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Analysing the Impact of Go-Around Occurrences at Large European Airports

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Abstract
Go-arounds (GoA) or missed approaches are standard flight procedures initiated when an approach is aborted for safety reasons, requiring pilots to reposition the aircraft for a subsequent landing attempt. This study leverages ADS-B data sourced from the OpenSky Network, collected at 20 major European airports between January 2019 and July 2023. Out of 6.7 million retrieved landing trajectories, 20,196 GoA were identified and analyzed. We conducted statistical evaluations on these GoA instances to compare the rates of GoA at different airports, market segments, and aircraft types. We also looked at the distributions of distance, duration, and fuel consumption of GoA for the different airports. Of particular note, we quantified the impact of a GoA on the surrounding arrival traffic by analyzing how GoA events affect Arrival Sequencing and Metering Area (ASMA) timings. Our results show that the rate of GoA at the assessed airports ranged from 1.5 to 6 occurrences per 1,000 landings. The median duration and distance of a GoA varied depending on the airport, falling between 11.5 and 16.5 minutes, and 36.5 and 58.2 NM respectively. During a GoA, an Airbus A320 typically consumes between 350 and 600 kg of fuel. Importantly, our findings demonstrate that a GoA occurrence can significantly impact the efficiency of arriving traffic at an airport, causing disruptions lasting up to an hour. ASMA timings tend to increase directly after a GoA occurs and peak for landings occurring 10 to 25 minutes after a GoA, with flight time increases ranging from 30 to 100 seconds, depending on the airport. These timings gradually return to their pre-GoA levels within the following hour, though certain airports may experience longer recovery periods. This comprehensive study on GoA provides a deeper understanding of their impact, offering valuable insights that can support data-driven decision-making in the aviation industry.

Keywords: Go-around; Safety; Airport Performance; Automatic Dependent Surveillance-Broadcast

Abbreviations: ADS-B: Automatic Dependent Surveillance-Broadcast; ASMA: Arrival Sequencing and Metering Area; ATC: Air Traffic Control; GoA: Go-Around; KDE: Kernel Density Estimation; OSN: Opensky Network;

1. Introduction

Safety is of utmost importance in aviation. For this reason, pilots and air traffic controllers can abort an approach if a safe landing cannot be continued for a number of reasons [1, 2, 3, 4], such as adverse weather conditions [5], approaches flown "too fast, too low, and too close" [6], unstable approaches [7], excessive workload, etc. In these cases, pilots are required to fly a Go-Around (GoA). This is a normal flight procedure in which the pilots abort an approach, climb to a safe altitude, reposition their aircraft, and then make another landing attempt. For instrument approaches, the flight path that aircraft must follow during a GoA is specified precisely in the form of a so-called *missed approach* procedure.

GoAs occur relatively rarely. As shown later in this study, the frequency of GoA varies between 1.5 and 6 events per thousand approaches flown. Because of their rarity, GoAs are considered safety relevant and require appropriate training of both air traffic controllers and the cockpit crew [8, 9]. Besides that, GoA can have a significant impact on the sustainability of a flight (e.g., due to reduced fuel efficiency as well as increased CO2 and noise emissions [10, 11, 12]), the operational performance of an airport or an airline (e.g., reduction in airport capacity [13], introduction of delays in flight schedules), as well as the perceived passenger experience.

The literature on GoA is mainly concerned with (i) the identification of factors that favour GoA, (ii) the detection and labelling of GoA events given trajectory data, (iii) the generation of artificial GoA trajectories, and (iv) the prediction of GoA events:

To address the question of which factors can lead to a GoA, Gariel, Spieser, and Frazzoli [14] evaluated a four-year data set of San Francisco International Airport using statistical analysis, while Dai, Liu, and Hansen [15, 16] applied a principal component logistic regression model to a six-month data set on New York John F. Kennedy Airport. It has been found that a variety of factors, such as adverse weather conditions (poor visibility, low ceiling), increased traffic density, or aircraft traffic on the ground of an airport may affect the occurrence of GoA events.

To detect and label GoA events, data sets containing trajectories of approaching aircraft are required. In the literature, data originating from secondary radar [14] or from Automatic Dependent Surveillance-Broadcast (ADS-B) [17, 18, 19] are mainly used for this purpose. For the actual process of detection and labelling, rule-based algorithms are applied [18, 16]. The detection of GoA events on the basis of trajectory data is computationally expensive. Therefore, Monstein et al. [20] made a data set of trajectories sourced from the Opensky Network (OSN) [21] available to the public, which contains more than 9 million trajectories labelled as landings and over 33,000 identified as GoA.

As GoAs are rare events, Krauth et al. [22] developed a method based on multivariate density models to generate artificial GoA trajectories. Subsequently, Krauth et al. applied this method in a Monte Carlo simulation-based collision risk model to estimate the probability of interaction between aircraft taking off at Zurich Airport and aircraft flying a GoA.

The prediction of GoA events is carried out both on a macroscopic as well as on a microscopic level. The macroscopic level addresses the prediction of GoA events for an airport system. In this regard, Chou, Tien, and Bateman [23] evaluated 18 different supervised machine learning models to investigate which method is best suited to predict GoA occurrences at Denver Airport. It turned out that a *CatBoost* model, which was fine-tuned for usage at the airport in question, yielded the best results. Moreover, Figuet et al. [19] proposed the use of a generalised additive model for the prediction of the GoA rate at Zurich Airport. The model considers a number of inputs, such as weather-related factors, traffic density information, aircraft and airline mix, etc., to estimate the probability of GoA in the next hour. In contrast, microscopic prediction models deal with individual flights or trajectories. Gariel, Spieser, and Frazzoli [14] developed a preliminary alert system for GoA prediction based on linear discriminant analysis. Figuet et al. [19] evaluated seven different machine learning classifiers to evaluate which GoA of aircraft approaching Zurich Airport can be predicted best. As such, a *random forest* classifier was found to perform best, albeit with a high false positive rate. Similarly, Puranik, Rodriguez, and Mavris [24] employed a *random forest* model for the online prediction of aircraft landing parameters (e.g., landing speed) and ultimately the probability of GoA. Finally, Dhief et al. [25] proposed a microscopic GoA prediction model based on the *CatBoost* and

XGBoost algorithms that are employed to predict GoA at Philadelphia and Van Nuys Airports.

