports also experience an increase in efficiency during summer (Fig. 4), i.e. when higher volumes of traffic are expected. The reason behind such inefficiencies varies from airport to airport: it can be related to the need of using holding patterns, or to the way approach trajectories interact with those of other airports (Fig. 7). In all cases, inefficiencies have a significant environmental impact, an aspect that cannot be neglected in our times [40].

From an operational point of view, the methodology here described can be used to evaluate and compare different approach procedures. As shown in Figs. 7 and 8, the distance and time flown below 10, 000 feet can be used as a proxy of the efficiency of the approach procedure. One can then identify abnormal flights, as e.g. those deviating more from a continuos descent; and further go back to analyse the exact dynamics of those flights, for instance by considering their trajectories as done in Fig. 6. Additionally, a simple performance indicator, or KPI, could be constructed, as illustrated by the horizontal lines in Fig. 8.

Such analyses can help improving the system at three different levels. First of all, one can consider a strategic time frame; a large number of historical operations (e.g. corresponding to one year or more) can be analysed in order to detect systemic inefficiencies arising from sub-optimal procedures, and propose changes accordingly. On a more tactical time scale, trajectories could be reviewed daily or weekly, to detect abnormal situations (e.g. specific adverse weather patterns) and eventually discuss solutions with the air traffic controllers. Finally, it would be feasible to develop a real-time trajectory analyser, monitoring the behaviour of incoming and departing aircraft and alerting when aircraft deviate from what expected - e.g. when the total distance flown below $10,000$ feet exceeds a threshold. These three approaches would be feasible thanks to the reduced computational cost and high understandability of the results. Additionally, the analyses here reported are easily generalisable to any airport, provided its idiosyncrasies are taken into account - as e.g. restrictions in allowed trajectories due to interactions with nearby airports.

When inefficiencies suggest the need for a change in the arrival procedures, two aspects have to be taken into account. The first is safety, as a complementary analysis will be required - a topic not discussed in this work. Also, changes in arrival procedures may affect delays and their propagation - a more efficient approach will reduce arrival delays, and potentially also secondary delays [41]–[44].

As a final point, it is worth noting that the approach here proposed can be applied beyond the landing phase. For instance, high resolution trajectory data could be used to analyse the efficiency of individual sectors or regions of the air space, to detect when aircraft have to deviate from an ideal, straight course [23], [45], [46].

As discussed in Section II, one important limitation of the present study is the use of an open-source data set of ADS-B messages. While ADS-B is a mature technology, its reliability is not complete. We here do not consider topics like security and malicious attacks [47]–[49], or bad position reports [50], which are outside the scope of this study. Still, the main limitation is that coverage is not complete, as public ADS-B networks rely on the contribution of volunteers; consequently, data for parts of approach trajectories, or even for full airports, may not be available. This has here been tackle in two ways: by deleting those flights for which a complete trajectory was not available; and by not considering airports for which a too small number of flights were available. Note that this last rule was not enforced in the case of four clearly marked airports (LEBL, LIRF, EGKK and LGAV), which indeed seem to yield biased results - see for instance Fig. 2. Such data incompleteness is nevertheless not a major problem for the study here presented. Even if some flights may be missing for each airport, the main conclusions still hold, as for instance the types of approaches discussed in Figs. 6 and 8.

To conclude, this contribution is an example of how large-scale collections of public data can be used to analyse air transport operations, above and beyond what can be obtained by classical approaches. While micro-scale models allow simulating the behaviour of aircraft under some given conditions, the definition of the latter ones is a non-trivial (and often subjective) process. Data analysis then constitutes a clear alternative, allowing characterising what the system *actually* did, as opposed to what it was *supposed* to do.

REFERENCES

[1] *EEA Air Pollutant Emission Inventory Guidebook 2013*, EMEP, Eur. Environ. Agency, Copenhagen, Denmark, 2013.

[2] D. N. Fry and D. A. DeLaurentis, "A new systems analysis: Perspectives on system-of-systems and regional transportation proof-of-concept study," in *Proc. 26th Int. Conf. Aeronaut. Sci.*, 2008, pp. 50–56.