While the literature on GoA is rather extensive, there is a notable lack of comprehensive macroscopic studies on GoA's impact on incoming airport traffic. Addressing this gap, our paper provides a macroscopic examination of GoA events at 20 major European airports. We focus on statistically analyzing the GoA rate and assessing the influence of GoA occurrences on the efficiency of nearby landing traffic. For this purpose, we have compiled an extensive ADS-B data set from the OSN, encompassing over 6.7 million arrival trajectories at these airports from January 2019 to June 2023. Within this data set, we identified more than 20,196 individual GoAs.

2. Data sets and Methodology

In this study, data originating from two different sources are merged. The first data set contains ADS-B trajectories sourced from the OSN [21], while the second data set was extracted from the EUROCONTROL *Network Manager* (EU-NM). Both data sets are introduced below in more detail.

2.1 ADS-B trajectories

For this study, we collected ADS-B data of landing trajectories from the OSN at 20 major European airports, covering a time period from January 2019 to July 2023. These 20 airports were selected from the 30 largest European airports in terms of movements. Table 1 summarises the number and distribution of landings that the OSN data set used in this study contains per airport.

Filtering. As the focus of this study lies on identifying GoA executed by aircraft operated in commercial aviation, we refined our data set by exclusively retaining airplanes equipped with turboprop or jet engines, as inferred from their ICAO aircraft type descriptions. Following this filtering process, our landing data set comprises of approximately 6.7 million flight trajectories.

GoA identification. Following Monstein et al. [20], GoAs were identified using the *traffic* Python library [26]: First, each segment of a trajectory is assigned to a specific flight phase, employing the algorithms introduced by Sun, Ellerbroek, and Hoekstra [27]. Then, portions of the trajectory that align with a runway at an airport for at least one minute are identified and, if two distinct runway-aligned segments are separated by a single climb phase, the trajectory is classified as a GoA. Having applied this classification algorithm to all 6.7 million flight trajectories mentioned above, 20,196 flights were identified as performing a GoA.

2.2 EUROCONTROL EU-NM

In its role as *Network Manager*, EUROCONTROL collects detailed data on flights, encompassing both planned and actual occurrences. In this study, two different data sets curated by EUROCONTROL are used to augment the OSN-based landings data set, namely market segment information and Arrival Sequencing and Metering Area (ASMA) data.

Market segment. Based on EUROCONTROL EU-NM data, a market segment can be assigned to an aircraft movement on the basis of the aircraft type, the aircraft operator, and the ICAO flight type. Thereby, EUROCONTROL distinguishes between seven different market segments, namely mainline, low-cost, business, regional, cargo, non-scheduled, and military.

Table 1. Distribution of the 6.7M collected and filtered landings at 20 European airports.

Airport ICAO	Airport Name	Country	# Landings	# GoAs
EDDB	Berlin Brandenburg Airport	Germany	147,801	451
EDDF	Frankfurt Airport	Germany	597,956	1,904
EDDM	Munich Airport	Germany	455,718	1,346
EGCC	Manchester Airport	United Kingdom	166,930	599
EGLL	London Heathrow Airport	United Kingdom	612,412	2,326
EGSS	London Stansted Airport	United Kingdom	223,578	641
EHAM	Amsterdam Airport Schiphol	Netherlands	552,492	1,036
EIDW	Dublin Airport	Ireland	254,502	899
EKCH	Copenhagen Kastrup Airport	Denmark	229,489	525
EPWA	Warsaw Chopin Airport	Poland	177,733	596
ESSA	Stockholm-Arlanda Airport	Sweden	219,014	590
LEMD	Adolfo Suárez Madrid–Barajas Airport	Spain	517,075	1000
LFPG	Charles de Gaulle International Airport	France	612,676	2,363
LFPO	Paris-Orly Airport	France	239,425	755
LIMC	Malpensa International Airport	Italy	196,487	445
LIRF	Rome–Fiumicino Leonardo da Vinci International...	Italy	325,878	488
LOWW	Vienna International Airport	Austria	292,967	1,029
LSGG	Geneva Cointrin International Airport	Switzerland	185,732	482
LSZH	Zürich Airport	Switzerland	284,497	1,031
LTFJ	Istanbul Sabiha Gökçen International Airport	Turkey	272,956	1673

Arrival Sequencing and Metering Area. An Arrival Sequencing and Metering Area (ASMA) is a virtual cylinder with radius 40 NM, whose center is located on the reference point of an airport. By using EUROCONTROL's Correlated Position Report data, which refers to data concerning the position of aircraft derived from Air Traffic Control (ATC) surveillance systems, the entrance of flights into the ASMA of the 20 major European airports considered in this study is detected. More precisely, the time of entry as well as the entry point, i.e., latitude and longitude, of each aircraft is recorded.

2.3 Merged data set

In a first step, metadata on the OSN-sourced ADS-B trajectories is extracted. Subsequently, this metadata is merged with its corresponding entries logged in the EUROCONTROL EU-NM data set on the basis of the day of flight, the destination airport, and the transponder address of the aircraft, i.e., the ICAO24 address. In the course of this, trajectories landing at Istanbul Sabiha Gökçen Airport could not be mapped, as this airport is not covered in the EU-NM data set. For all the other airports, more than 95% of the landings could be mapped with the EU-NM data set, with the exception of Manchester Airport for which only 51% of the trajectories could be mapped. The column names of the merged data set, the data types used, as well as a description of all columns are specified in Table 2.

2.4 Methodology

The methods section is divided into two parts. First we show how the GoA statistics were compiled, then how the impact of a GoA on arriving traffic is determined.

Table 2. Columns in the data set.

Column name	Type	Description
stop	date time	UTC time of landing.
icao24	string	Unique 24-bit (hexadecimal number) ICAO identifier of the aircraft concerned.
callsign	string	Aircraft identifier in air-ground communications.
airport	string	ICAO airport code where the aircraft is landing.
ILS	list	Designation of runways on which the aircraft performed its landing attempts.
GoA	Boolean	"True" if at least one GA was performed, otherwise "False".
n_attempts	integer	Number of approaches identified for this flight.
attempt_times	list	List of timestamps at which a landing is attempted.
market_segment	string	Flight market segment.
n_rwy_approached	integer	Number of unique runways approached by this flight.
AC_CLASS	string	Aircraft class.
C40_CROSS_TIME	string	Timestamp at which the aircraft enters the ASMA cylinder.
C40_BEARING	float	Bearing between aircraft and airport when entering the ASMA cylinder.
C40_CROSS_LAT	float	Aircraft latitude when entering the ASMA cylinder.
C40_CROSS_LON	float	Aircraft longitude when entering the ASMA cylinder.

2.4.1 GoA statistics

Initially, we created GoA statistics by calculating the GoA rate based of the landing airport, the market segment, and the aircraft type. To this end, we first divided the number of observed GoA incidents within each group by the total number of landings within that same group. Subsequently, we calculated the 95% confidence interval for each estimated GoA rate by employing the Clopper-Pearson interval method [28].

In a second step, we shifted our focus to the analysis of GoA segments. For this matter, we extracted the portions of flight trajectories that correspond to GoA. By this we refer to the part of a flight from the moment the aircraft crosses the landing runway threshold until it crosses the threshold for its next landing attempt. After identifying the GoA portions of all trajectories containing a GoA, we calculated the duration and distance of each GoA segment and aggregate statistics on a per-airport basis.

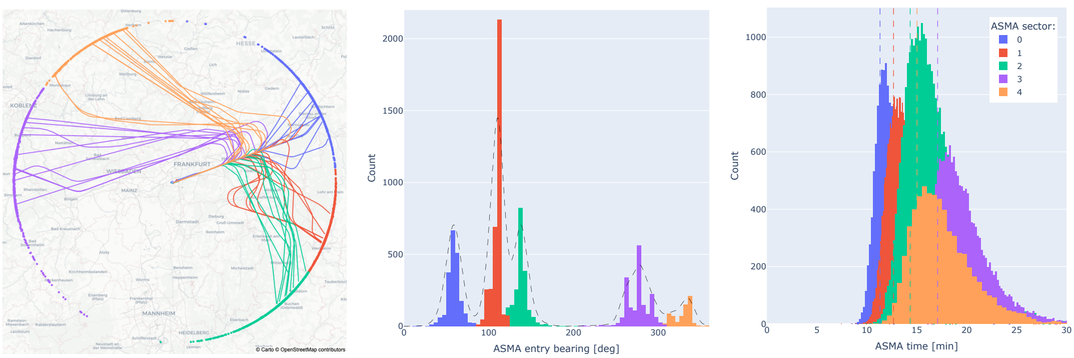
In a last step, we estimated the fuel consumption of aircraft performing a GoA. In this regard, we focused exemplary on GoA flown by aircraft of type Airbus A320. To calculate fuel consumption, we first extracted the flight portion between GoA initialization (i.e., the lowest altitude observed during the first approach) and touch-down. Then, we employed the fuel flow model implemented in the *OpenAP* library [29]. This model allows us to estimate fuel consumption using actual flight trajectory data (namely the altitude, the vertical rate, and the speed), with the caveat that it requires information on the aircraft's mass, which is not available in the ADS-B data. For this reason, we assumed a fixed mass value of 60 tons, i.e., 93% of the maximum landing weight, for each A320 when the GoA is initialized.

2.4.2 Impact of GoA on the arrival traffic

To investigate the impact of GoAs on other traffic arriving at an airport, we developed a methodology based on the ASMA timing method. As such, the ASMA timing method quantifies the actual duration of a flight between its last entry into the ASMA cylinder, see Section 2.2, and its landing time. With this methodology, we determined an *unimpeded ASMA time* that reflects the transit time in uncongested airspace conditions. To this end, the unimpeded time is statistically determined by calculating the 20th-percentile of the observed ASMA times of distinct groups of flights that share common parameters, including aircraft class, ASMA entry sector, and arrival runway. Subsequently, the *additional ASMA time* is determined for a given flight by calculating the difference between a flight's actual ASMA time and the corresponding *unimpeded ASMA time*.

The methodology introduced above is applied on a per runway basis. After retrieving all landings for a runway of interest, we retrieved the bearing between the airport and the aircraft at the moment it enters the ASMA cylinder. We then fitted the distribution of these bearings with a Gaussian kernel density estimation (KDE). The KDE approach allows us to smooth the data and estimate the underlying distribution. Subsequently, we extracted the modes, or peaks, of this distribution by identifying the local maxima of the fitted KDE. Following this, each individual landing is assigned to the nearest mode of the extracted bearings. If the first and last modes are separated by less than 15 degrees, they are considered as one to circumvent the 0 to 360 degrees discontinuity.

With the ASMA sectors identified, we calculated the *unimpeded ASMA time* for each combination of aircraft class and entry sector by determining the 20th-percentile of all ASMA times for each combination. To illustrate our methodology, we present an example for runway 25L at Frankfurt Airport in Figure 1. Subsequently, we calculated the *additional ASMA time* for each landing on this runway.