[3] G. Sugiyanto, P. B. Santosa, A. Wibowo, and M. Y. Santi, "Analysis of Hub-and-spoke airport networks in java island, based on cargo volume and freight ratio," *Procedia Eng.*, vol. 125, pp. 556–563, Jan. 2015.

[4] P. Lai, A. Potter, M. Beynon, and A. Beresford, "Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique," *Transp. Policy*, vol. 42, pp. 75–85, Aug. 2015.

[5] T. G. Reynolds, "Development of flight inefficiency metrics for environmental performance assessment of ATM," in *Proc. 8th USA/Eur. Seminar Air Traffic Manage. Res. Develop. (ATM)*, 2009, Paper #122. [Online]. Available: https://atm2003.eurocontrol.fr/8th-seminar-united-states-june-2009/papers/paper_122/view

[6] M. Alcabin, R. Schwab, S. Cheng, K.-O. Tong, and C. Soncrant, "Measuring vertical flight path efficiency in the national airspace system," in *Proc. 9th AIAA Aviation Technol., Integr., Oper. Conf. (ATIO) Aircr. Noise Emissions Reduction Symp. (ANERS)*, 2009, p. 6959.

[7] K. Kageyama and Y. Miyatsu, "A basic study on efficiency in Japanese airspace," in *Proc. 28th Int. Council Aeronaut. Sci. (ICAS)*, 2012, pp. 4125–4132.

[8] M. S. Ryerson, M. Hansen, and J. Bonn, "Time to burn: Flight delay, terminal efficiency, and fuel consumption in the national airspace system," *Transp. Res. A, Policy Pract.*, vol. 69, pp. 286–298, Nov. 2014.

[9] S. Pavlova and A. Zadorozhnia, "Analysis of free route airspace and performance based navigation implementation in the European air navigation system," *Proc. Nat. Aviation Univ.*, vol. 61, no. 4, pp. 28–35, Dec. 2014.

[10] C. A. Nava-Gaxiola and C. Barrado, "Performance measures of the SESAR southwest functional airspace block," *J. Air Transp. Manage.*, vol. 50, pp. 21–29, Jan. 2016.

[11] A. Cook, S. Belkoura, and M. Zanin, "ATM performance measurement in Europe, the US and China," *Chin. J. Aeronaut.*, vol. 30, no. 2, pp. 479–490, Apr. 2017.

[12] A. Cook, G. Tanner, V. Williams, and G. Meise, "Dynamic cost indexing–managing airline delay costs," *J. Air Transp. Manage.*, vol. 15, no. 1, pp. 26–35, Jan. 2009.

[13] O. Turnbull, A. Richards, J. Lawry, and M. Lowenberg, "Fuzzy decision tree cloning of flight trajectory optimisation for rapid path planning," in *Proc. 45th IEEE Conf. Decis. Control*, Dec. 2006, pp. 6361–6366.

[14] H. Zolata, C. Celis, V. Sethi, R. Singh, and D. Zammit-Mangion, "A multi-criteria simulation framework for civil aircraft trajectory optimisation," in *Proc. ASME Int. Mech. Eng. Congr. Expo.*, 2010, pp. 95–105.

[15] K. Palopo, R. D. Windhorst, S. Suharwardy, and H.-T. Lee, "Wind-optimal routing in the national airspace system," *J. Aircr.*, vol. 47, no. 5, pp. 1584–1592, Sep. 2010.

[16] C. Tsotskas, T. Kipouros, and M. Savill, "Biobjective optimisation of preliminary aircraft trajectories," in *Proc. Int. Conf. Evol. Multi-Criterion Optim.* Berlin, Germany: Springer, 2013, pp. 741–755.

[17] A. Gardi, R. Sabatini, S. Ramasamy, and T. Kistan, "Real-time trajectory optimisation models for next generation air traffic management systems," *Appl. Mech. Mater.*, vol. 629, pp. 327–332, Oct. 2014.

[18] R. S. F. Patrón, A. Kessaci, and R. M. Botez, "Horizontal flight trajectories optimisation for commercial aircraft through a flight management system," *Aeronaut. J.*, vol. 118, no. 1210, pp. 1499–1518, Dec. 2014.