(a) ASMA entry points and 10 randomly sampled trajectories per sector.
(b) ASMA entry bearings distribution and the fitted KDE.
(c) ASMA time distribution and 20th percentiles.

Figure 1. ASMA entry points / bearings, associated entry sectors, and corresponding ASMA time distributions for runway 25L at Frankfurt Airport.

To assess the impact of GoA on landings at an airport, we compared the *additional ASMA times* before and after a GoA. Our methodology, applied to every GoA occurrence, starts with the following steps:

1. **Baseline - Pre-GoA *Additional ASMA Time:*** We established a baseline by computing the median *additional ASMA time* for landings within the 20-minute interval preceding a GoA.
2. **Post-GoA *Additional ASMA Time:*** We calculated the median additional ASMA times for successive 10-minute intervals following the GoA, ranging from [0, 10min], [1, 11min], up to [50, 60min].
3. **Go-Around Arrival Induced Delay:** The Go-Around Arrival Induced Delay (GoAID) for each 10min window was determined by subtracting the pre-GoA median from the respective post-GoA median additional ASMA times.

After calculating the GoAID for each time window of every GoA occurrence, we aggregated these values at an airport level. This entailed determining the median GoAID for each interval across all GoA occurrences at the airport. For example, the median GoAID for the [0, 10min] period provides insight into the typical delay experienced during this interval following a GoA at that airport.

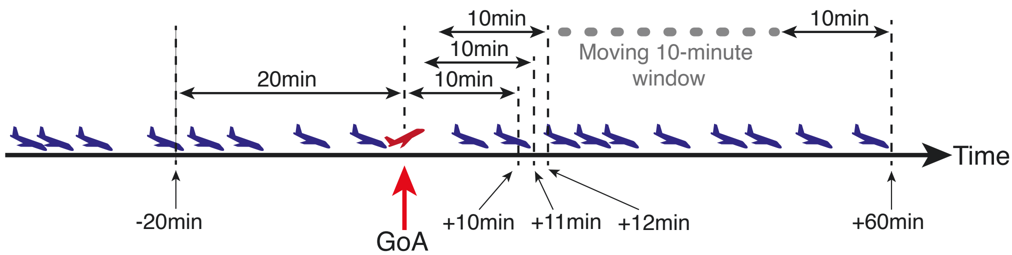


Figure 2. Illustration of the *Go-Around Induced Delay* (GoAID) calculation.

To verify whether the GoAID times are directly related to GoA events, we employed a control group approach. Specifically, we applied our analysis methodology to landing sequences that have not been affected by any GoA occurrence. To create these control groups, we randomly selected time periods at each airport during which no GoA occurrences were observed. Ten control groups for each airport were created. This comparative analysis between GoA and non-GoA periods allowed us to discern whether there exists a significant difference in GoAID times. If the GoAID times exhibit notable distinctions during GoA periods as opposed to non-GoA periods, it strongly suggests that GoAs have a discernible impact on landing delays.

3. Results

This section first presents a series of GoA-related statistics. Then, ASMA timings are used to show how GoAs influence the efficiency of an airport and its arriving traffic.

3.1 Statistics

Statistical information on the observed GoAs is provided below. This includes information on the rate of GoA, the distance and duration of the GoA, and the fuel consumption of Airbus A320 aircraft during GoA.

GoA Rates. The observed GoA rate per airport is illustrated in Figure 3. As such, the GoA rate varies from slightly below 1.5 GoA per 1,000 landings for Rome Fiumicino Airport up to a rate of 6 for Sabiha Gökçen Airport in Istanbul, with most airports recording a value below 3.8 GoA per 1,000 landings. On average, the 20 large European airports analysed in this study show a GoA rate of 3.1 per 1,000 landings.

Figure 4 contains the observed GoA rate for different market segments over the period from January 2019 to July 2023. The figure indicates on the one hand that the *Non-Scheduled* and *Regional* market segments recorded a lower GoA rate of approximately 2.2 GoA per 1,000 landings. On the other hand, the *Mainline*, *Cargo*, and *Low-Cost* segments exhibited a higher rate of approximately 3.2 GoA per 1,000 landings. The *Business Aviation* segment occupied an intermediate position, with a GoA rate of about 2.6 per 1,000 landings.

Figure 5 illustrates the GoA rate according to different types of aircraft. A clear variation is noticeable in the GoA rate across numerous airframe typecodes, with rates ranging from 1 to 4.5 GoA per 1,000 landings.

GoA distances and duration. Table 3 summarizes the different quartiles for GoA execution time and distance at different airports. Median times vary from 11.5 minutes for London Stansted Airport

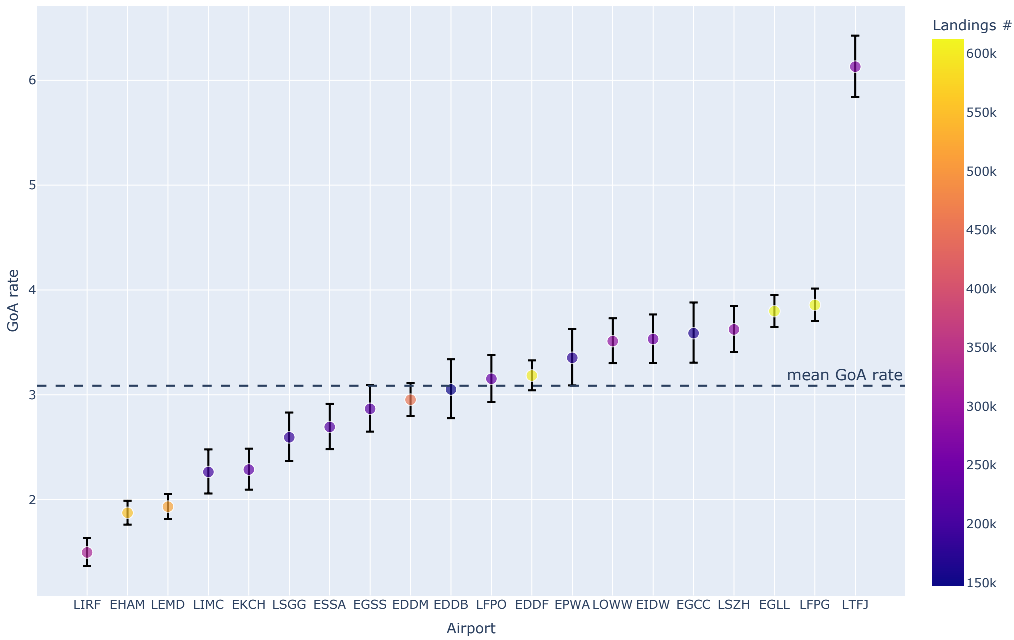


Figure 3. Observed GoA rate per airport type and the 95% CI. The dashed line refers to the mean GoA rate per airport.

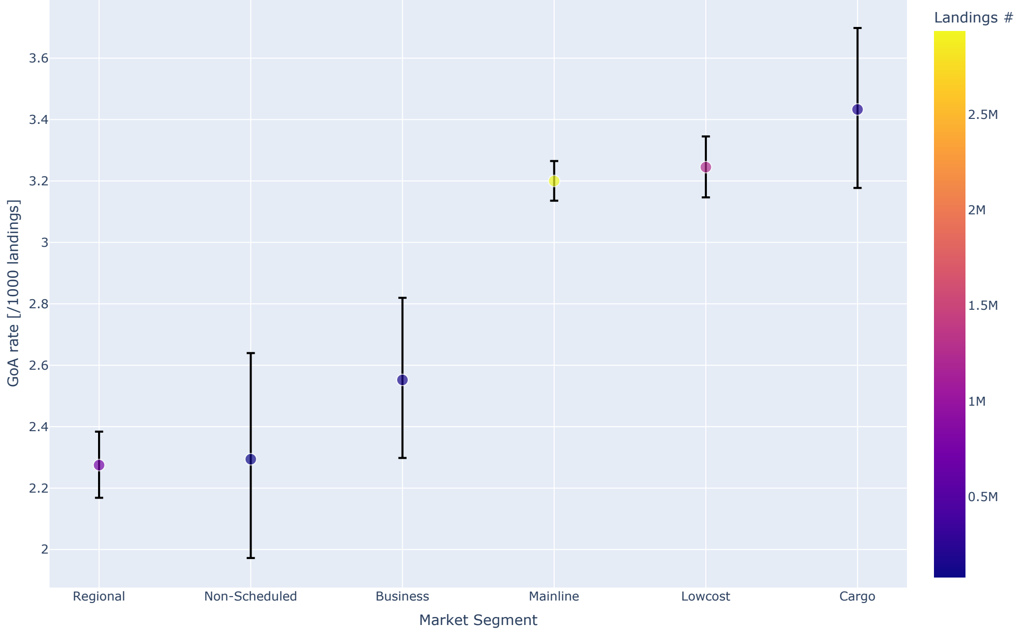


Figure 4. Observed GoA rate, expressed as number of GoA per 1,000 landings, per market segment and the 95% CI. The color of the dot represents the number of observed landings for the corresponding market segment.

and 16.5 minutes for Madrid Barajas Airport, while the median distances are ranging from 36.4 NM to 58.2 NM. It is interesting to note that some GoA are particularly long. For example, the longest GoA contained in the data set used in this study was executed at Paris Charles de Gaulle Airport. It

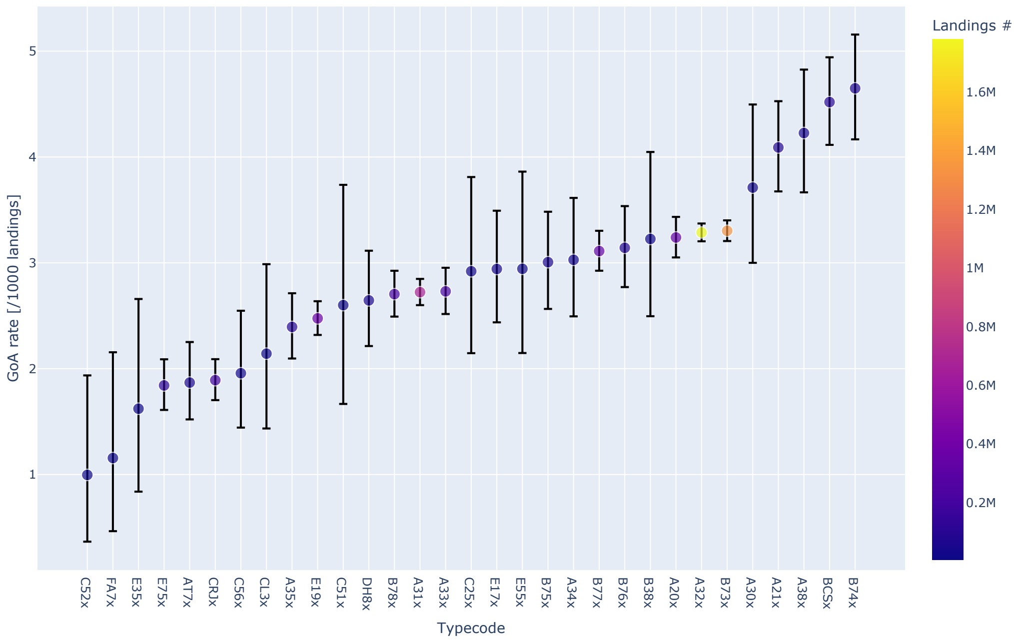


Figure 5. Observed GoA rate per aircraft type and the 95% CI.