[19] X. Prats, F. Bussink, R. Verhoeven, and A. Marsman, "Evaluation of in-flight trajectory optimisation with time constraints in a moving base flight simulator," in *Proc. IEEE/AIAA 34th Digit. Avionics Syst. Conf. (DASC)*, Sep. 2015, p. 1F3-1.

[20] A. Gardi, M. Marino, S. Ramasamy, R. Sabatini, and T. Kistan, "4-dimensional trajectory optimisation algorithm for air traffic management systems," in *Proc. IEEE/AIAA 35th Digit. Avionics Syst. Conf. (DASC)*, Sep. 2016, pp. 1–7.

[21] T. Mihetec, S. Steiner, and D. Odić, "Utilization of flexible airspace structure in flight efficiency optimization," *PROMET-Traffic Transp.*, vol. 25, no. 2, pp. 109–118, Jan. 1970.

[22] I. Gerdes, A. Temme, and M. Schultz, "Dynamic airspace sectorisation for flight-centric operations," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 460–480, Oct. 2018.

[23] J. M. Hoekstra, R. N. H. W. van Gent, and R. C. J. Ruigrok, "Designing for safety: The 'free flight' air traffic management concept," *Rel. Eng. Syst. Saf.*, vol. 75, no. 2, pp. 215–232, Feb. 2002.