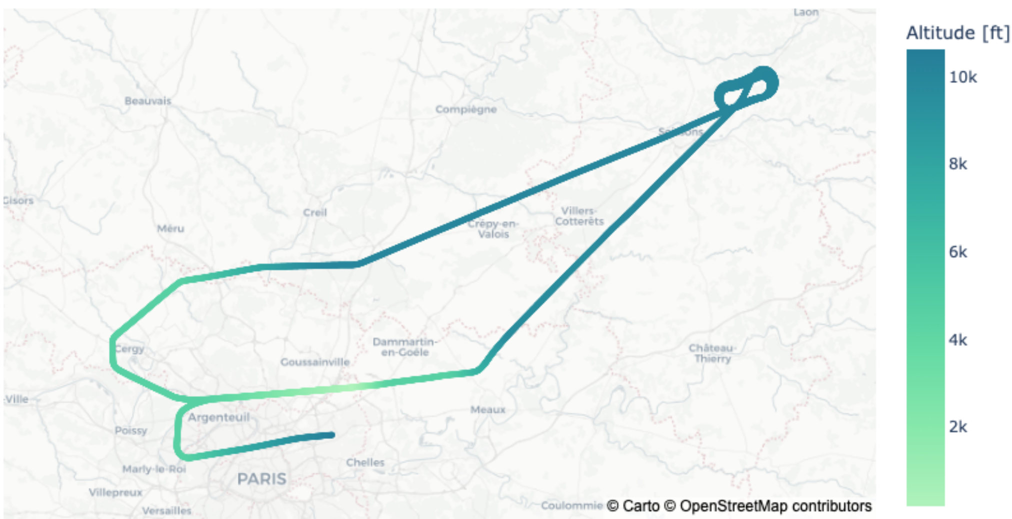


Figure 6. Trajectory of the longest observed GoA in the data set used (Distance: 376 NM, Duration: 2 h 05 min). It is flown by an ATR-72 landing at Paris Charles de Gaulle Airport.

lasted for more than 2 hours and covered a distance of 376 NM, as illustrated in Figure 6.

GoA fuel consumption. Figure 7 contains a box plot showing the distribution of the fuel consumption of the 2,417 GoA flown by aircraft of type Airbus A320 contained in the data set used in this study. These A320-related GoA are analyzed on a per airport-basis. As such, the fuel consumption of an Airbus A320 during a GoA typically ranges between 300 and 600 kg, depending on the airport and on the length/duration of the GoA.

Table 3. GoA distance flown and duration statistics per airport. Q_1, Q_2 and Q_3 refer to the first, the second, and the third quartile, respectively. The table is sorted by ascending median GoA duration.

Airport	GoA Distance (NM)				GoA Duration (min)			
	Q_1	Q_2	Q_3	Max	Q_1	Q_2	Q_3	Max
EGSS	33.1	36.6	43.2	151.6	10.5	11.5	13.9	44.2
EKCH	33.2	36.9	44.7	253.2	10.6	11.7	14.1	68.6
EHAM	31.8	36.3	45.6	137.3	10.5	11.9	15.3	37.0
EGCC	33.1	37.8	49.5	215.3	10.6	12.0	15.5	59.9
LIRF	33.5	39.3	51.6	243.4	10.5	12.0	15.8	63.3
EDDM	36.9	42.2	49.8	184.2	11.1	12.5	15.0	58.7
ESSA	36.9	40.2	47.4	82.5	11.3	12.5	14.8	24.2
LOWW	35.8	41.2	51.4	90.5	11.1	12.7	15.5	27.6
EGLL	38.1	41.7	47.7	184.0	12.1	13.3	15.5	52.6
LSZH	39.4	44.1	54.6	294.7	12.2	13.5	17.0	92.8
EPWA	38.8	43.6	55.0	145.4	12.1	13.6	17.1	39.0
LIMC	38.1	44.5	62.8	336.8	11.7	13.7	18.8	94.0
EDDB	39.8	44.9	53.9	204.3	12.4	13.8	16.5	66.3
LFPO	38.8	44.7	57.4	153.5	11.9	13.8	17.6	39.4
EIDW	41.8	46.9	57.0	173.4	12.8	14.4	17.7	54.4
LTFJ	42.5	48.6	61.8	179.2	12.6	14.5	18.2	45.7
LFPG	44.8	49.2	58.2	376.1	13.5	14.8	17.6	124.8
EDDF	47.5	52.5	61.4	158.2	14.2	15.6	18.3	43.3
LSGG	45.5	52.1	60.9	122.2	14.5	16.2	18.5	30.5
LEMD	47.4	57.3	77.3	160.5	14.1	16.4	21.0	41.6

3.2 GoA impact on the arrival traffic

In Figure 8, the impact of GoA on the arriving traffic of an airport is quantified by comparing the ASMA timings before and after GoA events. We can observe considerable differences between when a GoA is performed and the matched control groups, where no GoAs were executed. Indeed, the red curve (with GoA) is systematically different from the blue curves (control groups). It is noticeable that most airports evaluated in this study demonstrate a similar trend, with the *additional ASMA time* reaching a peak value within the 5-25 minute period that follows a GoA occurrence. For instance, at airports such as Milan Malpensa and Dublin, the GoAID peaks at approximately 100 seconds. This indicates that, on average, landings occurring between 10 and 20 minutes after a GoA spend an additional 100 seconds in the ASMA cylinder compared to those before the GoA. Conversely, at some airports, the GoAID is consistently lower, remaining below 50 seconds throughout the hour-long observation period. Notably, Madrid Barajas Airport is the least affected, with a maximum GoAID of 21 seconds. Furthermore, it is noticeable that the *recovery speed*, which specifies the time until the GoAID returns to pre-GoA levels (i.e., a value of 0) after a GoA occurrence, varies among the airports. At some airports, a recovery occurs within approximately 30 minutes, while at others, the GoAID does not completely return to zero within the hour under consideration after a GoA.

4. Discussion

This study examined GoA rates at 20 large European airports on the basis of OSN trajectory data. The GoA rates shown in Section 3.1 exhibit large variations with respect to the airports, aircraft types, and market segments investigated. Specific airport examples, such as Istanbul's Sabiha Gökçen Air-

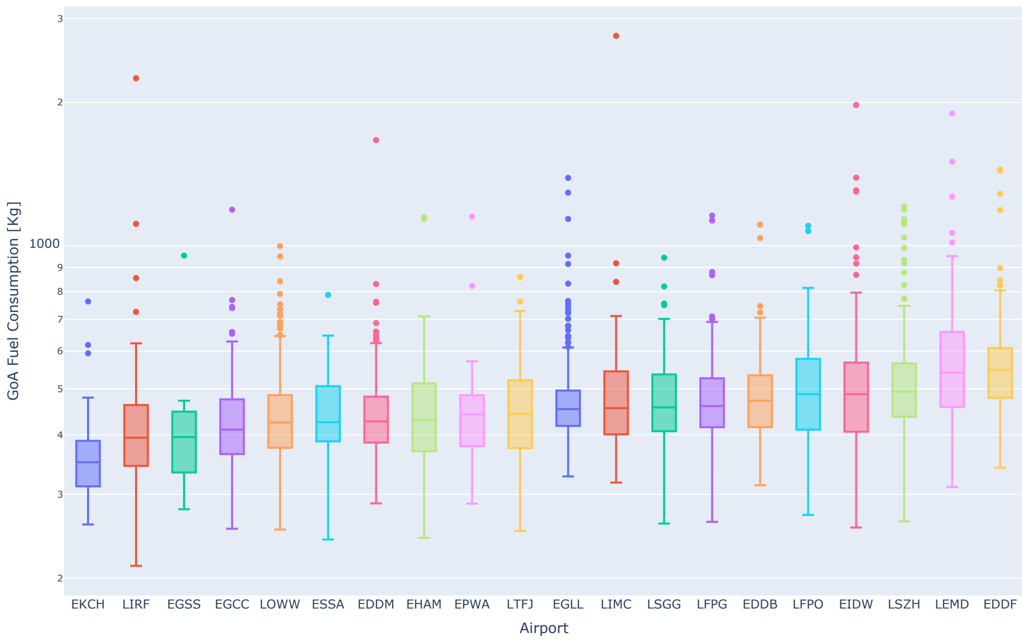


Figure 7. Box plot showing the fuel consumption of Airbus A320s in kilograms during the GoA phase, i.e., from GoA initiation until touchdown, for different airports. The y-axis is logarithmic.

port, London Heathrow, and Paris Charles de Gaulle, were identified as the airports with the highest GoA rates, highlighting the role of operational procedures and regulatory implementations, e.g., Simultaneous Independent Parallel Approaches performed at Istanbul's Sabiha Gökçen Airport, Time Based Separation at London Heathrow, or reduced separation minima on final approach at Paris Charles de Gaulle, which could be further analysed for their impact on GoA rates. Moreover, the correlation of GoA rates with aircraft types was explored. Factors such as in-homogeneous approach speeds, climb rates, energy management, and safety procedures for varying aircraft types, could be possible causes of the observed GoA rate variations. Finally, factors such as operational protocols, economic pressure, and scheduling flexibility could contribute to variations in GoA rates across different market segments. For instance, mainline and cargo carriers, operating larger aircraft, might have higher GoA rates due to stricter safety standards. It can thus be stated that the interplay of all these factors makes the causality analysis for GoA extremely complex.

The GoA execution time and distance across different airports were analyzed. Factors such as airport layout, ATC efficiency, surrounding terrain, prevailing weather conditions, operational procedures, and local regulations could possibly influence GoA execution times, as exemplified by the comparison between Madrid Barajas Airport and London Stansted Airport. Longer GoA execution times and distances could have multiple impacts, including increased fuel consumption as shown for example for aircraft of type Airbus A320 in Section 3.1, emissions, noise pollution, operational delays, ATC workload, passenger inconvenience, safety risks, and financial costs to airlines. These findings highlight the importance of understanding and mitigating GoA impacts to enhance airport operations and aviation sustainability.

The observed increase in ASMA timings following GoA occurrences indicates the necessity for additional time to safely sequence incoming traffic. The observed increase in ASMA timings could stem from various factors, such as the need for expanded spacing, increased ATC workload, and the re-sequencing of arriving flights. Subsequently, these enhanced requirements clearly reflect the