[24] P. Dell'Olmo and G. Lulli, "A new hierarchical architecture for air traffic management: Optimisation of airway capacity in a free flight scenario," *Eur. J. Oper. Res.*, vol. 144, no. 1, pp. 179–193, Jan. 2003.
[25] J.-P.-B. Clarke, N. T. Ho, L. Ren, J. A. Brown, K. R. Elmer, K.-O. Tong, and J. K. Wat, "Continuous descent approach: Design and flight test for Louisville international airport," *J. Aircr.*, vol. 41, no. 5, pp. 1054–1066, Sep. 2004.
[26] L. Jin, Y. Cao, and D. Sun, "Investigation of potential fuel savings due to continuous-descent approach," *J. Aircr.*, vol. 50, no. 3, pp. 807–816, May 2013.
[27] A. Murrieta Mendoza and R. Botez, "Vertical navigation trajectory optimization algorithm for a commercial aircraft," in *Proc. AIAA/3AF Aircr. Noise Emissions Reduction Symp.*, Jun. 2014, p. 3019.
[28] V. F. Ribeiro, D. A. Pamplona, J. A. T. G. Fregnani, I. R. de Oliveira, and L. Weigang, "Modeling the swarm optimization to build effective continuous descent arrival sequences," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 760–765.
[29] T. Prevot, B. Crane, E. Palmer, and N. Smith, "Efficient arrival management utilizing ATC and aircraft automation," in *Proc. Int. Conf. Hum.-Comput. Interact. Aeronaut. (HCI-Aero)*. Toulouse, France: EURISCO, 2000, pp. 183–188.
[30] T. K. Simić and O. Babić, "Airport traffic complexity and environment efficiency metrics for evaluation of ATM measures," *J. Air Transp. Manage.*, vol. 42, pp. 260–271, Jan. 2015.
[31] A. Lemetti, T. Polishchuk, R. Sáez, and X. Prats, "Evaluation of flight efficiency for Stockholm Arlanda airport arrivals," in *Proc. IEEE/AIAA 38th Digit. Avionics Syst. Conf. (DASC)*, Sep. 2019, pp. 1–8.
[32] J.-P. Clarke, J. Brooks, G. Nagle, A. Scacchioli, W. White, and S. R. Liu, "Optimized profile descent arrivals at Los Angeles international airport," *J. Aircr.*, vol. 50, no. 2, pp. 360–369, Mar. 2013.
[33] C. Gong and D. Mcnally, "Dynamic arrival routes: A trajectory-based weather avoidance system for merging arrivals and metering," in *Proc. 15th AIAA Aviation Technol., Integr., Oper. Conf.*, Jun. 2015, p. 3394.
[34] M. Schäfer, M. Strohmeier, V. Lenders, I. Martinovic, and M. Wilhelm, "Bringing up OpenSky: A large-scale ADS-B sensor network for research," in *Proc. 13th Int. Symp. Inf. Process. Sensor Netw. (IPSN)*, Apr. 2014, pp. 83–94.
[35] G. Williams, "GPS for the sky: A survey of automatic dependent surveillance-broadcast (ADS-B) and its implementation in the United States," *J. Air L. Com.*, vol. 74, p. 473, 2009.
[36] R. Salcido, A. Kendall, and Y. Zhao, "Analysis of automatic dependent surveillance-broadcast data," in *Proc. AAAI Fall Symp. Ser.*, 2017, pp. 225–230.
[37] Z. Šidák, "Rectangular confidence regions for the means of multivariate normal distributions," *J. Amer. Stat. Assoc.*, vol. 62, no. 318, pp. 626–633, Jun. 1967.
[38] J. Sun, J. Ellerbroek, and J. M. Hoekstra, "Openap: The open-source aircraft performance model and associated toolkit," Delft Univ. Technol., Delft, The Netherlands, Tech. Rep., 2020. [Online]. Available: https://www.researchgate.net/publication/332013573_OpenAP_An_open-source_aircraft_performance_model_for_air_transportation_studies_and_simulations
[39] E. Roux, *Turbofan Turbojet Engines: Database Handbook*. Berlin, Germany: Elodie Roux, 2007.
[40] A. W. Schäfer and I. A. Waitz, "Air transportation and the environment," *Transp. Policy*, vol. 34, pp. 1–4, Jul. 2014.
[41] Y. Guleria, Q. Cai, S. Alam, and L. Li, "A multi-agent approach for reactionary delay prediction of flights," *IEEE Access*, vol. 7, pp. 181565–181579, 2019.
[42] L. Belcastro, F. Marozzo, D. Talia, and P. Trunfio, "Using scalable data mining for predicting flight delays," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 1, pp. 1–20, Oct. 2016.
[43] G. Gui, F. Liu, J. Sun, J. Yang, Z. Zhou, and D. Zhao, "Flight delay prediction based on aviation big data and machine learning," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 140–150, Jan. 2020.
[44] S. Belkoura, J. M. Pe na, and M. Zanin, "Beyond linear delay multipliers in air transport," *J. Adv. Transp.*, vol. 2017, Jun. 2017, Art. no. 8139215.
[45] S. Belkoura, J. M. Peña, and M. Zanin, "Generation and recovery of airborne delays in air transport," *Transp. Res. C, Emerg. Technol.*, vol. 69, pp. 436–450, Aug. 2016.
[46] C. Bongiorno, G. Gurtner, F. Lillo, R. N. Mantegna, and S. Miccichè, "Statistical characterization of deviations from planned flight trajectories in air traffic management," *J. Air Transp. Manage.*, vol. 58, pp. 152–163, Jan. 2017.
[47] D. McCallie, J. Butts, and R. Mills, "Security analysis of the ADS-B implementation in the next generation air transportation system," *Int. J. Crit. Infrastruct. Protection*, vol. 4, no. 2, pp. 78–87, Aug. 2011.
[48] A. Costin and A. Francillon, "Ghost in the air (traffic): On insecurity of ADS-B protocol and practical attacks on ADS-B devices," in *Proc. Black Hat USA*, 2012, pp. 1–12.
[49] M. Strohmeier, V. Lenders, and I. Martinovic, "On the security of the automatic dependent surveillance-broadcast protocol," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 1066–1087, 2nd Quart., 2015.
[50] E. Spinielli, R. Koelle, M. Zanin, and S. Belkoura, "Initial implementation of reference trajectories for performance review," in *Proc. 7th SESAR Innov. Days Belgrade (Serbia)*, 2017. [Online]. Available: https://www.sesarju.eu/node/3438

MASSIMILIANO ZANIN was born in Verona, Italy, in 1982. He received the Ph.D. degree in computer engineering from the Universidade Nova de Lisboa, Portugal, in 2014.

He is currently a Researcher with the Institute for Cross-Disciplinary Physics and Complex Systems, Palma de Mallorca, Spain. His main research interests include complex networks and data science, from a theoretical perspective and through their application to several real-world problems. Throughout his career, he has published more than 80 articles in international journals and more than 50 contributions in conferences, reaching an H-index of 25. He has participated in several European competitive research projects. He is currently the PI of the ERC StG ARCTIC, on the analysis and modeling of delay propagation in air transport.