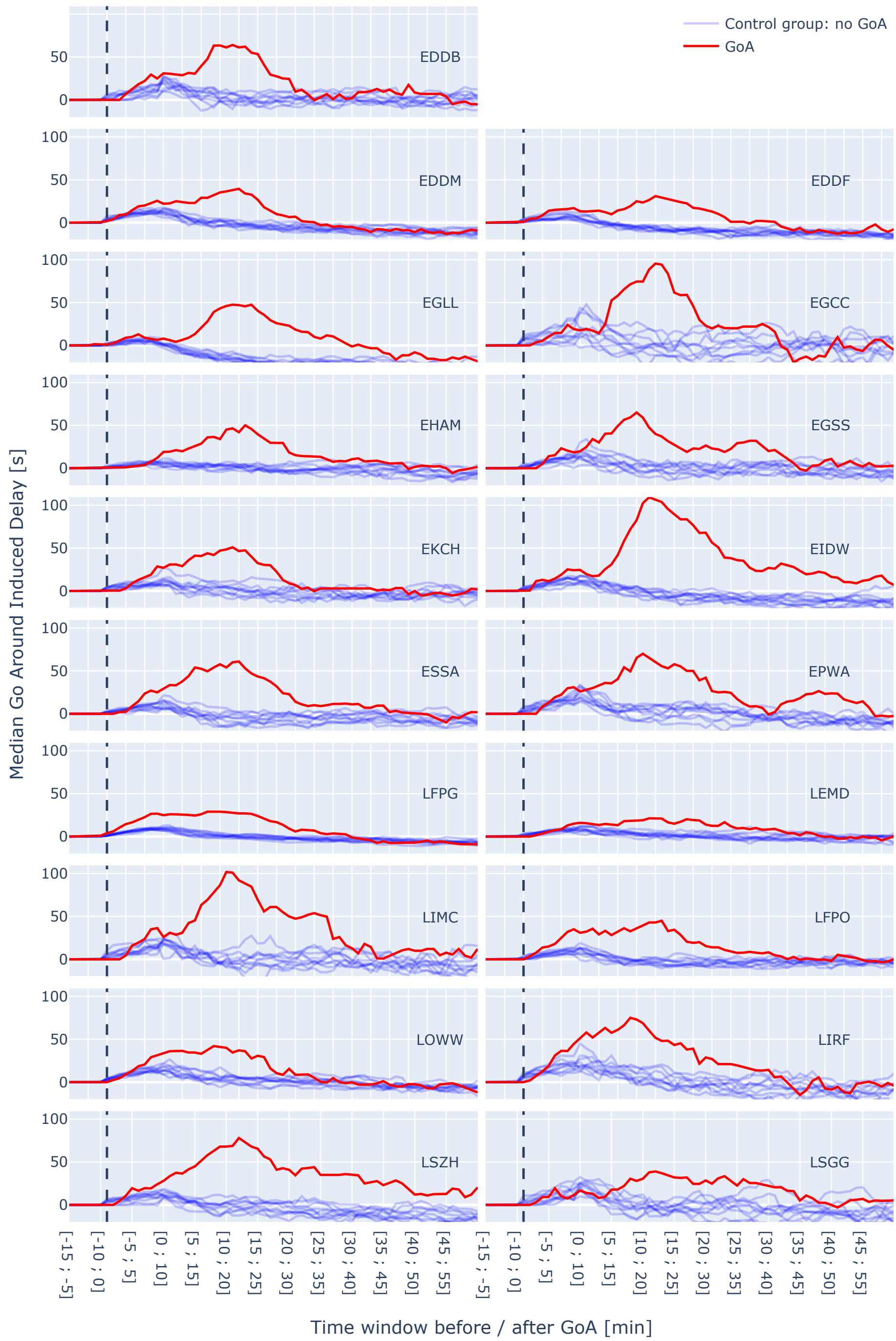


Figure 8. This graph displays the median GoAID times in red, measured in seconds. These times are calculated by comparing a 20-minute window before a GoA event with various 10-minute intervals before and after the GoA. The blue translucent lines represent data from ten control groups per airport, where no GoA occurred, using the same time analysis method. Dashed vertical lines mark the separation between pre- and post-GoA time periods.

operational challenges faced in managing such events, suggesting the necessity for strategies to augment arrival sequencing productivity post GoA occurrences. Future research could delve into the exact reasons for ASMA time variations among different airports. An in-depth exploration of relevant variables, such as runway configuration, air traffic density, and the types of involved aircraft may offer valuable insights.

This study has a number of limitations. The method used in this study to detect GoA based on trajectories of landing aircraft is not perfect. On the one hand, the method cannot detect GoA of flights that diverted to another airport for the final landing. On the other hand, flights that do not align long enough with the extended runway axis may not be detected as GoA. Furthermore, this study is based on a data set, which includes trajectories observed in the period from January 2019 to July 2023. Because this data set contains the period in which international air traffic was affected by the COVID19 pandemic, it must be assumed that the results of this study are influenced by these traffic fluctuations.

5. Conclusion and Outlook

This study investigated the GoA rates at 20 large European airports based on OSN-sourced aircraft trajectory data. For this purpose, a data set consisting of 6.7 million trajectories of aircraft landing at these airports in the period of January 2019 and July 2023 was compiled. A rule-based algorithm was then used to identify those trajectories in the data set that contained one or more GoAs. A comprehensive examination of the resulting 20,196 trajectories that involve a GoA revealed large differences in terms of GoA rates between different airports, market segments, and aircraft types. Besides, the analysis shed light on the operational challenges posed by GoA execution, resulting in increased fuel consumption. The observation of inflated ASMA timings post-GoA events encapsulates the additional time requisites to ensure safe arrival sequencing, underlining the operational hurdles in managing such unforeseen events within a tightly coordinated arrival sequence.

Our findings highlight the interconnected nature of aviation operations, illustrating how a solitary GoA maneuver extends its influence beyond the individual aircraft, altering the landing sequence of subsequent flights. This understanding becomes essential in the light of recent optimization efforts aimed at enhancing runway capacity and fuel efficiency, such as approaches with steeper glideslopes and reduced separation of aircraft on final approach, especially if this leads to higher GoA rates. The quest for optimizing airport operations while ensuring paramount safety and minimizing environmental footprint necessitates a continued exploration and understanding of GoA dynamics. For this reason, several extensions to this research are possible, such as quantifying the expected total delay one single GoA adds to an airport system. Subsequently, the insights from this study pave the way for informed decision-making and strategic planning towards achieving these overarching goals in the aviation sector.

Author contributions

- Benoit Figuet: Conceptualization, Data Curation, Methodology, Software, Writing – Original Draft, Writing – Review & Editing
- Rainer Koelle: Conceptualization, Writing – Review & Editing
- Esther Calvo Fernández: Data Curation, Writing – Original Draft, Writing – Review & Editing
- Manuel Waltert: Conceptualization, Writing – Original Draft, Writing – Review & Editing

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Reproducibility statement

All the relevant code for the reproduction of the results is available on a public Git repository: https://github.com/figuetbe/OSN23-GoA

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